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Dmytro Ivanko

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Thesis for the degree of
Philosophiae Doctor
Faculty of Engineering
Department of Energy and Process Engineering

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Preface

The studies presented in this thesis were performed within the framework of the "Energy for domestic hot water in the Norwegian low emission society" project. This project was carried out in cooperation with the Norwegian University of Science and Technology (NTNU) and the research organization SINTEF Community. The project is a part of the ENERGIX-programme of the Research Council of Norway. The doctoral work was conducted under the supervision of Professor Natasa Nord at the Department of Energy and Process Engineering of NTNU, and co-supervision of senior research scientists Igor Sartori and Thale Sofie Wester Plesser at SINTEF Community.

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First of all, I wish to express my deepest gratitude to my supervisor Professor Natasa Nord for the tremendous support and guidance during my PhD research. I admire her in-depth knowledge, responsible attitude to PhD supervision, and huge contribution to this work. Professor Natasa Nord not only dedicated herself to this project, but also encourage me to develop myself as a researcher and professional. Without her help and suggestions, the goal of this PhD project would not have been realized.

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I am incredibly grateful to my close friends from Norway and Ukraine. I wish to express my sincere appreciation to Vladimir Nakhodov and Carlos Pfeiffer for giving me advice when I needed them, for being my friends and role models. Thanks to Denis Mishchenko and Oleg Lutskov, who shared with me the most relaxed moment of my life.

I dedicated this work to my parents, Elena and Oleg. In addition, I want to express my appreciation to my sister Katya, her husband Andrei, and nephews Vlad and Nikita. I am very lucky to have such a wonderful, caring, and loving family.

Abstract

Domestic hot water (DHW) systems are an integral component of buildings and a substantial consumer of energy. Due to the introduction of highly insulated structures, the share of DHW heat use in the total energy balance of buildings is continuously increasing. In modern passive houses, DHW heat use already exceeds the energy need for space heating. Despite this fact, the application of sustainable and energy efficient solutions in DHW systems is not widespread in Norway. The significant opportunities for energy savings have yet to be realized. Therefore, improving energy efficiency in DHW systems offers substantial potential for further energy savings in buildings in Norway.

Utilization of demand side management, better design and sizing, progressive tariffs, low-temperature heating systems, wastewater technologies, combined DHW systems based on traditional and renewable energy sources, and other sustainable technologies and management solutions in DHW systems are essential for achieving energy efficiency in buildings. The proper implementation of these solutions requires the use of advanced data analysis, representative profiles, and accurate predictive models of DHW heat use. Nevertheless, the regulations applied for DHW heat use analysis and modeling, as well as knowledge about actual DHW heat use in buildings in Norway, contain many gaps. This PhD work aimed to improve the methods of DHW heat use analysis and achieve a better understanding of the DHW heat use in buildings in Norway.

The thesis starts with the consideration of the problems associated with the collection and preprocessing of the DHW heat use data. Firstly, the attention in this thesis was paid to the issue of restoring information about the DHW heat use in conditions when only the total heat use in buildings is measured. Further, the selection of influencing variables and prediction modeling for DHW heat use were investigated. Finally, the methods for development and analysis of representative DHW heat use profiles for residential and non-residential buildings were presented. At the end of the thesis, the work addressed the problems of total heating and DHW heat use planning and profiles analyses for buildings in Norway in normal conditions and during the COVID-lockdown.

In this thesis, the study of DHW heat use was carried out based on data measured in hotels, nursing homes, schools, and apartment blocks. The periods of data collection varied for different buildings. In most cases, the hourly values over 1-3 years were received. However, for the particular buildings, only the monthly DHW heat use and 2-second measurements for several months were collected. Therefore, depending on the data

availability, different data processing techniques were used to analyze DHW heat use. The data handling and modeling in the presented work were performed with the Python software tools.

The obtained from different sources data revealed that imperfection of measurement systems in buildings was a serious obstacle for DHW heat use analysis. Unfortunately, in many buildings in Norway, the heat meters measure the total heat use only, typically not divided into space heating (SH) and DHW. Therefore, the method for splitting the hourly total heat use into SH and DHW heat use was proposed. The method was based on the energy signature curve and the singular spectrum analysis. The results showed that the application of this method allowed us to extract useful information about hourly DHW heat use.

Further, the PhD thesis addressed the DHW heat use prediction modeling in two widespread situations. The first situation considers the prediction based only on historical data of DHW heat use. In the second situation, additional variables that affect DHW heat use were selected and applied for the modeling. These variables were identified by using the Wrapper approach. The most accurate model for DHW heat use was selected from different time series and machine learning techniques. For a hotel building, the Prophet model performed best for accurate prediction in both situations.

The comparison of the actual DHW heat use in building with existing national and international standards showed that the standards commonly used in Norway are not accurate enough and cannot correctly express the daily variation of DHW heat use. Application of these profiles in building simulation tools may lead to significant overestimation of the heat use.

To improve the existing approaches for profiles development, the methods that allowed us to build unified profiles for the months and days of the week with similar characteristics of the DHW heat use were recommended. The profiles based on measurements for different categories of the building were proposed. After, the method for statistical grouping of the DHW hourly heat use was applied to recognize the timing of the peak, average, and low heat use in the considered buildings.

The data from the educational institutions in Norway were used for the analysis of the total heat use in normal conditions and during the COVID-lockdown. The investigation found that the shape of the heat use profiles on weekdays before and during the COVID-lockdown remains almost unchanged, although the occupancy was largely reduced. This fact showed that some buildings during the COVID-lockdown were using energy inefficiently. Moreover, the month after the reopening of the buildings was characterized by a remarkable increase in heat use, regardless of the warmer weather conditions. For heat use planning in educational institutions, the following scenarios were developed: operation according to a normal year setting; reducing the heating to the level of the night heat use; and using settings that were applied during the lockdown. The study showed that applying the proper setting of the heating system during a pandemic may help us to reduce energy use in buildings.

This thesis proposed methods for DHW heat use analysis, predictive models, and profiles prediction to provide the basis for further implementation of energy saving measures and improving the energy efficiency of DHW systems in Norway.

Sammendrag

Varmtvannssystemer er en integrert komponent i bygninger og en betydelig forbruker av energi. På grunn av strengere byggtekniske krav som medfører sterkt isolerte konstruksjoner, øker andelen varmtvannsbruk i det totale energiforbruket til bygninger kontinuerlig. I moderne passivhus overstiger bruk av varmtvann allerede energibehovet for romoppvarming. Til tross for dette er anvendelsen av bærekraftige og energieffektive løsninger i varmtvannssystemer ikke utbredt i Norge. De betydelige mulighetene for energibesparelser har ennå ikke blitt realisert. Forbedring av energieffektivitet i varmtvannssystemer gir derfor et betydelig potensiale for ytterligere energibesparelser i bygninger i Norge.

Utnyttelse av ulike teknologier som såkalt behov-utnyttelse (demand response) i bygninger, bedre design og dimensjonering, progressive tariffer, lavtemperatursystemer, spillvarme, kombinerte varmtvannssystemer basert på tradisjonelle og fornybare energikilder, og andre bærekraftige teknologier samt med styringsløsninger i varmtvannssystemer er avgjørende for å oppnå energieffektivitet i bygninger. Riktig implementering av disse løsningene krever bruk av avansert dataanalyse, representative profiler og nøyaktige prediktive modeller for varmtvannsbruk. Likevel er det fortsatt nødvendig å forbedre regelverket som benyttes som underlag for analyser og modellering av varmtvannsbruk, samt kunnskap om faktisk varmtvannsbruk i bygninger i Norge. Dette doktorgradsarbeidet hadde som mål å forbedre metodene for varmtvannsanalyse og oppnå en bedre forståelse av varmtvannsbruken i bygninger i Norge.

Oppgaven starter med å vurdere problemene knyttet til innsamling og forbehandling av varmtvannsforbruksdataene. Deretter ble spesiell oppmerksomhet gitt til spørsmålet om å hente igjen informasjon om varmtvannsbruk under forhold der kun det totale varmeforbruket i bygninger måles. Videre ble det valgt ut påvirkningsvariabler og prediksjonsmodellering for varmtvannsbruk ble undersøkt. Følgelig ble metodene for utvikling og analyse av representative varmtvannsforbruksprofiler for bolig og andre bygningstyper presentert. Til slutt tok arbeidet for seg problemene med total oppvarming og planlegging av varmtvannsbruk, og profilanalyser for bygninger i Norge under vanlige forhold og under COVID-nedstengning.

I denne oppgaven ble studien av varmtvannsforbruk basert på måledata fra hotell, sykehjem, skoler og boligblokker. Perioden for datainnsamling varierte for de forskjellige bygningene. I de fleste tilfellene ble data over 1-3 år mottatt. For de utvalgte bygningene ble

det imidlertid bare samlet inn månedlige varmtvannsforbruk og 2-sekunders målinger for flere måneder. Avhengig av datatilgjengelighet, ble de forskjellige databehandlingsteknikkene brukt til å analysere varmtvannsforbruk. Datahåndteringen og modelleringen i det presenterte arbeidet ble utført med Python sine programvareverktøy.

De innhentede dataene avslørte at ufullkommenhet i målesystemer i bygningene var en alvorlig hindring for varmtvannsanalyse. Dessverre er det slik at i mange bygninger i Norge måler varmemålere bare det totale varmeforbruket, og det er vanligvis ikke delt inn på romoppvarming og varmtvann. Derfor ble det foreslått en metode for oppdeling av det totale timebruken av varme på romoppvarming og varmtvannsforbruk. Metoden var basert på energisignaturkurven og singular spektrumanalyse. Resultatene viste at anvendelsen av denne metoden gjør det mulig å hente ut nyttig informasjon om bruk av varmtvann hver time.

Videre adresserte avhandlingen modellering av forutsigelse av varmtvannsforbruk i to utbredte typer situasjoner. Den første situasjonen er prediksjonen kun basert på historiske data om varmtvannsbruk. I den andre situasjonen ble flere variabler som påvirker varmtvannsbruk brukt og valgt for modelleringen. Disse variablene ble identifisert ved hjelp av Wrapper-tilnærmingen. Den mest nøyaktige modellen for varmtvannsbruk ble valgt fra forskjellige tidsserier og maskinlæringsmetoder. For en hotellbygning fungerte Profetmodellen best i begge situasjoner.

Sammenligningen av faktisk varmeforbruk for varmtvann i bygging med eksisterende nasjonale og internasjonale standarder viste at standardene som ofte brukes i Norge ikke er nøyaktige nok og ikke kan uttrykke den daglige variasjonen av varmtvannsbruk. Anvendelse av disse profilene i bygningssimuleringsverktøyet kan føre til betydelig overvurdering av varmebruk til varmtvannssystemer.

For å forbedre eksisterende metoder for profilutvikling, ble det anbefalt å bruke metodene som tillot oss å utvikle lignende profiler for månedene og ukedagene med lignende egenskaper ved varmtvannsforbruk. Profilene basert på målinger for forskjellige kategorier av bygningen ble foreslått. Deretter ble metoden for statistisk gruppering av varmtvannsforbruk for hver time brukt for å gjenkjenne tidspunktet for topp-, gjennomsnitts- og lavvarebruk i de aktuelle bygningene.

Data fra utdanningsinstitusjoner i Norge ble brukt til analysen av den totale varmebruken under normale forhold og under COVID-nedstengning. Undersøkelsen fant at formen på varmebrukprofilene på ukedager før og etter COVID-nedstengning forble nesten uforandret, til tross for at belegget ble svært redusert. I tillegg var det slik at måneden etter gjenåpning av bygningene var karakterisert av en formidabel økning av varmebruk, uavhengig av værforholdene. For planlegging av varmebruk i utdanningsinstitusjonene, ble følgende scenario utviklet: styring i tråd med et normalt år, redusere varmen til nivå for nattbruk, bruk av innstillingene som ble brukt under nedstengningen. Studien viste at anvendelse av rett innstilling på varmesystemet under en pandemi kan hjelpe oss å redusere energibruk i bygninger.

Denne oppgaven foreslo metoder for analyse av varmtvannsforbruk, utvikling av prediktive modeller samt med profileringsprognoser for å gi grunnlag for videre implementering av energisparetiltak og forbedring av energieffektiviteten til varmtvannsanlegg i Norge.

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Abbreviations

ANN	– artificial neural network
ARIMA	– autoregressive integrated moving average
ARMA	– autoregressive moving average
ASHRAE	– American Society of Heating, Refrigeration and Air Conditioning Engineers
CPT	– change point temperature
DHW	– domestic hot water
EU	– European Union
EPBD	– energy performance of buildings directive
ESC	– energy signature curve
ES	– exponential smoothing
GMDH	– group method of data handling
HSM-ES	– hybrid summer-signature method
MSE	– mean squared error
nZEB	– nearly zero energy buildings
OECD	– Organization for Economic Cooperation and Development
PLSR	– partial least squares regression
RQ	– research question
R2	– coefficient of determination
SSA	– singular spectrum analysis
SH	– space heating
SHEU	– survey of household energy use
SVD	– singular-value decomposition
SVR	– support vector regression
TUS	– time-of-use survey
TD	– temperature-dependent
TI	– temperature-independent

List of symbols and indexes

This section expounds the meaning of the symbols used in PhD thesis. The symbols are arranged in the order of their appearance in the text of the work.

List of symbols in Chapter 3. Methods for splitting measurements of the total heat demand in a hotel into domestic hot water and space heating heat use

$f(x)$ $(-)$	– is a piecewise regression model for the energy signature curve
x (°C)	– is an independent variable in a piecewise regression, which is the outdoor temperature for the considered case
β_i $(-)$	– the i^{th} coefficient of the piecewise model
ε $(-)$	– residual error
E_{SH} $(-)$	– SH heat use model
E_{DHW} $(-)$	– the model of the DHW heat use
E_{TH} $(-)$	– the measured total heat use
E_{Loss} $(-)$	– the heat losses in the DHW system
E_{TH} $(-)$	– the time series of the total hourly heat use in the building
E_i $(-)$	– the heat use in i^{th} hour
N $(-)$	– number of the elements in the data sample
L $(-)$	– the window length
$\tilde{e}_n$ $(-)$	– elementary time series components
$\tilde{e}_i$ $(-)$	– ith elementary time series component
$\sum \tilde{e}_k$ $(-)$	– sum of the components selected from $\tilde{e}_i$ that related to space heating
E'_{SH} $(-)$	– SSA model of space heating heat use
E'_{DHW} $(-)$	– SSA model of domestic hot water heat use

List of symbols in Chapter 4. Methods for DHW heat use prediction modeling in buildings

$g(t)$ $(-)$ – is a trend of the Prophet model for non-periodic changes

$s(t)$ $(-)$ – is a seasonal (periodical) component of the Prophet model

$h(t)$ $(-)$ – is a component of the Prophet model that takes into account the effects of holidays and other untypical days with irregular schedules of DHW heat use

Gst_{art} $(-)$ – artificial variable that reflects the hourly influence of the guests presence on DHW heat use

Cgp_i $(-)$ – the coefficients for the guest DHW use intensity for ith-hour on the given day

$Cgp_{Lag1.i}$ $(-)$ – the coefficients for the guest DHW use intensity for ith-hour on one day before

Gst $(-)$ – number of guests on a given day

Gst_{Lag1} $(-)$ – number of guests on the day before

List of symbols in Chapter 5. Methods of development and analysis of DHW heat use profiles

$g(t)$ $(-)$ – is a trend of the Prophet model for non-periodic changes

T_{cal} $(-)$ – calculated t-test statistical value

T_{cr} $(-)$ – critical value t-test statistical value

$\bar{E}_{prof1}$ (kW) – mean values of the DHW heat use in the first considered data sample

$\bar{E}_{prof2}$ (kW) – mean values of the DHW heat use in the second considered data sample

S_{prof1} (kW) – standard deviations of the DHW heat use profiles in the first considered data sample

S_{prof2} (kW) – standard deviations of the DHW heat use profiles in the second considered data sample

n_{prof1} $(-)$ – number of elements in the first in the first considered data sample

n_{prof2} $(-)$ – number of elements in the first in the second considered data sample

$E_{profi.j}$ $(-)$ – DHW heat use in j-th element in *i*-th data sample

i $(-)$ – number of data sample

$j\ (-)$	– number of element in the data sample
$f_{cal}\ (-)$	– calculated value of Fisher's criterion
$f_{cr}\ (-)$	– critical value of Fisher's criterion
$n_{i.j}$ (%)	– number of matches, when the DHW profiles of i-th and j-th days were similar
$N_{i.j}\ (-)$	– number of the weeks, when statistical tests showed that the i-th and j-th days were similar
$N_{total}\ (-)$	– number of the weeks in the statistical data sample of DHW heat use
$E\ (-)$	– the sorted sample of DHW heat use, where $E_{i+1} > E_i$, i is the number of element in sample E
$R_1\ (-)$	– the first statistical subsample in the statistical grouping of the hourly DHW heat use method
$R_2\ (-)$	– the second statistical subsample in the statistical grouping of the hourly DHW heat use method
$\bar{E}_{group.1}\ (kW)$	– mean values of the DHW heat use in the first group
$\bar{E}_{group.K-1}\ (kW)$	– mean values of the DHW heat use in the next to the last group
$M_{group.1}\ (-)$	– numbers of the elements in the first group
$M_{group.K-1}\ (-)$	– numbers of the elements in the next to the last group
$S_{group.1}\ (-)$	– standard deviations in the first group
$S_{group.K-1}\ (-)$	– standard deviations in the next to the last group
$T_{cr.1}\ (-)$	– critical values of the t-criteria for the first group
$T_{cr.K-1}\ (-)$	– critical values of the t-criteria for the the next to the last group
$E_{min}\ (kW)$	– critical border that separate the average and peak DHW heat use
$E_{max}\ (kW)$	– critical border that separate the minimum and average DHW heat use

List of symbols in Chapter 6. Results and discussions

$Eon\ (kW)$	– energy use for other needs
$Rm\ (-)$	– number of booked rooms in a hotel
$T\ (°C)$	– outdoor air temperature
Rh (%)	– relative humidity
$Ff\ (m/s)$	– mean wind speed
$Pa\ (Pa)$	– atmospheric pressure
$DoW\ (-)$	– the day of the week
$Mth\ (-)$	– month

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1. Introduction

1.1. Motivation

Energy efficiency and decarbonization are essential considerations for the functioning and development of the energy industry in European countries. Among all the sectors, the building stock is one of the most energy-intensive in the European Union (EU). The Energy Performance of Buildings Directive (EPBD) estimates the share of energy use in building as 40% of the total energy use in the EU [1]. Energy saving in buildings is crucial from both an economic and environmental perspective [2]. For this reason, the European Commission (EC) develop a set of long-term and short-term goals for increasing energy efficiency in buildings [3]. For example, the Energy roadmap 2050 [4] set the target for 80–95% CO_2 emission reduction by 2050, when compared to the 1990 level. In order to achieve this ambitious goal, all technical systems in buildings must be designed and operated in such a way as to ensure efficient energy use.

Out of all the technical systems in buildings in Europe, space heating (SH) and domestic hot water (DHW) are the most significant consumers of energy [5]. Until recently, in European countries, including Norway, a lot of effort has been put into the investigation of the SH systems performance [6]. Meanwhile, the DHW heat use was considered as a small part of the energy needs required for heating. Therefore, DHW heat use has obtained little focus, especially in countries with a cold climate [7]. Currently, the situation is changing. With the implementation of highly insulated structures, the SH heat use in buildings is continuously decreasing. At the same time, the reduction of heat use in DHW systems remains insignificant [8]. Currently, the share of the DHW energy is approximately 20% in regular apartment buildings [7] and reaches 50% in passive houses and well-insulated buildings [9]. The projections of energy demand for buildings show that DHW heat use tends to increase in the nearest future [10]. For this reason, achieving more efficient DHW heat use is a critical issue for further energy saving in buildings.

DHW systems are an important part of buildings technical systems in Norway, which ensure a high level of hygiene and living conditions. A comprehensive comparison of DHW heat use in buildings in Scandinavian countries is performed in the nineties [11]. Scandinavian countries share a similar living standard, comparable patterns of household formation, and a similar climate. Nevertheless, the research study on electricity use in

Scandinavian households concludes that the national average electricity use per capita for the DHW heating in Norway has almost not changed for 15 years, and remains high when compared with other European countries [11]. More recent research confirms this statement, and it shows that the average individual DHW use reaches 40 L/person/day in Norway, while in Denmark it is 20 L/person/day [12]. Currently, sustainable and energy efficient solutions for DHW systems in Norway are not fully implemented. In this regard, DHW systems in Norway have a huge potential for improving energy performance.

Operation of DHW systems is a complex and a multidisciplinary issue. DHW heat use in buildings is strongly affected by technical, economic, environmental, health, and comfort aspects. These conditions lead to various possibilities for energy saving in DHW systems, as shown in Fig. 1.

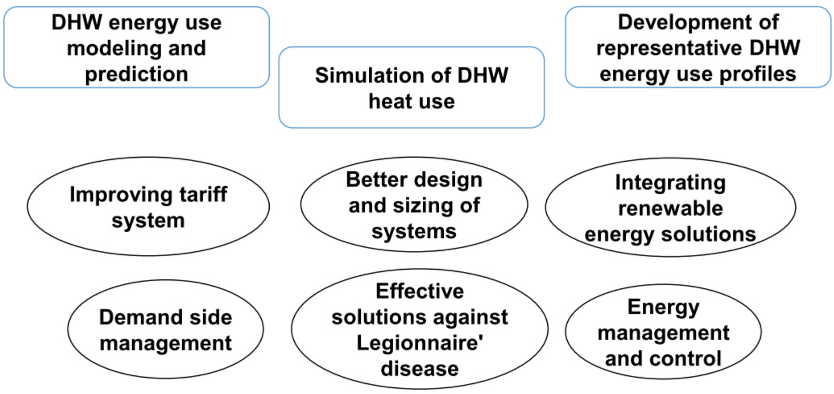

Fig. 1 Data analysis as a tool for improving energy efficiency

The proper implementation of energy saving solutions for DHW systems, as shown in Fig. 1, requires the use of data-driven analysis, simulation tools, accurate predictive modeling, and representative profiles.

The issue of DHW heat use analysis in buildings is investigated by many leading researchers in Norway and abroad [7]. Due to the specific technical characteristic of the buildings, their location and differences in user behavior, as well as the quality of available data, currently, there is no unique method of performing data-driven analysis of the DHW heat use.

Practice shows that the knowledge about DHW heat use in residential and non-residential buildings in Norway is currently incomplete [13]. The investigations of DHW heat use performed in other countries are not representative for Norwegian conditions [14]. The methods and profiles for DHW heat use analysis presented in national and international standards cannot correctly reflect the actual DHW heat use [15]. Thus, the development of methods for DHW heat use analysis and investigation on the DHW heat use for different types of buildings in Norway are required.

1.2. Thesis objective, research questions, and tasks

The main objective of the PhD research is to improve the methods for data-driven analyses of DHW heat use and to achieve a deeper understanding of DHW heat use in buildings in Norway. Primarily, the research is intended to develop accurate prediction models and representative profiles for DHW heat use in Norway, which may be used for increasing energy efficiency in DHW systems.

The study was carried out based on statistical data obtained from schools, hotels, nursing homes, and apartment buildings. These buildings have diverse operating regimes and technological solutions for DHW systems. Therefore, the methods proposed in the PhD thesis were aimed at being applicable for analysis in various categories of buildings. Finally, the following research questions (RQ) were identified:

RQ 1 : Which data preprocessing techniques should be used before applying data-based analysis?

RQ 2 How can information on the DHW heat use be restored from measurements of the total heat use in buildings?

RQ 3 : What factors affect DHW heat use in buildings and should be taken into account when modeling and developing DHW heat use profiles?

RQ 4 : How to perform accurate prediction of DHW heat use and what models should be used for this purpose?

RQ 5 : How can the methods for developing and analyzing DHW heat use profiles be improved?

RQ 6 : How can the heat use in buildings be modeled for conditions of COVID-lockdown?

In order to answer the research questions and achieve the objective of the PhD research, the following tasks were defined:

- Explore the peculiarities of heat use measurements in Norwegian buildings, the problems of data collection and preprocessing required for further DHW heat use analysis.

- Develop the approach for splitting the measurements of the total heat use in a building into the DHW and the SH heat use. Solving this problem should allow us to gain valuable information about the DHW in buildings where only one heat meter for the total heat use is available.
- Identify variables that have a significant impact on DHW heat use in different types of residential and non-residential buildings in the condition of the north climate and behavioral traditions in Norway.
- Built accurate hourly and daily predictive models of DHW heat use for various sets of influencing variables and conditions of modeling
- Improve methods for the development and analysis of DHW heat use profiles based on statistical methods.
- Create representative profiles of DHW heat use for different types of buildings in Norway and compare them with profiles proposed in standards and other literary sources.

1.3. Thesis organization

According to the research tasks, the thesis was divided into eight main chapters. The chanters have the following content:

- Chapter 2 presents an overview of the implementation of sustainable and energy saving solutions in DHW systems, challenges in DHW heat use data collection and preprocessing, DHW heat use analysis, predictive modeling, and profiles development for residential and non-residential buildings in Norway and abroad. This chapter demonstrates the limitations of existing knowledge about DHW heat use in buildings and motivates further improvements.
- Chapter 3 considers the issues of the Energy Signature Curve (ESC) development and splitting the measurements of the total heat demand in buildings into DHW and SH heat use.
- Chapter 4 presents the methods for DHW heat use prediction modeling in the following situations: Situation 1, only historical data about DHW heat use are known; Situation 2, the additional parameters that could influence DHW heat use are available. Further, in this chapter, the influence of different parameters on DHW heat use was investigated.

- Chapter 5 introduces the methods for development and analysis of DHW heat use profiles. It represents the statistical methods for assessing the similarities of the profiles by days of the week and seasons. Based on this assessment, the unified profiles for days of the week and month with similar parameters of DHW heat use may be identified. Furthermore, the method of a statistical grouping of the DHW hourly heat use for recognizing the timing of the peak, average, and low heat use is shown.
- Chapter 6 contains the results and discussions from the performed studies as a summary of the papers collection. Each paper covers the specific topic and aspects of the DHW heat use analysis.
- Chapter 7 demonstrates the main conclusions of the PhD study.
- Chapter 8 shows the limitations of the research and recommendations for the further work.

The main results of the PhD research were introduced in the papers attached at the end of the thesis. The list of these papers is given below in Section 1.4.

1.4. Publications

The PhD thesis consists of 11 papers: four papers in high-quality journals, six papers in international conference proceedings, and one in the popular science journal. The publications correspond to the research questions addressed in the PhD study and their relation to research questions is given in Table 1.

Table 1 Relationship among research questions and publications

<table>
<tr><th rowspan="2">Publication number</th><th colspan="11">Publication number</th></tr>
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Publishing information and author contribution to the papers are given below.

Paper I

T. Tereshchenko, **D. Ivanko**, N. Nord, I. Sartori, Analysis of energy signatures and planning of heating and domestic hot water energy use in buildings in Norway. *The 13th REHVA World Congress CLIMA 2019, E3S Web of Conferences*, Volume 111, 2019, 06009

Author contribution: The paper was initiated by Tymofii Tereshchenko and me. I contributed to the development of the methodology for the SH and DHW heat use planning, mathematical modeling, testing the research methodology, and writing the original draft. Tymofii Tereshchenko conducted a literature review, data curation, data-driven analysis of heat use, and writing the original draft. Igor Sartori and Professor Natasa Nord provided valuable feedback for improving the research methodology, carried out supervision, revision, and editing of the paper.

Paper II

S.K. Lien, **D. Ivanko**, I. Sartori, Domestic hot water decomposition from measured total heat load in Norwegian buildings, in: *International Conference Organised by IBPSA-Nordic, 13th–14th October 2020, OsloMet. BuildSIM-Nordic 2020*. Selected papers, SINTEF Academic Press, 2020.

Author contribution: The concept of the paper was defined by the joint efforts of all co-authors. I prepared the literature review, data processing and computational modeling, restoring DHW heat use profiles based on considered methods, and wrote a part of the original draft. Synne Krekling Lien carried out data processing and computational modeling, testing the methodology, and writing the original draft. Igor Sartori compared the case study results with reference DHW heat use obtained from different sources. In addition, he conducted supervision, revision, and editing of the paper.

Paper III

D. Ivanko, A.L. Sorensen, N. Nord, Splitting measurements of the total heat demand in a hotel into domestic hot water and space heating heat use. *Energy,* Volume 219, 2021, 119685

Author contribution: The paper was initiated by me. I contributed to methodology development, data processing and computational modeling, testing the research methodology, and writing the original draft. Ase Lekang Sorensen was responsible for data curation, reviewing, and editing of the paper. Professor Natasa Nord held supervision, revision, and editing of the paper.

Paper IV

D. Ivanko, N. Nord, A.L. Sorensen, I. Sartori, T.S. Wester Plesser, H.T. Walnum, Prediction of DHW energy use in a hotel in Norway. *10-th International Conference on Indoor Air Quality, Ventilation and Energy Conservation in Buildings IAQVEC 2019. IOP Conference Series: Materials Science and Engineering.* Volume 609, 2019, 052018

Author contribution: The conceptualization of the paper was done by me. I, as the principal author, developed the methodology for DHW heat use prediction, tested the research methodology based on a case study, wrote the original draft of the paper. The co-authors Ase Lekang Sorensen, Igor Sartori, Thale Sofie Plesser, and Harald Taxt Walnum performed data curation, reviewing and editing of the paper. Professor Natasa formulated the research objectives, conducted supervision, revision, and editing of the paper.

Paper V

D. Ivanko, A.L. Sorensen, N. Nord, Selecting the model and influencing variables for DHW heat use prediction in a hotel in Norway. *Energy and Building,* Volume 228, 2020, 110441

Author contribution: The paper was initiated by me. I contributed to identifying variables that influence DHW heat use, developing prediction models, testing the proposed methods, and writing the original draft. Ase Lekang Sorensen carried out data curation, reviewing and editing of the research paper. Professor Natasa Nord performed the formal analysis for the research methodology and conducted supervision, revision, and editing of the paper.

Paper VI

D. Ivanko, N. Nord, A. Tartaglino, Analysis of DHW energy use profiles for energy simulations in a hotel located in Norway. *REHVA European HVAC Journal*, Volum 56 (4), 2019.

Author contribution: The paper was initiated by me and Professor Natasa Nord. I carried out the development of DHW heat use profiles, simulated DHW heat use, prepared results and conclusions of the investigation, and wrote the original draft. Andrea Tartaglino and Natasa Nord developed the simulation model for the investigation. Professor Natasa Nord conducted supervision, revision, and editing of the paper.

Paper VII

H.T. Walnum, A.L. Sorensen, B. Ludvigsen, **D. Ivanko**, Energy consumption for domestic hot water use in Norwegian hotels and nursing homes. *10-th International Conference on Indoor Air Quality, Ventilation and Energy Conservation in Buildings IAQVEC 2019. IOP Conference Series: Materials Science and Engineering.* Volume 609, 2019, 052020

Author contribution: The conceptualization of this paper was done by the joint efforts of all co-authors. Harald Taxt Walnum, as the principal author, performed data curation and analysis, DHW heat use profiles comparison, and writing the original draft. Dmytro Ivanko, Ase Lekang Sørensen, Bjørn Ludvigsen carried out the formal analysis, revision, and editing of the paper.

Paper VIII

D. Ivanko, H.T. Walnum, N. Nord, Development and analysis of hourly DHW heat use profiles in nursing homes in Norway. *Energy and Building*, Volume 222, 2020, 110070

Author contribution: The paper was initiated by me. I proposed the methodology for DHW heat use profiles development and analysis, contributed to DHW heat use modeling and analysis, tested the proposed methods, and wrote the original draft. Harald Taxt Walnum carried out data curation, reviewing and editing of the paper. Professor Natasa formulated the research objectives, held supervision, revision, and editing of the paper.

Paper IX

D. Ivanko, N. Nord, A.L. Sorensen, T.S. Plesser Wester, H.T. Walnum, I. Sartori, Identifying typical hourly DHW energy use profiles in a hotel in Norway by using statistical methods. *The 13th REHVA World Congress CLIMA 2019, E3S Web of Conferences*, Volume 111, 2019, 04015

Author contribution: The conceptualization of the paper was done by me. I carried out the literature review, developed the methodology, tested the research methodology, and wrote the original draft of the paper. The co-authors Ase Lekang Sorensen, Igor Sartori, Thale Sofie Plesser, and Harald Taxt Walnum conducted data curation, reviewing and editing of the paper. Professor Natasa carried out the formal analysis of the study, supervision, revision, and editing of the paper.

Paper X

D. Ivanko, N Nord, A.L. Sorensen, H.T. Walnum, Analysis of monthly and daily profiles of DHW use in apartment blocks in Norway. *Nordic Symposium on Building Physics in Tallinn, Estonia, NSB 2020 E3S Web of Conferences,* Volume 172, 2020, 12002

Author contribution: The paper was initiated by me. I conducted the literature review, developed and analyzed monthly and daily profiles of DHW use in the apartment block in Norway, and wrote the original draft of the paper. Ase Lekang Sorensen, Harald Taxt Walnum, and Professor Natasa Nord carried out supervision, revision, and editing of the paper.

Paper XI

D. Ivanko, Y. Ding, N. Nord, Analysis of heat use profiles in Norwegian educational institutions in conditions of COVID-lockdown. *Submitted to Journal of Building Engineering (Status 17/2/2021: Minor revision)*

Author contribution: The paper was initiated by me. I proposed methods for scenario-based analysis and planning of heat use in educational institutions for conditions of COVID-lockdown, performed data analysis and computational modeling, and wrote the original draft of the paper. Yiyu Ding conducted data curation and analysis, revision, and editing of the paper. Natasa Nord provided valuable recommendations for improving the research methodology, carried out supervision, revision, and editing for the research paper.

2. Literature Review

This chapter is structured as follows. Section 2.1 presents sustainable and energy efficient solutions for DHW systems and explains the need for data-driven analysis in order to implement them. Section 2.2 considers the issues of DHW data collection and describes preprocessing techniques that were used in PhD investigation. Section 2.3 describes the problem of extracting information about the SH and DHW heat use in buildings where the only one meter for the total heat use is operating. Section 2.4 discusses the influencing variables that existing publications suggest to use to explain the variation of the DHW heat use in buildings. Section 2.5 is dedicated to the problem of DHW heat use prediction. Section 2.6 considers the issue of DHW heat use profiles development and analysis.

It is important to stress that the majority of existing publications are focused mainly on the analysis and modeling of DHW volumetric use rather than heat use. It is well known that these two parameters have a strong positive correlation [7]. In addition, the factors that affect the DHW volumetric use have a similar effect on the DHW heat use. Since not so many publications are dedicated to DHW heat use analysis, both the literature review for DHW volumetric and heat use was included in the literature review.

2.1. Sustainable and energy efficient solutions in DHW systems

The introduction of modern technical energy solutions in DHW systems is essential for energy efficiency in buildings [16]. The requirements related to these solutions are discussed below.

Wastewater technologies are considered as one of the promising solutions for achieving energy saving in DHW systems. These technologies are based on the idea of gaining benefits from the reuse of water. The conceptual designs for DHW heating systems with the application of wastewater technologies are considered in [17]. The research shows that the DHW system control is prioritized to operate with the wastewater technologies and heat pumps. This control should be performed based on DHW predictive models and profiles.

Using solar-assisted DHW water heating systems in buildings becomes popular all over the world [18]. The prediction of DHW heat use is necessary for the optimal operation of these systems [19]. Different types of DHW heating systems are investigated in [20]. This study summarises that DHW energy use may be reduced by using combined techniques based on traditional and renewable energy solutions. However, due to the unstable behavior of renewable energy sources, development of accurate prediction models of DHW heat use is becoming crucial for successful operation of combined DHW heating systems.

Operation of the DHW systems is associated with sanitary and health safety problems. Among them, the appearance of the Legionella bacterium in DHW systems is a severe issue [21]. Legionella bacterium may lead to different forms of pneumonia and even death. The conditions for Legionella spreading are water temperatures from 25°C to 42°C, nutrients, and stagnating water. Therefore, many countries, including Norway, develop regulations to minimize the risk of the Legionella disease appearance. For example, despite energy ineffectiveness, to prevent chances of the bacteria growth, the DHW systems in Norway store and distribute hot water at the temperatures above 60°C. Currently, the different solutions that allow us to use low-temperature DHW systems and at the same time to avoid Legionella risks were developed [22]. Some of these solutions require knowledge of the profiles and timing when DHW water is used.

The economic analysis of DHW pricing is performed in [23]. The study shows that the DHW use positively correlated with income and reacts to the changes in water prices. Therefore, the introduction of better energy or heat tariffs is a way of reducing the DHW use in buildings. However, in order to implement advanced and flexible energy or heat tariffs, in-depth knowledge about profiles and prediction models of DHW use are necessary.

Energy management and control systems are powerful tools for implementing effective heat management activities and strategies in buildings. They enable us to reduce unnecessary heat use, respond correctly to tariff changes, save energy costs, and facilitate the utilization of other technical energy solutions. Data-driven analysis is a key element of these systems [24].

Building simulation software tools are a powerful instrument for estimating energy use in buildings. Most of these software tools such as IDA ICE, EnergyPlus, TRNSYS, TRANSOL, etc. require DHW profiles as the basis for the simulation of DHW systems performance in buildings [7]. For example, it is noted that the variations between the simulated and the real heat use for DHW are caused by inappropriate profiles from standards [25].

The study of Bohm [26] shows that the efficiency of domestic hot water systems should be improved. Heat losses from the hot water tanks and the circulation systems in single-family houses, semi-detached houses, blocks of flats, schools, and institutions are found to be very high, and equals approximately to 65% of DHW energy use. In order to avoid these losses, the proper design, sizing, and operation of DHW systems are required. Practical experience shows that the profiles from standards that are commonly used for heat system design often do not correspond to the real state of the art [27]. These profiles could lead to oversizing of the components for DHW systems and additional financial and energy losses [28]. The development of more accurate profiles will help to improve this situation.

As we can see, the proper functioning of the energy saving solutions in buildings is based on the application of accurate DHW usage profiles and predictive models that are capable to capture the real heat use in buildings. Therefore, it is important to develop the approaches that will help to improve the DHW heat use analysis and modeling for different types of buildings.

2.2. Data collection and preprocessing techniques

Prior to applying certain methods for analyzing the DHW heat use or other related parameters, it is necessary to collect reliable data. The time-frequency of data measurements is an important feature that should be considered. The paper [29] investigates the effect of measurement intervals on the DHW peak flow rate in different Norwegian. Within the analysis, the measured peak flow rate is calculated as a moving average for different time steps. Compared to using an interval of 2 s, averaging the data over 10-second shows underestimation of the peak flow rate by a factor of 0.8-1.0, and 0.67-0.94 for a 30-second interval. The work presented in [30] also determined that the resolution of data has a large influence on the measured and simulated peak flow rates. The authors conclude that hourly data may be used for the DHW heat use analysis. However, for the design of the peak flow rates, it is better to use data collected with a higher frequency.

Although data sampling with high time-frequency resolution may give us valuable information about DHW heat use, hourly measurements of heat use are the most commonly used for buildings in Norway. Hourly time resolution is convenient for storing and analyzing DHW heat use data. Therefore, in this work, the preference was given to hourly data. However, to make a broader study, the investigations based on other data resolutions were also performed.

After the data resolution for analysis was identified, the data samples for all the variables should be time-synchronized and reshaped with the same time resolution. In this work, the Python software tools were used for corresponding data handling.

Practice shows that the data obtained from measurement systems of the buildings or other sources usually cannot be used for the analysis of DHW heat use without preprocessing. Pre-processing covers a number of issues. The outliers, incorrect data, gaps of information may occur in data samples. For example, due to problems with the measurement systems, negative or unrealistically high values of DHW heat use may appear in data samples. In addition, the temporary changes in DHW heat use that do not represent regular DHW system performance may occasionally occur (systems maintenance, repairs, etc.). Throughout the investigation, the data which do not correspond to physical principles and generally accepted norms were removed from consideration. The statistical tests were used to identify and remove these types of data. In detail, these tests are considered in [31].

2.3. Splitting measurements of the total heat demand in buildings into SH and DHW heat use

The European Directive 2018/844 [32] claims that analysis of the energy performance of buildings should be conducted based on calculated or actual energy use. The estimations shall reflect the typical energy use for SH, DHW, and other technical systems in a building [32]. This approach to analysis is important for the development of energy-saving solutions for all the technical components in buildings. The proper implementation of this approach requires that energy meters are installed for the main energy-consuming systems in buildings. As a part of the smart meter promotion strategy, at least 80% of the EU electricity meters should be replaced by smart meters until 2020 [33]. Smart heat meters, on the other hand, are usually not available in buildings [34]. A significant share of buildings uses only one heat meter for the total heat use. In such systems, this single meter cannot measure the SH and DHW heat use separately. SH and DHW systems have different regimes of work and influencing factors on their performance. Accordingly, the analysis of heat use in these two systems should be performed independently [35]. Separate statistical data for the DHW and the SH heat use are essential for improving a number of issues, such as SH and DHW systems sizing, designing of energy management and control systems, as well as improving the existing standards, the prediction models and the energy use profiles. Thus, the separation of the total heat demand into the components associated with the SH and DHW heat use is an important task.

Several research groups investigate the problem of extracting the SH and the DWH heat use from the total heat use measurements [36, 37]. However, due to nontrivially of the problem and different requirements to results set by the researchers, there is no unique method for performing such data analysis. Some of the existing solutions are discussed in the text below.

A method for separating the total heat demand in the building into SH and DHW heat use is presented in [36]. In this research, 10-minute resolution data from a single-family house in Denmark is used. The method assumes that the DHW heat use generates short-lived spikes in the time series. Opposite, the SH heat use changes slowly during the day due to climate and user behavior. For this reason, the authors in [36] propose to estimate the SH heat use by a non-parametric kernel smoother. All the values significantly above the kernel smoother are considered as the DHW heat use spikes. Currently, this method is not yet verified by the SH and the DHW heat use data which are measured separately.

Splitting weekly heat use from one meter into DHW and SH is considered in [37]. The authors in [37] assume that the period when the outdoor temperature is higher than the base temperature [38] is only the DHW heat use period. In this way, they found DHW heat use for several warm weeks during the year. Afterward, the same authors proposed to use the DHW monthly variation factors to extrapolate the DHW heat use from warm months to other months of the year [37]. For dwellings in the United Kingdom, these factors are given in the standard [39]. However, for Norwegian conditions, the factors are not developed.

The research work in [40] shows a method that estimates the hourly SH and the daily DHW heat use profile. The mentioned study uses the hourly values of the total heat demand in the building. The method includes the following steps: 1) the daily total heat use profile for an average summer day is calculated; 2) the non-DHW use is calculated as a minimum of the total heat use profile for an average summer day or average for hours from 0:00–04:00 o'clock; 3) the DHW profiles are calculated by deducting the non-DHW heat use from the value of the heat use at each hour of the day. This study in [40] shows that the above method gives satisfactory results when the DHW use during summer is at least at the same level as the space heating. The method does not consider the DHW heat use in other periods, except for the warm season.

Some authors propose to use the models and profiles of the SH and DHW heat use created based on statistical data from the buildings stock databases [41, 42]. For instance, the Neural Networks model of the SH and DHW heat use in typical Canadian households is considered in [41]. The model uses data from the 1993 Survey of Household Energy Use (SHEU) database, which represents information from the Canadian housing stock. Similar models may serve as a basis for the separation of the SH and DHW heat use in typical buildings. However, their development requires the availability of the appropriate database. Moreover, the accuracy of the splitting for individual buildings will be questionable.

Linear regression models may be used to predict heat demand in buildings, e.g. as done in [43]. Pedersen in [44] and Sørensen et al. in [45] use linear regression models to separate DHW from the total heat delivery. For instance, the linear regression model for the total heat delivery that takes into account the outdoor temperature, hour of the day, weekdays, and holidays is proposed in [45]. When estimating DHW, the outdoor temperature is set to the approximate break-point temperature of the model, resulting in a DHW daily load profile with hourly mean values [45].

The separated SH and DHW heat use profiles are also modeled in [42]. The modeling approach is the coupling of the behavioral, stochastic, and energy balance models. The synthetic load profile captures the typical hourly, daily, and annual characteristics of the DHW heat use. The SH model is a combination of a simplified physical method with a behavioral model for standardized buildings. The approach requires knowledge about the activity categories, such as occupant's presence at home, sleeping, hygiene, and cooking activities. Such modeling approach may give good results, but the data required for new studies on a bigger scale (hotels, nursing homes etc.) requires much effort and usually not feasible.

The literature review shows that the problem of splitting the hourly total heat use into the parts related to the SH and DHW is not yet solved, especially for larger buildings with limited knowledge about the users. Some of the above-mentioned methods allow us to obtain general models of SH and DHW heat use for particular buildings category, but not for an individual building [41]. The other methods solve the considered problem only for several warm months [40]. The number of methods requires extensive knowledge about user behavior, which limits their application [42]. For this reason, further investigations on this topic are necessary.

2.4. Identifying variables affecting the DHW volumetric and heat use

Identifying influencing variables with significant impact on the DHW heat use in the building is an initial step for both prediction modeling and profiles development. There is a number of scientific papers that analyze the influence of different factors on DHW volumetric and heat use, as shown in Table 2.

Most of the articles in Table 2 assume that the number of occupants, seasons, day of the week, and time of the day have a significant influence on the DHW heat use. The information about activities, such as occupant's presence, sleeping, hygiene and cooking, as well as a time when appliances are in use (sinks, showers, baths, clothes washer, and dishwasher) gives a better understanding of the DHW heat use [42]. Opinion on the influence of certain parameters on DHW heat use varies in different studies. For example, in the article [46], the occupant's presence is considered as an essential variable, while research [47] revealed the weak correlation between occupant's presence and DHW use in households. It should be noticed that the factors influencing DHW heat use may vary from one building type to another and may depend on the location of the building. For instance, in the investigation in [48], it is concluded that the influence of seasons, the outdoor temperature, and rainy days on DHW in the dwellings is negligible. However, in the articles [49, 50], the seasons and the outdoor temperature are considered as essential variables and taken into account. Therefore, to determine the variables that affect the DHW heat use in Norway, it is necessary to conduct a study based on reliable statistical methods collected from buildings located in this country.

Table 2 Investigations of variables that have a significant impact on DHW volumetric use and heat use

Influencing variables	Authors
Number of occupants, day of the week	Ferrantelli, Ahmed [51]
Day of the week	de Santiago, Rodriguez-Villalón [48]
Number of rooms in the flat, area of the flat	Chmielewska, Szulgowska-Zgrzywa [52]
The magnitude of the drains, the start times of DHW use, the time between drains	Beeker, Malisani [53]
Activities, number of DHW tap starts, time of tapping, the duration of tapping	Fischer, Wolf [42]
Flow rates, cold and supply temperatures	Verhaert, Bleys [30]
Type of the tap (conventional mixer tap or low flow electronic tap)	Fidar, Memon [54]
Activities, appliances	Good, Zhang [55]
Outdoor temperature, season, number of tenants, type of building (apartment or detached), the location, the household area, month, density of water, specific heat of water, reference temperatures, cold inlet temperature	Gutierrez-Escolar, Castillo-Martinez [49]
Socioeconomic characteristics, activities, appliances, and type of apparatuses that use water	Fan, Liu [56]
Occupant behavior, appliances, demographic conditions, and occupancy rate	Swan, Ugursal [46]
Draw-off temperatures	Barteczko-Hibbert, Gillott [57]
Appliances, flow rates and times of DHW use	Hendron and Burch [58]
The day of the week, time of the day, season, appliances, age of occupants (seniors or not), pay or does not pay for hot water	Lutz, Liu [59]
Family size, season, day of the week, time of the day	Papakostas, Papageorgiou [50]
Occupant behavior, type of building, appliances, type of the tap	Wahlstrom, Nordman, Pettersson [60]
Season, day of the week, time of the day, behavior and individual differences in how people use DHW	Bagge, Lotti [47]

2.5. DHW heat use prediction modeling in buildings

The number of publications dedicated to prediction modeling in DHW systems is considerably small compering to other buildings energy systems [19]. The review of the methods proposed by different researchers for the DHW volumetric and heat use prediction is presented below.

The application of artificial neural networks (ANNs) for DHW modeling in Canadian households is considered in [41]. The DHW heat use as an ANNs model of draw-off temperatures is presented in [57]. The model is tested in three residential DHW systems. The archived ANNs model accuracy is higher than 89% for the trained data. However, the use of the ANN model for new data obtained from other systems shows significant inaccuracy. Creation of easy to use forecasting model of DHW use is considered in [61]. Autoregressive moving average (ARMA) model as a solution to this problem is proposed. The ARMA model takes into consideration the periodicity of the week, the water use of the days before, and random fluctuations of the DHW use. The model based on data from eight apartments in France is examined in [61].

The heat use in a large housing cooperative in Norway is investigated in [45]. In this work, the linear regression model is used for modeling the DHW heat use in apartments.

The survey of DHW use in 626 apartments in Poland is carried out in [52]. The authors create a database of DHW use for residential buildings with different parameters. The configuration of apartments in these buildings is randomly selected by using the bootstrap method. Based on the database, the regression model is constructed. This model considers DHW use as a function of the number of rooms and the floor area [52].

The stochastic analysis of the DHW use for 65 apartments is performed in Hungary [62]. As an input for the stochastic model, the authors use the number of apartments in the building, the duration curve, daily average, the minimum and the maximum values of the DHW use.

The issue of the DHW use forecasting for demand-side management in residential buildings in the UK is reviewed in [63]. Various time series forecasting techniques, such as exponential smoothing, seasonal autoregressive integrated moving average, seasonal decomposition by Loess model and a combination of them, were tested on data from 120 dwellings.

A model for DHW use prediction that consists of 16 equations is proposed in [59]. These equations take into account season, day of the week, and hours with similar DHW use.

To improve the model, the authors propose to consider additional factors to adjust the predicted hot water use. These factors include the availability of dishwashers, cloth washers, age of occupants, and whether the residents should pay for the DHW use or not.

The existing articles are mostly focused on the DHW use in residential buildings. Practice shows that for residential buildings, information about DHW use is more opened and accessible [7]. For this reason, the DHW heat use prediction for non-residential buildings has not received enough attention. Despite this fact, the share of DHW heat use in non-residential buildings is significant. Therefore additional studies for these types of buildings are needed [15].

As we can see from the above considered papers, various methods may be used for the DHW heat use prediction, and there is no best technique for solving this problem. The most accurate model for a specific building or group of buildings should be selected from several modeling techniques. In such a way, the models that consider the characteristics of the buildings, their type, and available data will be taken into account. Unfortunately, such an analysis has not yet been carried out for buildings in Norway. Therefore, it is necessary to perform an investigation and give recommendations for the DHW heat use prediction for Norwegian conditions.

2.6. Existing methods for development and analyses of DHW heat use profiles

DHW heat use profiles are the primary instrument for estimating the DHW heat use in the buildings [7]. Analysis of these profiles shows how the heat use for DHW changes in different time intervals [64]. These profiles allow us to determine the hours of peak energy loads and other energy load characteristics of the building. Depending on available information, the profiles may be obtained from the standards, developed based on measured, or calculated DHW heat use [7].

Practice shows that profiles obtained based on measurements are more reliable and better reflect the actual DHW heat use in the buildings. Therefore, many publications recommend using the measurement data for DHW heat use investigations [7]. For example, weekdays and weekends load profiles for DHW heat use in Norwegian buildings, which use a heat supply from district heating, is investigated in [65]. For calculations, the authors use hourly measurements obtained by regular heat meters. Hourly DHW profiles for five groups of buildings with 1, 3, 10, 31, and 50 residents are developed based on measurement data from Finnish apartments in [66].

If the measured data for the DHW heat use are not available, the calculational approaches for identifying DHW heat use profiles may be used. For instance, the common approach applies the following parameters for DHW heat use calculation: average DHW use in l/(person·day), occupant number, DHW supply temperature and cold-water temperature, and DHW usage profile [7]. The so-called bottom-up approach for DHW profiles development is based on operating schedules for the primary DHW energy users (showers, baths, sinks, dishwashers, and clothes washers) and occupant activities. As an illustration, the Building America House Simulation Protocols document provides guidance for such analysis in new and existing apartment buildings [67]. Lombardi in [68] shows that domestic water use can be presented as the result of probabilistic use of domestic appliances, each one with its particular characteristics. The research of Good and Zhang in [55] share the experience of calculation for DHW heat use profiles based on occupant activities. Time-use data of activities in households in Sweden are used for generating DHW profiles in [69]. Most of the above reviewed research works are dedicated to the apartments and households, meaning that required parameters were easier to obtain. However, in non-residential buildings obtaining in-depth knowledge about occupant activities and equipment operation become time consuming and expensive task [7]. The available input data limits the practical application of bottom-up approaches.

In certain publications, instead of DHW heat use measuring or calculating, the profiles from the standards are used for system design, simulation, and heat use analysis. Comparing the actual DHW heat use profiles with the standards, and their verification, are also not going unnoticed. For example, the comparison of the actual DHW profiles in apartments with profile proposed by the American Society of Heating, Refrigeration and Air Conditioning Engineers (ASHRAE) is conducted in [70]. The research shows that the primary difference between the actual and the ASHRAE derived data is that the water use is less evenly distributed in the actual data, and there are higher peaks and lower troughs and much less use in the early morning hours in the actual data. Differences in shapes and parameters of the actual DHW heat use profiles for particular types of buildings and profiles presented in publications and standards are considered in [71]. As a conclusion, in this work, the authors recommend relying on actual profiles obtained from measurement systems for the analysis of DHW use in the existing buildings.

The literature review showed that there is no single method for developing and analyses of DHW profiles. Usually, analyses of profiles, dividing them by influencing variables (day of the week, month etc.), determining the hours of peak energy loads are carried out intuitively, not based on statistical methods. This situation may lead to incorrect interpretation of profiles for certain buildings. Therefore, the methods for performing data-driven analysis of DHW heat use profiles in buildings should be improved.

3. Method for splitting measurements of the total heat demand in buildings into SH and DHW heat use

Chapter 3 presents methods that were used in Papers I-III for restoring information about the SH and the DHW heat use from the measurements of the total heat use in buildings. In addition, the ESC method in Section 3.1 was used for SH heat use modeling in Paper XI.

The methods in Chapter 3 are considered in two sections. Section 3.1 is dedicated to the application of the ESC to extract the information about the SH and the DHW heat use from the total heat use in buildings. Section 3.2 proposes the method which is based on the singular spectrum analysis (SSA) for the decomposition of the SH and the DHW heat use.

3.1. Energy Signature Curve for the SH and the DHW heat use analysis

The method proposed in this thesis used the assumption that the SH and the DHW have different factors affecting them. It is well known that the main influencing factor on the SH heat use is the outdoor temperature [72, 73]. In addition, for DHW use, a seasonal variation is found related to the outdoor temperature [74]. However, on an hourly basis, the research in [75] shows that the correlation between the DHW use and the outdoor temperature is insignificant. Thus, the regression model between the total heat use in buildings and the outdoor temperature is caused by the SH. Meanwhile, the DHW heat use can be found in the residuals of this model.

The ESC is a powerful instrument for heat use analysis in buildings [76]. It shows the relationship between the heat use in an observed building and the outdoor temperature [44, 77]. An example of the ESC is shown in Fig. 2.

For a building with a heating season and no cooling taking into consideration, the ESC often consists of two parts. These parts are divided by the change point temperature (CPT), see Fig. 2. The CPT is a critical outdoor temperature that sets the boundary between the start and the end of the heating season. At the right-hand side of the CPT, the SH use in the building is limited. The part of the curve at the left-hand side of the CPT shows the SH season. Usually, in this period, the SH heat use is significantly higher than the DHW heat use. The function at the right-hand side of the CPT shows the warm season when SH is not required. During this time, the main share of heat use is related to the DHW system.

Nevertheless, depending on the system type, a small amount of heat use associated with the operation of the SH system may occur.

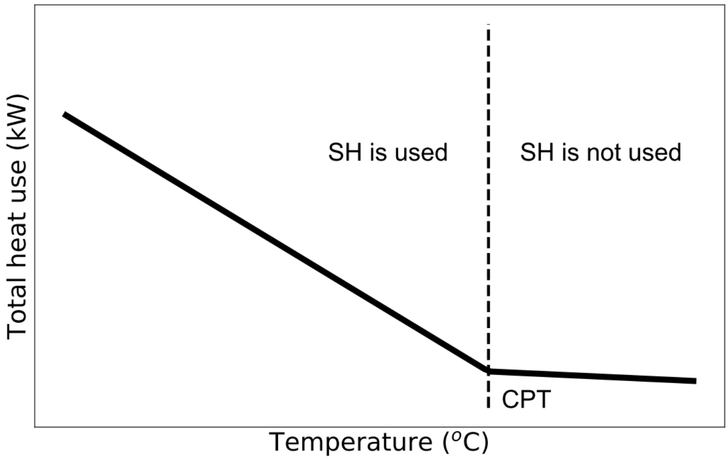


Fig. 2. An example of the energy signature curve

For some buildings, the last day of the heating season or the CPT is known. If the CPT is known, the ESC can be built by using the least square method for two parts of the model, see Fig. 2. Otherwise, the CPT may be identified by using the piecewise regression method. This method allowed us to find the CPT and construct separate models for the two parts of the ESC as the following:

$$f(x) = \begin{cases} \beta_0 + \beta_1(x - CPT) + \varepsilon & \text{If } x < \text{ CPT} \\ \beta_0 + \beta_2(x - CPT) + \varepsilon & \text{If } x > \text{ CPT} \end{cases} \tag{3.1}$$

where $f(x)$ is a model for the ESC, x is the outdoor temperature, β_0, β_1, β_2 are the coefficients of the piecewise model, and ε is the residual error.

The research work within this PhD showed that the ESC model explained well the behavior of the SH heat use. However, since the total heat use also includes DHW, the model was shifted relative to the SH heat use by a certain constant value. In this work, this value was called the shifting coefficient. The shifting coefficient can be revealed from the behavior of the SH system in the warm season, when the outdoor temperature is above the CPT. During the warm season, there were hours when the SH heat use in the building was equal to zero. The research presented in [38] showed that the minimum value of the ESC coincides with these hours. Thus, in this study, the coefficient of shifting was defined to be equal to the minimum value of the total heat use determined by the ESC. Extracting this coefficient from the ESC allowed us to obtain the SH heat use model. Finally, the following equation was suggested for the SH heat use model:

$$E_{SH} = f(x) - \min(f(x)) \tag{3.2}$$

The values of the total heat use, which lies above the modeled SH heat use gave information about the trend of the DHW heat use [36]. Therefore, initially, it was assumed that the positive residuals, obtained as the difference between the total heat use and the modeled SH heat use, represented the DHW heat use. When the negative values appeared in the residuals, the DHW heat use was supposed to be equal to zero. In a DHW system with continuous circulation, the DHW system operates continuously to deliver hot water. Accordingly, the system losses should be added to the DHW heat use obtained from the residuals. These losses may be found as an average value of the heat use at the night time, as proposed in [40]. Then the model of the DHW heat use may be identified by the following:

$$E_{DHW} = \begin{cases} E_{TH} - E_{SH} + E_{Loss} & \text{If } E_{TH} > E_{SH} \\ E_{Loss} & \text{If } E_{TH} \le E_{SH} \end{cases} \tag{3.3}$$

where E_{TH} is the measured total heat use and E_{Loss} presents the heat losses in the DHW system.

Finally, the SH heat use was balanced according to the DHW heat use model. The SH heat use model was recalculated as a difference between the actual total heat use and the DHW heat use obtained by Equation 3.3. In addition, it was introduced a condition that both the DHW and the SH heat use should be positive. In a case, if one of these parameters becomes negative, the negative value was compensated from another parameter until both of them become positive. In such a way, all the values for the restored DHW and SH heat use were positive, and their sum was equal to the total heat use.

The flowchart of the above-introduced algorithm for splitting SH and DHW heat use based on the ESC is shown in Fig. 3.

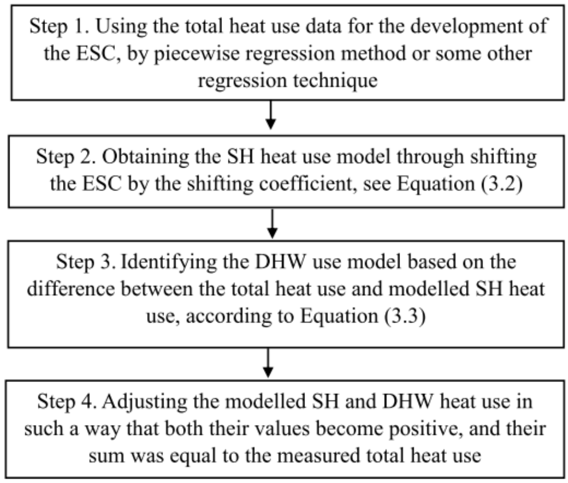


Fig. 3. Flowchart of the algorithm for splitting the total heat use into the SH and the DHW heat use by using the ESC

The proposed method based on the ESC might give a reasonable estimation for the trend of the SH heat use. However, the ESC is using linear functions. For this reason, it cannot capture spikes and rapid fluctuations of the SH heat use. The residuals of the ESC model also contained some noise from the SH. This noise reduced the accuracy of the DHW model. To capture the spikes in the SH heat use in a better way and to improve both the SH and the DHW heat use models, the additional analysis was suggested. Particularly, after the application of Equation (3.2), a time series decomposition was applied. For this purpose, the SSA was used. This step is further explained in Section 3.2.

3.2. Application of Singular Spectrum Analysis for identifying the SH and DHW heat use

SSA is a useful method for time series analysis and data mining [78]. This method allowed us to decompose the time series of the total heat use into a sum of components, $\tilde{e}_i$. The components may give an interpretation of the time series structure. There are several software tools in Python [79] and R [80] for the SSA. The two groups of the components, related to the SH and the DHW heat use, could be found. The summation of the components within each group made it possible to restore the SH and the DHW heat use from the total heat use.

In this PhD work, the time series $E_{TH} = (E_1, E_2, \dots, E_N)$ of the total hourly heat use in the building was analyzed. Where E_i is the hourly heat use, and *N* is the number of the elements in the data sample. For a one-year hourly data sample, *N* was equal to 8760.

The algorithm of the SSA is well developed and presented in many articles and books [81, 82]. For example, the book [81] gives detailed explanations of the SSA technique, as well as examples of its application.

In order to separate the SH and the DHW heat use by the SSA method, two main problems were solved. The first problem was the selection of an appropriate window length *L* for the SSA decomposition. The SSA does not have strict recommendations for the selection of the optimal window length. Therefore, quite often, the trial and error method is applied. The second problem was identifying the groups of the components related to the SH and DHW. These two problems were attempted to be solved based on the SH heat use model obtained by the ESC method, as described in Section 3.1, see Equation (3.2). The SSA was iteratively applied for different windows length L (2, 3,…,$N/2$). On each iteration for L_i the SSA components were calculated. Out of all the components, only the components associated with the SH heat use were identified. These components were selected in such a way that their additive sum has a maximum correlation with the SH heat use model, see Equation (3.2), as the following:

$$corr(E_{SH}, \sum \tilde{e}_k) \rightarrow max \tag{3.4}$$

where $\sum \tilde{e}_k$ is the sum of the components selected from $\tilde{e}_i$.

From the considered window lengths, the one that gives the maximum value for Equation (3.4) was selected. For the best window length, the new SH heat use model as a sum of the components was identified. This SSA model was also shifted in a similar way as in Equation (3.2):

$$E'_{SH} = \sum \tilde{e}_k - \min(\sum \tilde{e}_k) \tag{3.5}$$

Using the E'_{SH} and E_{TH}, the new model for the DHW heat use (E'_{DHW}) was identified by Equation (3.3). Finally, the values for both the restored SH heat use and the DHW heat use were balanced in such a way that both became positive, and their sum was equal to the total heat use. The SH heat use model was recalculated as a difference between the actual total heat use and the DHW heat use obtained by Equation 3.3. In addition, it was introduced a condition that both the DHW and the SH heat use should be positive. In a case, if DHW or SH heat use became negative, the negative value of this parameter was compensated from another parameter until both of them become positive. The flowchart of the algorithm for splitting the SH and DHW heat use based on SSA is shown in Fig. 4.

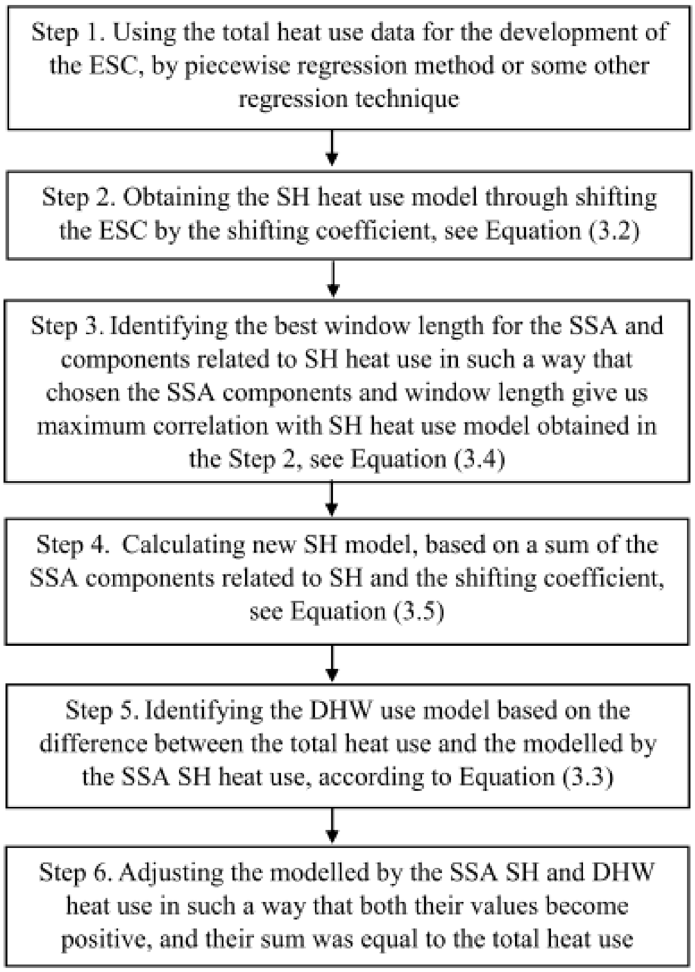


Fig. 4. Flowchart of the algorithm for splitting the total heat use into the SH and the DHW heat use by using the SSA

4. Methods for DHW heat use prediction modeling in buildings

Traditionally, predictive modeling includes the following main steps: selecting the influencing variables, identifying the method for prediction, and determining the parameters of this model. This chapter follows this way of DHW heat use model development.

Chapter 4 introduces the methods that were used to determine the influencing variables and develop daily and hourly predictive models for DHW heat use in Papers IV-V. The chapter consists of two sections that are dedicated to modeling in Situation 1 and Situation 2. In Situation 1, only information from the historical DHW heat use was used for prediction. While in Situation 2, additional variables that affect the DHW heat use were selected and included in the prediction model.

Situation 1 is presented in Section 4.1 and it meant the hourly prediction based on the historical time series of DHW heat use. Section 4.2 considers the issue of identifying variables that affect DHW heat use, followed by making prediction when using these variables. For this purpose, time series and machine learning techniques were used. In addition, in Section 4.2, a method that introduced the artificial variable reflecting the hourly intensity of the guests DHW use and improved the accuracy of the hourly DHW models for hotels was proposed.

4.1. Prediction based on the historical time series of DHW heat use

For certain types of buildings, information about user presence and other explanatory variables are unknown. In these conditions, only DHW heat use data from previous periods of time can be used for prediction. Practice shows that the DHW heat use may vary at different hours of the day, day of the week, and months. For this reason, the preference was given to methods that allowed us to make a prediction based on the historical time series of the DHW heat use and additionally take into account the day, week, and month when the DHW heat use occurred. Among different methods, such as classical methods for time series analyses, Exponential Smoothing (ES) and Autoregressive Integrated Moving Average (ARIMA), and modern methods of machine learning, Neural Network (ANN), Prophet, and XGBoost, were considered.

The ES method uses recurrence relations between the current and the previous values of the parameter. According to ES, predictions are calculated by applying weighted averages where the weights are exponentially decreasing as observations come further from the past [83]. In detail, the ES method is presented in [83]. According to [83], ES uses the following equation for prediction:

$$\hat{E}_{T+1|t} = \alpha \cdot E_T + (1-\alpha) \cdot \hat{E}_{T|t-1} \tag{4.1}$$

where $\hat{E}_{T+1|t}$ is the predicted value and $\hat{E}_{T|t-1}$ is the prediction for the previous moment of the time. E_T is the most recent observation. α is the smoothing parameter, accepted from 0 to 1.

The ARIMA method predicts the next step in the sequence as a linear function of the differenced observations and residual errors at previous time steps [84]. This method combines autoregressive (AR), Moving Average (MA) and the integrated (I) parts in one model. An integrated part of the model performs a differentiation preprocessing step of modeling that removes the non-stationarity of the time series. AR and MA are the core of prediction. The algorithm and theoretical bases of ARIMA modeling technique are well explained in [84].

The Prophet is a package for time series prediction developed by Facebook [85]. Prophet uses the additive regression model $E(t)$ that includes the following components:

$$E(t) = g(t) + s(t) + h(t) \tag{4.2}$$

where $g(t)$ is the trend for non-periodic changes that may be obtained by a simple Piecewise Linear Model. $s(t)$ is the seasonal (periodical) component of the model obtained based on the Fourier series. $h(t)$ is the component of the model that takes into account the effects of holidays and other untypical days with irregular schedules of the DHW heat use.

XGBoost is a machine learning prediction technique based on the gradient boosting decision tree method [86]. XGBoost sequentially sums the prediction of multiple weak learners, such as regression trees models, in order to ensemble a robust prediction model [87]. By adding additional regression trees models in such a way, the errors made by the initial model are reduced. The regression trees models are added until further improvements of the initial model can no longer be obtained. The gradient boosting is related to a gradient descent algorithm that is used in XGBoost to minimize the loss when adding new models [88]. Mathematically, gradient boosting can be represented by the following equation [88]:

$$\hat{E}_i = \sum_{k=1}^{K} f_k\left(X_i\right), f_k \in \mathrm{F} \tag{4.3}$$

where $\hat{E}_i$ is the predicted DHW heat use. X_i are influencing variables. K is the number of functions (regression trees) in the function space F.

In XGBoost the parameters of the functions can be found automatically by solving the following optimization function [88]:

$$obj(\theta) = \sum_{i}^{n} l(\hat{E}_i, E_i) + \sum_{k=1}^{K} \Omega\,(f_k) \quad (4.4)$$

where l is the differentiable loss function. Ω is the regularizing function that introduces penalties for the complexity of the model. A more extensive introduction to XGBoost modeling technique and its mathematical apparatus is given in [89].

Artificial Neural Network (ANN) is a powerful modeling technique that mimics the behavior of the brain with its homogeneous elements - neurons. For prediction, classification, and solving of other tasks, ANN uses the number of simple nonlinear functional blocks that are called neurons. Multiple neurons are organized into layers [90], where the actual processing of data is performed via a system of weighted connections [89]. The ANN represents the group of mathematical models of high complexity. This method demonstrates good results for nonlinear relationships among variables. In this work, the ANN model with the two-layer feed-forward network [91] was used for the DHW heat use prediction.

In order to estimate the accuracy of the DHW heat use models, cross-validation was used. The prediction for all the above-mentioned methods, except ANN, was performed in Python, using Statsmodels, XGBoost, and Prophet packages [92]. For Neural Networks modeling, the Neural Network Toolbox in MATLAB software was utilized [91]. The comparison of the models was performed based on the Coefficient of Determination (R2), Mean Absolute Error (MAE), and Mean Squared Error (MSE) criteria of the model adequacy [92].

4.2. Prediction based on the variables that have a significant influence on the DHW heat use

Compared to Section 4.1, Section 4.2 considers more favorable conditions for the DHW heat use prediction. In these conditions, in addition to DHW heat use data from previous periods of time, information about occupancy and other explanatory variables are known. The procedure for the DHW heat use prediction in this section includes three main steps: data preprocessing, identifying variables that affect DHW heat use, and selection of the best model for hourly prediction of DHW use. The preprocessing step included removing outliers and unrealistic data. For hotels, as a part of preprocessing, a method for introducing an artificial variable, which reflects the influence of hourly guest presence on DHW heat use, was proposed. This method, in detail, is explained in Section 4.2.1. The set of variables that affect the DHW heat use was selected according to the Wrapper approach. This approach is explained in Section 4.2.2. Afterward, the selected set of influencing variables was used as input for modeling. The accuracy evaluation of various machine learning methods for the DHW heat use prediction was carried out. General information about the considered methods is presented in Section 4.2.3.

4.2.1 Preprocessing the daily data of the guest presence in hotels

It is well known that occupancy has a significant effect on DHW heat use in buildings [7]. Among all influencing factors, the number of guests being present in a hotel is typically the key factor that affects DHW heat use the most.

Traditionally, a hotel booking system stores information about the number of guests who were booked into the hotel for each day. For a given date, both the number of guests booked in one day before, Gst_{Lag1}, as well as on the observed day itself, Gst, are influencing the DHW heat use. In general, Gst shows the number of guests who are staying in the hotel after 15.00 o'clock, and Gst_{Lag1} reflects information about people who are leaving before 12:00 o'clock. Nevertheless, despite the official check-in/out time, in practice, the actual time when guests are arriving and leaving may vary. Sometimes guests arrive before the set time of check-in, and it happens that some guests can stay longer in the building after the check-out time.

The daily profiles in the hotel showed that the highest DHW heat use occurs before 12:00 o'clock. Consequently, the influence of Gst_{Lag1} on daily DHW heat use may be more significant than Gst. For this reason, it is crucial to take both factors Gst and Gst_{Lag1} into account in the model.

The investigation showed that using Gst and Gst_{Lag1} allowed us to perform a quite accurate daily prediction of DHW heat use. However, if we consider the hourly analysis of the DHW heat use, Gst and Gst_{Lag1} do not give sufficient information about hourly occupancy in the hotel. These parameters do not show whether the guests are present in the hotel at certain hours or not. For this reason, the considered factors cannot substantially enhance the accuracy of the hourly model of the DHW heat use. To increase the accuracy of the hourly model, an additional artificial variable (Gst_{art}) was proposed to reflect the hourly influence of the guests presence on the DHW heat use. The following equation was proposed to determine the numerical value of the Gst_{art} for each separate hour:

$$Gst_{art} = Gst \cdot Cgp_i + Gst_{Lag1} \cdot Cgp_{Lag1.i} \quad (4.5)$$

where Cgp_i and $Cgp_{Lag1.i}$ are the coefficients for the guest DHW use intensity for *ith*-hour, which were identified based on the number of people booked into the hotel on the observed day *Gst* and one day before Gst_{Lag1}.

In order to identify the coefficients of the guest DHW use intensity for *ith*-hour the following optimization problem was solved:

$$\max(corr(\left\{\begin{matrix} Cgp_{i=1} \cdot (\overrightarrow{Gst}) + Cgp_{Lag1.i=1} \cdot (\overrightarrow{Gst_{Lag1}}), \ldots, Cgp_{i=24} \cdot (\overrightarrow{Gst}) \\ +Cgp_{Lag1.i=24} \cdot (\overrightarrow{Gst_{Lag1}}) \end{matrix}\right\}, \{\vec{E}_{i=1}, \ldots, \vec{E}_{i=24}\})) \quad (4.6)$$

where Cgp_i and $Cgp_{Lag1.i}$ are the target variables. $\vec{E}_i$ is the vector of the DHW energy use data in the hotel in *ith*-hour, $\overrightarrow{Gst}$, $\overrightarrow{Gst_{Lag1}}$ are vectors of the daily number of guests booked into the hotel on the given day and one day before.

By solving the optimization problem in Equation (4.6), the values of the coefficients for the guest DHW use intensity for each hour of the day might be obtained. These Cgp_i and $Cgp_{Lag1.i}$ coefficients were maximizing the correlation between Gst_{art} and the DHW heat use. Application of these coefficients for the guest DHW use intensity for *ith*-hour made Gst_{art} based predictions more accurate.

4.2.2 Wrapper approach for selecting the influencing variables of the DHW heat use

Choosing the proper set of influencing variables is a crucial step for the DHW heat use prediction. The use of irrelevant and redundant input variables in the model leads to an increase in computational demand, an inadequate interpretation of the model, and generally makes prediction more complicated and less accurate. Traditionally, three different approaches may be used for feature selection: Filtering, Wrapper, and Embedded method [93].

In this work, the Wrapper method was used for optimal variables selection. This method is one of the most precise methods, because it detects possible interactions between variables and takes into account the specific characteristics of the prediction algorithm [93]. According to the Wrapper method, first, all the variables were sorted by the absolute value of the correlation criteria between a variable and the DHW energy use. Afterward, an iteration algorithm was applied. In each iteration step, one additional variable from the sorted list of the variables was added to the model. For each step, parameters and accuracy criteria of the model were recalculated. The obtained criteria of model accuracy on a current step were compared with the criteria from the previous step. Thus, parameters that do not improve the accuracy of the model were identified and eliminated from the model, and a set of variables that made predictions more precise was selected. Despite the higher computational time compared to commonly used analysis based on the correlation matrix (Filtering method), the application of the Wrapper method is a more potent instrument for assessing the impact of different combinations of variables on the DHW heat use and selecting their proper set for accurate prediction [93].

4.2.3 Prediction techniques for modeling DHW heat use based on influencing factors

The advanced time series techniques have the ability to take into account explanatory variables. For this reason, some models in Section 4.1 were also used for prediction in current conditions. In addition to the models in Section 4.1, the availability of data on influencing factors allowed us to apply more diverse prediction techniques.

Group Method of Data Handling (GMDH) is a computer-based method for calculating complex multivariable models. GMDH stands on self-organization theory for mathematical models. The method recursively combines selective sub-models (base function) to obtain a more accurate predictive model. At each step of the modeling, the number of sub-models included in the main model is gradually growing. In this way, the accuracy and complexity of the model are increasing. The GMDH allows us to find a model structure with optimal complexity based on the minimum value of an external criterion [94]. As base functions in GMDH various models may be used: linear, polynomials, exponential, etc.

Partial Least Squares Regression (PLSR) is a powerful instrument for prediction in conditions when a large number of independent variables is used in the model. PLSR works well with highly collinear variables, too. This method performs the decomposition of the initial data into a subspace of latent variables (scores and loadings). Latent variables are representing the main features of co-variance among the dependent and the independent variables [95]. PLSR calculates the linear regression model via the projection of the predicted variables and the observable variables to a subspace of the latent variables [95].

Support Vector Regression (SVR) is based on the computation of a linear regression function in high dimensional feature space [96], where the input data are mapped via a nonlinear function. SVR is minimizing the generalized error bound [97]. The generalization error bound includes the training error and a regularization term that controls the complexity of the hypothesis space [97]. The comprehensive overview of this method is given in [98].

Ridge and LASSO methods are used to deal with overfitting and variables that may be affected by multicollinearity [99]. Both these methods are based on principals of regularization, i.e. introduction penalties to the coefficients of features. Ridge Regression is penalizing the square of the magnitude of coefficients [100]. LASSO introduces penalties to the absolute value of the magnitude of the coefficients [100].

In Section 4.2, the general principles for the DHW heat use modeling were applied in the same way as in Section 4.1. The best model was selected based on R2, MAE, and MSE criteria of the model adequacy. The prediction for the methods mentioned above was performed in Python, using Statsmodels and GmdhPy packages.

5. Methods for development and analyses of DHW heat use profiles

Chapter 5 presents methods that were used for the development and analyses of DHW heat use profiles in Papers VIII-IX. The methods for the analyses of DHW profiles included the four main steps as shown in Fig. 5.

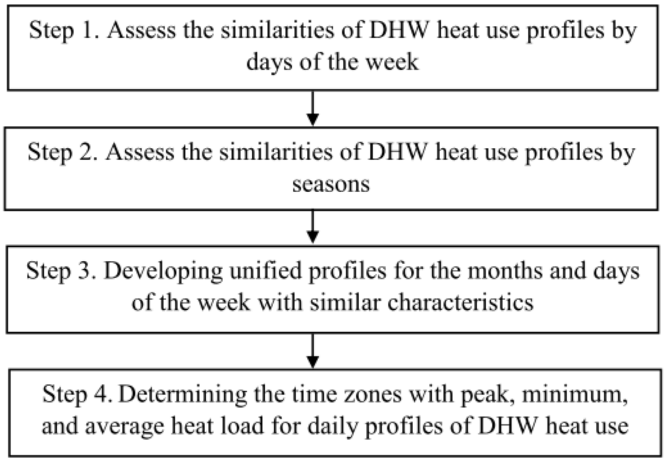


Fig. 5. Methods for the analysis of DHW heat use profiles

The three following sections cover the methods that were used to solve issues in shown Fig. 5. Section 5.1 describes the method for comparison of the DHW heat use profiles from different days of the week and assessing their similarities. In this study, we did not assume beforehand that the profiles might be divided in a certain way. Student's t-test and Fisher's exact test were used for solving this issue. By using this method, the data tests may be used for samples with standard normal distribution and t-distribution. This allowed us to determine the statistically justified days of the week with similar DHW heat use profiles. In Section 5.2, a method for determining the duration and boundaries of time zones with peak, minimum, and average heat use during the day was showed. In Section 5.3, a statistical method for identifying the number of seasons, as well as the months included in each season, was described. By using this method, the impact of seasonality on DHW heat use was considered.

5.1. Comparing the similarity of DHW heat use profiles in different days of the week

To determine the days of the week with similar characteristics of the DHW heat use, a method based on test statistics was proposed. The similarity of two DHW heat use profiles was checked based on the Student's t-test and Fisher's exact test. Appropriate tests may be used for samples with the standard normal distribution and t-distribution.

By applying the Student's t-test, it was possible to check if the mean values of the DHW heat use from two days of the week were equal or not. To achieve this, the DHW heat use within each day was considered as a statistical sample with 24 elements, which represented the number of hours in the day. The t-test statistical value was calculated as the following:

$$T_{cal} = \frac{\left[\bar{E}_{prof1} - \bar{E}_{prof2}\right]}{\sqrt{\frac{S^2_{prof1}}{n_{prof1}} + \frac{S^2_{prof2}}{n_{prof2}}}} \tag{5.1}$$

where $\bar{E}_{prof1}$, $\bar{E}_{prof2}$ are the mean values of the DHW heat use in the first and second samples. S_{prof1}, S_{prof2} are the standard deviations of the DHW heat use profiles in the first and second samples. n_{prof1}, n_{prof2} are the number of elements in the first and second samples. Finally, the equation for the standard deviation for *i*-th day was written as:

$$S_{profi} = \sqrt{\frac{\sum(E_{profi.j} - \bar{E}_{profi})^2}{n_{profi} - 1}} \tag{5.2}$$

where i is the number of the sample, j is the number of elements in the sample, $E_{profi.j}$ is the DHW heat use in j-th element in *i*-th sample.

The obtained value for t-criteria, T_{cal}, was compared with the critical value, T_{cr}. T_{cr} may be found in the literature for different degrees of freedom and significance level k. The comparison may lead to three possible situations as the following:

- If $T_{cal} \le T_{cr}\ (n_{prof1} + n_{prof2} - 2, k = 0.05)$, then the mean values of the first and the second samples are similar;
- If $T_{cal} \ge T_{cr}\ (n_{prof1} + n_{prof2} - 2, k = 0.01)$, then the mean values of the first and the second samples have a significant difference;
- If $T_{cal} \le T_{cr}\ (n_{prof1} + n_{prof2} - 2, k = 0.01)$ and $T_{cal} \ge T_{cr}\ (n_{prof1} + n_{prof2} - 2, k = 0.05)$, then the mean values of the first and the second

samples may be considered as similar. However, the final decision should be done based on the knowledge of researchers.

Meanwhile, the Fisher's criterion allowed us to estimate the similarity of two samples by variances:

$$\mathrm{f_{cal}} = \frac{\max\left(\mathrm{S^2_{prof1}},\ \mathrm{S^2_{prof2}}\right)}{\min\left(\mathrm{S^2_{prof1}},\ \mathrm{S^2_{prof2}}\right)} \tag{5.3}$$

The comparison obtained by calculations of the Fisher criterion, f_{cal} with its critical value, f_{cr} led to the following results:

- If $f_{cal} \leq f_{cr}$ $(n_{prof1} + n_{prof2} - 2, k = 0.05)$, then the variances of the first and the second samples are similar;
- If $f_{cal} > f_{cr}$ $(n_{prof1} + n_{prof2} - 2, k = 0.05)$, then the variances of the first and the second samples have significant difference.

The two profiles are considered to be similar if both the Student's t-test and the Fisher's exact test show the same results. If at least one of two tests shows that the mean values or variances of profiles in the first and the second samples are not similar, it is possible to conclude that the profiles are dissimilar and should be analyzed separately.

Splitting the DHW profiles by the days of the week should be made based on a large dataset, which represents DHW heat use during the year. Therefore, in this study, it was proposed to divide initial statistical data into separate weeks. Within each week, all combinations of the daily DHW profiles should be compared among themselves by the Student's t-test and the Fisher exact test. For instance, profiles for Monday and Thursday, Monday and Wednesday, Saturday and Sunday and so on should be compared. Afterward, for all the combinations of days, the number of the weeks can be identified, when statistical tests show that profiles in considered pairs of days are similar. For further analysis, for each combinations of days of the week, the number of matches of the DHW profiles in percentage can be found as:

$$\mathrm{n_{i.j}} = \mathrm{N_{i.j}} \cdot 100/\mathrm{N_{total}} \tag{5.4}$$

The elements in Equation (5.4) are the following: $\mathrm{n_{i.j}}$ is the number of matches in percentage, when the DHW profiles of i-th and j-th days were similar. $N_{i.j}$ is the number of the weeks, when statistical tests showed that the i-th and j-th days were similar. N_{total} is the total number of the weeks in the statistical data sample of the DHW heat use. i is the day of the week of the first comparable profile (from 1 to 7). j is the day of the week of the second comparable profile (from 1 to 7). For better clarity, the results could be presented in the form of the matrix of matches as in Table 3.

Table 3. Form of the matrix of matches

	Mo.	Tu.	We.	Thu.	Fr.	Sa.	Su.
Mo.	$n_{1.1}$	–	–	–	–	–	–
Tu.	$n_{2.1}$	$n_{2.2}$	–	–	–	–	–
We.	$n_{3.1}$	$n_{3.2}$	$n_{3.3}$	–	–	–	–
Th.	$n_{4.1}$	$n_{4.2}$	$n_{4.3}$	$n_{4.4}$	–	–	–
Fr.	$n_{5.1}$	$n_{5.2}$	$n_{5.3}$	$n_{5.4}$	$n_{5.5}$	–	–
Sa.	$n_{6.1}$	$n_{6.2}$	$n_{6.3}$	$n_{6.4}$	$n_{6.5}$	$n_{6.6}$	–
Su.	$n_{7.1}$	$n_{7.2}$	$n_{7.3}$	$n_{7.7}$	$n_{7.5}$	$n_{7.6}$	$n_{7.7}$

Based on the matrix of matches, the groups of the days of the week with the similar profiles for the DHW heat use could be identified. Namely, the days of the week, which have $n_{i.j} \geq 100 - error$, have similar characteristics of the DHW heat use and should be placed in one group and analyzed together. The value of the error included the accuracy of the Student's t-test, the Fisher's exact test, and the percentage of days in the year when the building is not in operation in typical regimes such as holidays.

5.2. Determining the time zones with peak, minimum, and average heat load for daily profiles of DHW heat use

To implement energy management in buildings, it is essential to identify the typical duration and boundaries of time zones with the peak load, the minimum, and the average heat load during the day. To solve this issue, it was proposed to perform statistical grouping of the hourly heat use of the DHW system based on the method presented by Nakhodov in [101]. Initially, this method is used for identification of the tariff zones of electrical energy use in the power system. In this work, the method was adapted for analysis of DHW heat use in buildings. The method allowed us to divide the hours of DHW heat use into several groups with statistically different mean values within each group. It is based on an iteration procedure and analysis of the mean values of DHW heat use by applying the Student's t-test. In this case, a DHW heat use profile was considered as a statistical sample e. The sample contained N=24 elements (hours) with the DHW heat use in these hours equal e_j (where e_j is the DHW heat use in the *j-th* hour. j is the number of the element in the sample). The flowchart for the algorithm for determining the time zones with the peak, the minimum, and the average heat load for daily profiles of the DHW heat use is shown in Fig. 6.

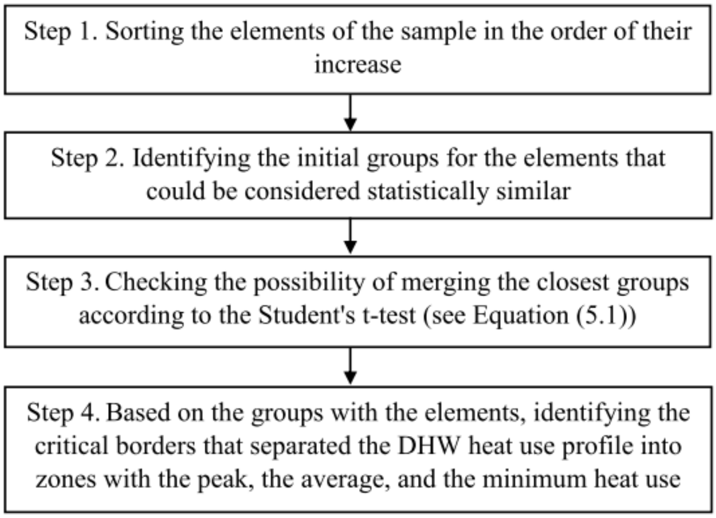


Fig. 6. Flowchart for the algorithm for determining the time zones with the peak, the minimum, and the average heat load for daily profiles of DHW heat use

The detailed algorithm of the method for determining the time zones was as the following:

Step 1. Sorting the elements of the sample in the order of their increase

The elements e_j in the sample e were sorted in the order of their increase. Such an arrangement of elements from smaller values of the hourly DHW heat use to higher values allowed us to obtain the sorted sample E with N elements E_i (where $E_{i+1} > E_i$, i is the number of elements in sample E).

Step 2. Identifying the initial groups for the elements that could be considered statistically similar

Based on the sample E, an iterative procedure of generating of two statistical subsamples R_1 and R_2 with variable number of elements was applied. For each step of iteration, sample R_1 contained M elements, while R_2 should have M+1 elements. The elements in samples R_1 and R_2 were taken consistently from the initial sample E. With each iteration, the number of elements M in these subsamples increased by one. The value of M varied from 1 to 23.

For each step of these iterations, the value of the Student's t-test for the two subsamples R_1 and R_2 were calculated by using Equation (5.1).

For instance:

iteration 1) $R_1 = [E_1]$, $R_2 = [E_1, E_2]$, M=1, and T_{cal1};

iteration 2) $R_1 = [E_1, E_2]$, $R_1 = [E_1, E_2, E_3]$, M=2, and T_{cal2};

………..

iteration 23) $R_1 = [E_1, E_2 \dots E_{23}]$, $R_1 = [E_1, E_2 \dots E_{24}]$, M=23, and T_{cal23};

Step 3. Checking the possibility of merging the closest groups according to Student's t-test

Based on the iteration procedure in Step 2, the series of t-criteria for all the combinations of the subsamples R_1 and R_2, T_{cal} =[T_{cal1},T_{cal2} … T_M] were found.

If an ordered sample of hourly DHW heat use was monotonous, then the numerical values of the elements in this sample increase evenly. In that case, the series of the t-criteria obtained by the iteration procedure would also be monotonous. This means that the values of the t-criteria obtained by Equation (5.1) would decrease monotonically with each next iteration ($T_{cal1} > T_{cal2} \dots > T_M$). If the ordered sample of the hourly DHW heat use was uneven, then a monotonic decrease of the calculated values of the t-criteria would be violated by periodic abrupt growth ($T_{cali} < T_{cali+1}$). Thus, the identification of points of growth of the calculated values of the t-criteria allowed us to determine between which hours there is a noticeable statistical difference of the DHW heat use. This assumption allowed us initially to divide hours in the profile of DHW heat use into several groups. Each of these groups was the sample of data, where DHW heat use data varied monotonously. Created in this way, neighboring groups of hourly DHW heat use could be checked in terms of the possibility for their further merge. For this purpose, the data samples of the two neighboring groups were assessed by the Student's t-test (see Equation (5.1)). As a result, the calculated value of the t-criteria, T_{cal}, could be compared with the critical value, T_{cr}. This comparison could lead to the three possible situations such as:

- If $T_{cal} \le T_{cr}$ $(n_{group1} + n_{group2} - 2, k = 0.05)$, then the mean values of the two groups were similar and should be merged;
- If $T_{cal} \ge T_{cr}$ $(n_{group1} + n_{group2} - 2, k = 0.01)$, then the mean values of the two groups were different and they should be considered separately;
- If $T_{cal} \le T_{cr}$ $(n_{group1} + n_{group2} - 2, k = 0.01)$ and $T_{cal} \ge T_{cr}(n_{group1} + n_{group2} - 2, k = 0.05)$, then the mean values of the two groups could be considered as similar. However, the final decision should be made based on the knowledge of the researcher.

After the groups were merged based on the above explained conditions, the new set of groups was created. The calculations in Step 3 should be repeated from the beginning with the new set of groups in the sample. Iterative calculations in Step 3 were continued until the t-test showed that no groups can be merged together and that the total number of groups could not be reduced.

Step 4. Based on the groups with the elements, identifying the critical borders that separated the DHW heat use profile into zones with the peak, the average, and the minimum heat use

Critical borders that separated the DHW heat use profile into zones with the peak, the average, and the minimum heat use may be identified by the following:

$$\mathrm{E_{min}} = \overline{\mathrm{E}}_{\mathrm{group.1}} + \mathrm{T_{cr.1}}(\mathrm{M_{group.1}} + 1 - 2, k = 0.01)\sqrt{\frac{\mathrm{S^2_{group.1}}}{\mathrm{M_{group.1}}}} \tag{5.5}$$

$$\mathrm{E_{max}} = \overline{\mathrm{E}}_{\mathrm{group.K-1}} + \mathrm{T_{cr.K-1}}(\mathrm{M_{group.K-1}} + 1 - 2, k = 0.01)\sqrt{\frac{\mathrm{S^2_{group.K-1}}}{\mathrm{M_{group.K-1}}}} \tag{5.6}$$

where $\overline{E}_{group.1}$, $\overline{E}_{group.K-1}$ are the mean values of the DHW heat use in the first group and the next to the last group. $M_{group.1}$, $M_{group.K-1}$ are the numbers of the elements in the first group and the next to the last group. $S^2_{group.1}$, $S^2_{group.K-1}$ are the standard deviations in the first group and the next to the last group. $T_{cr.1}$, $T_{cr.K-1}$ are the critical values of the t-criteria for the first group and the next to the last group.

The hours in which the DHW heat use was below E_{min} should be considered as the zone with the minimum DHW heat use. If the DHW heat use was between E_{min} and E_{max}, it could be assumed that in these hours, the DHW heat use was in a zone of the average heat use. The hours with the DHW heat use higher than E_{max} lied within the zone of the maximum heat use.

5.3. Determining the seasons of DHW heat use

The method described in Section 5.2 may be applied in order to identify the groups of months with similar characteristics of the DHW heat use. In this case, in contrast to the sample of 24 hours for each daily profile as considered in Section 5.2, the initial sample contains 12 elements for the monthly DHW heat use during the year. The basic principles and procedure of calculations in both hourly and monthly analysis were the same. As a result, the number of seasons of the DHW heat use in the year and the months included in each season could be identified.

6. Results and discussions

Chapter 6 gives a summary of the publications, which represent the primary outcomes of this PhD work. The titles of sections in this chapter coincide with the titles of the papers in Section 1.4. Each section in this chapter was dedicated to a specific paper. Chapter 6 contains a brief overview, results, and discussions for a particular problem related to DHW heat use analysis and modeling. More detailed descriptions and results of the research are presented in Papers I-XI.

The order of the subsections follows the order of papers in Section 1.4 and the structure of the thesis. Sections 6.1-6.3 investigate the problem of restoring information about the SH and the DHW heat use from the measurements of the total heat use in buildings. These chapters give the motivation to separate the SH and the DHW heat use analysis in buildings. Sections 6.4-6.5 consider the issue of selecting the best model and influencing variables for DHW heat use prediction. Sections 6.6-6.10 are devoted to the problem of development and analysis of DHW heat use profiles in different building types in Norway. Section 6.11 addressed the problems of the total DHW and SH heat use profiles analyses and scenario-based modeling for Norwegian buildings in normal conditions and during the COVID-lockdown. Section 6.12 summarizes the results of studies presented in the publications.

6.1. Analysis of energy signatures and planning of heating and domestic hot water energy use in buildings in Norway

Section 6.1 and Paper I explored the problem of heat use planning in buildings. The case study for this research was a school located in Oslo, Norway. Even though the considered building is modern and constructed according to the passive house standard, the measurement system for heating in this school is simplified. This measurement system allowed us to obtain information only on the hourly total heat use, not divided into SH and DHW. The observed school is connected to the district heating and has only meter for the heat measurement, while if necessary, sometimes electricity is used for heating.

The ESC method, see Section 3.1, was applied for the analysis of heat use in a school. To recall, the ESC consists of two different parts: temperature-dependent (TD) and temperature-independent (TI) heat use. The TD part of the heat use is characterized by the SH and the DHW heat use in the cold season. During this period, the SH system is in operation and generates the main heat load. The TI part is the heat use in the warm season. In the warm season, SH is not needed, and therefore DHW use is the primary consumer of heat. In order to make a more accurate analysis, the TD and TI parts were considered individually. First, the correlation and the PCA analysis were applied to estimate the influence of different parameters on heat use in the school. Afterward, the data-driven modeling for the TI and the TD heat use was executed.

The study showed that weekends and weekdays influence both the TD and the TI heat use in the school. Moreover, in working hours (from 7 o'clock till 17 o'clock on weekdays) the heating use is fluctuating and is higher compared to the other time of the week. In non-working hours and weekends, the heat use is much lower and more uniform.

For the TD heat use, the seasonality and the outdoor temperature are the essential variables that should be considered. The electricity use has a moderate positive correlation with the TD heat use heating. It might be that some school areas are heated up with electrical panels, and this is the reason for the positive correlation. Further, the temperature lag of 14 hours was identified as a parameter that considered the thermal inertia of the building. For the TD heat use, several modeling techniques were compared by statistical criteria. The investigation showed that a multiple linear regression resulted in better accuracy for the TD heat use modeling than SVR, PLSR, and LASSO models. The R2 for the regression model was equal to 0.832.

It was found that the TI part of the heat use, related to the DHW use, may be observed from April to October. The PCA of the TI heat use showed that hour of the day, day of the week, and seasonality were influencing parameters. However, unlike the TD part, the TI heat use has no other explanatory variables. Therefore, instead of a regression model, the profiles for working days and weekends were used to explain the TI heat use for each month from April to October. The value of R2 showed that the proportion of the total outcome variation described by the profiles was equal to 0.71. Moreover, the profiles obtained in this way were quite informative and allowed us to retrieve information about daily and monthly variations of the TI heat use for the summertime.

The approach proposed in the Paper I suites for the total heat use planning in building. Analyses of the TI part of the heat use may give some hints about DHW heat use in the warm months. However, the results indicate that for better understanding and modeling of the DHW heat use in buildings, the more advanced methods should be applied. For this reason, the method for splitting the total heat use into the SH and DHW is required. Thus, Sections 6.2-6.3 are dedicating to this issue.

6.2. Domestic hot water decomposition from measured total heat in Norwegian buildings

This section discusses in more detail the problem of splitting the total heat use into DHW and SH heat use. The analysis performed in this study aimed at comparing and verifying different methods for restoring typical DHW heat use profiles from the total heat use in buildings. Three methods were tested for solving this problem: the seasonal method (SM), the energy signature method (ESM), and the hybrid summer-signature method (HSM-ES). The first two of these methods are well known and commonly used. The hybrid summer-signature method is a modified approach that was proposed in Paper II.

The seasonal method assumes that there is no heat demand for SH between June 1st and August 31st, and the total heat use during these summer months is used only for DHW purposes. Consequently, the DHW profiles for these months may be restored and extended for the rest of the year. ESM makes a similar assumption. However, instead of a summertime assumption, the TI part of the ESC was used to identify the period when the DHW use is the primary heat consumer. When using the HSM-ES, linear regression is applied to calculate the expected value of the total heat use in the summer months for the given hour at a given outdoor temperature. This method assumed that the heat use was solely for the DHW heating purposes at higher outdoor temperatures. Thus, the results of the modeling at temperatures above 16°C allowed us to restore the DHW heat use profile. An extensive explanation of all the three methods is given in Paper II.

For the investigation, one- to three-year period of hourly measurements in 78 Norwegian buildings were used for restoring typical DHW heat use profiles. The buildings are comprised of apartments and hotels. The restored profiles were compared with the actual DHW heat use profiles obtained from several sources.

The DHW heat use profiles developed based on the considered methods and the reference profile are shown in Fig. 7. In Fig. **7** the reference profile is obtained from the real measurements. All the three methods allowed us to recreate the hourly variation of the DHW heat use. Nevertheless, the average daily profiles for the apartments and the hotels, created with the HSM-ES, were most similar to the reference profiles obtained from the real measurements. These HSM-ES profiles were "smoother", with less sharp morning and evening peaks compared to the other decomposition methods. Obtained by HSM-ES method profiles for the hotels showed a high morning peak, and a slight increase in the DHW heat use towards the evening/night, with a significant decrease in energy use during the late night. For the apartment buildings, the profiles demonstrated two prominent peaks that occurred in the morning and evening, a small reduction of the DHW heat use during day time, and a significant decline at the late night.

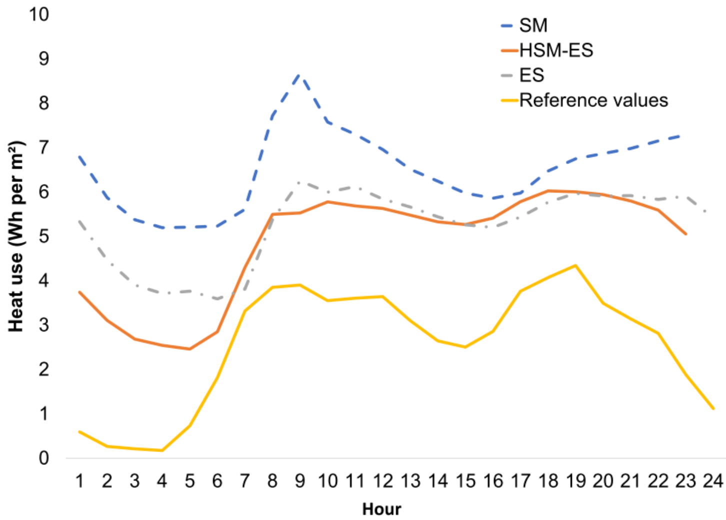


Fig. 7 Restored profiles of DHW heat use

The investigation also showed certain limitations of the considered methods. These methods do not allow to consider the seasonal variation of the DHW heat use and changes in the number of residents in buildings within the year. As a result, the comparison of the developed DHW heat use profiles and the measurements indicated that all the three methods, have high chances to overestimate the heat use for the DHW purposes. For this reason, the considered methods are more suitable for planning the maximum values of the DHW heat demand, rather than the average DHW heat use.

Splitting the total heat use into SH and DHW heat use on an hourly basis is more informative and useful than restoring typical DHW heat use profiles. Thus, the research presented in Section 6.3 aims to develop a method that allowed us to restore hourly values for the SH and the DHW heat use for the entire year.

6.3. Splitting measurements of the total heat demand in a hotel into domestic hot water and space heating heat use

Section 6.3 presents a method for splitting the total hourly heat use into the SH and the DHW. The splitting follows the assumption that the outdoor temperature is the main parameter explaining the hourly SH heat use, while the hourly DHW heat use was not influenced by this parameter. Following this assumption, the modeled SH heat use was extracted from the total heat use by using the ESC and SSA methods. The method is explained in detail in Paper III, and in Section 3.2.

The method was tested based on the one-year hourly data received at a hotel located in Oslo, Norway. At this hotel, two energy meters measured the actual SH and DHW heat use separately. The sum of their readings characterized the actual total heat use in the building. Thus, the investigation was performed in such a way that the results of the total heat use splitting could be compared and verified based on the actual measurements from two separate meters for DHW and SH.

Using the piecewise regression method, the ESC with the CPT equal to 16°C was developed for the considered building. As it was mentioned before, the "classical" ESC method assumes that the TI part of the ESC is fully dedicated to DHW. The measurements in the hotel showed that all the time in the warm months, even after the CPT, a certain amount of heat was consumed by the SH system. When the outdoor temperature was above the CPT, SH was responsible for 7% of the heat use, while 93% was associated with DHW. Meanwhile, during the whole year, the SH contributed to 75% of the total heat use and 25% was related to DHW. The SH heat use in the warm season might be explained by the fact that the control valve for the heat exchanger connecting the SH system to the district heating was wrongly sized or had faults. This meant that even this control valve was completely closed, some amount of the water flow passed and gave the SH use even above the outdoor temperature of 16°C. This heat amount was not usefully used in the building, yet it was just heat loss circulating in the system [102].

The analysis showed that the method that used the ESC and the SSA decomposition well explained the trend of the SH heat use in the hotel. Fig. 8 and Fig. 9 show the results of splitting the total heat use in the hotel into SH and DHW based on SSA for February. For the yearly data sample, R2 for the SSA SH heat use model reached 0.97, while for the DHW heat use R2 was 0.76. Moreover, the SSA allowed us to capture hourly spikes of the SH and DHW heat use.

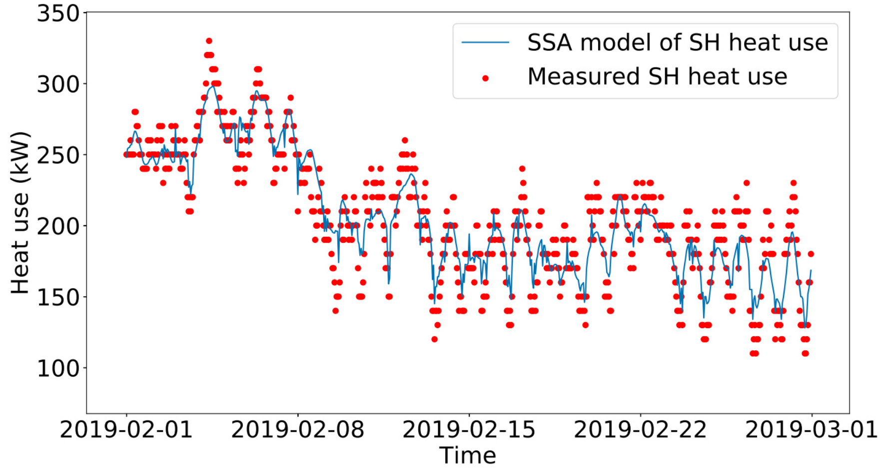


Fig. 8 Restored SH heat use based on the SSA

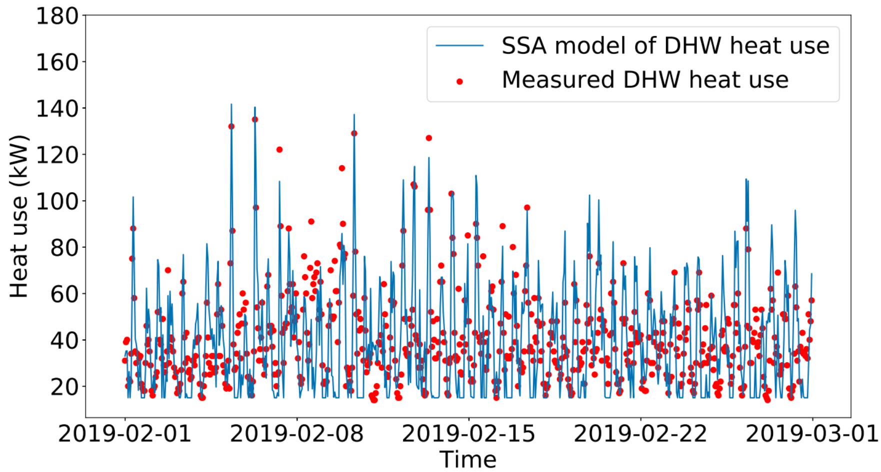


Fig. 9 Restored DHW heat use based on the SSA

Fig. 10 shows that the restored DHW and SH heat use may be used for identifying the typical heat use profiles. The proposed method allows restoring well the average daily load profiles for the SH and the DHW heat use. The profiles obtained from the SSA model well captured the timing of the peak heat use during an average day. The profiles showed that the morning peak of the DHW use in the hotel occurs from 7:00 to 9:00 o'clock and the evening peak from 21:00 to 23:00 o'clock. Comparing to the DHW, the profile of the SH heat use was more uniform. However, it also showed a small increase in heat use in the morning and night-time.

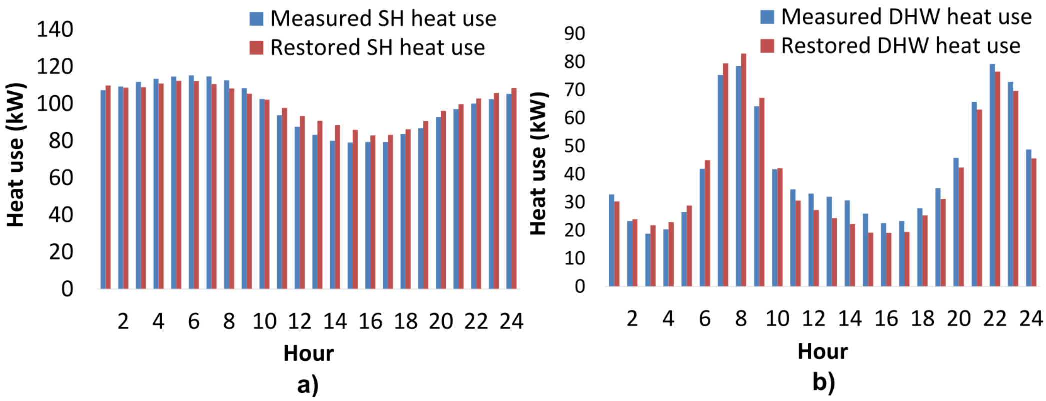


Fig. 10 Restored hourly SH and DHW heat use profiles: a) SH heat use and b) DHW heat

The average monthly profile for the restored SH heat use was representative, compared to the actual SH heat use. This profile captured well the seasonal variation of the SH heat use. The months with the coldest outdoor temperature (November, December, January, February and March) showed the highest SH use. At the same time, in the warm season (May, June, July, August and September), the SH heat use was small. The monthly DHW heat use profile had inaccuracy for the months in the warm season. In these months, significant spikes of DHW heat use occurred, most likely related to an increased number of guests in the hotel in the warm season [75]. In addition, due to the unnecessary SH heat use that occurred after the CPT in the hotel, it was difficult to capture precisely the DHW heat use from the ESC model for warm months.

The proposed method allowed us to split the SH and the DHW heat use from the total heat use. Even though the obtained values of the SH and the DHW heat use have particular inaccuracy, their application may still be useful. Both models for the SH and the DHW well represented the general trends of SH and DHW use. They provide essential information for solving energy saving issues in the heating systems of buildings.

6.4. Prediction of DHW energy use in a hotel in Norway

Section 6.4 and Paper IV present the results of daily prediction modeling of DHW heat use. The prediction modeling was performed using data collected in a hotel, located in Norway.

Identifying influencing variables with significant impact on the DHW heat use in the building is an initial step for prediction. The variables *Gst* and Gst_{Lag1}, which represent the number of guests on an observed day and the day before, were investigated. The data of energy use for other needs (*Eon*) and the number of booked rooms (*Rm*) were also examined. In addition, the influence of the following meteorological parameters was analyzed: the outdoor air temperature (*T*), the relative humidity (Rh), the mean wind speed (*Ff*), the atmospheric pressure (*Pa*). The influence of the day of the week (*DoW*) and month (*Mth*) was also considered.

The influencing variables that affect the daily DHW heat use were selected based on the Wrapper approach. The main parameters for daily DHW here use modeling in the hotel were *Gst* and Gst_{Lag1}. *Rm* was highly correlated with the number of guests and was taken out of the model, because it did not give additional information and quality to the model. *DoW*, *T, Rh, Eon*, and *Mth* in the daily model improved the models, but not much. For example, when adding all these parameters to the model, depending on the modeling approach, R2 coefficient increased by 5-15%. Thus, if the target of modeling is to build a more accurate model, then these parameters may be considered, as we have done in this paper. However, if a simple model is preferable, then only data about the number of guests in the hotel may be used.

The selection of the DHW energy use model and modeling techniques should be made individually for each building, taking into consideration its characteristics. For this reason, eight modeling techniques were applied for daily prediction, and the most accurate models were selected among them. Fig. 11 shows good results obtained by using SVR.

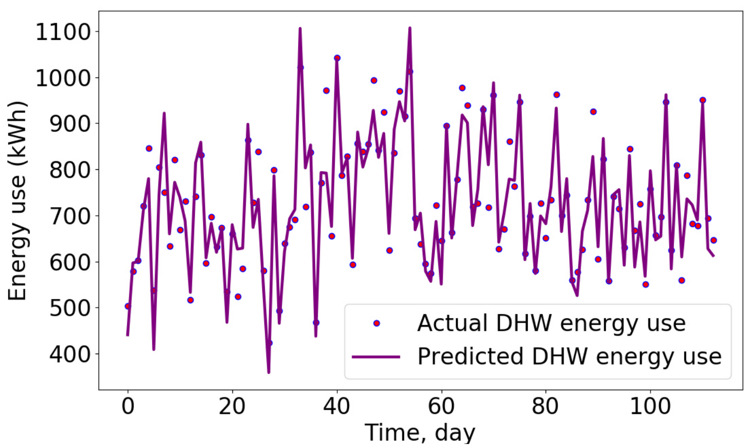


Fig. 11 Daily modeling of the DHW heat use based on the SVR method

The models were tested using both the cross-validation approach and one year ahead prediction. The best model for the daily prediction was the SVR. For the daily model, R2 equals 0.881 for the SVR model based on the cross-validation of the data set, and 0.777 for one year ahead data set.

6.5. Selecting the model and influencing variables for DHW heat use prediction in a hotel in Norway

Section 6.5 shows more in-depth research of DHW heat use modeling with the focus on hourly prediction. The case study for this investigation was heat use in a hotel located in Eastern Norway.

For accurate prediction, it is crucial to select a proper set of input variables. These variables should include the main factors that affect the DHW heat use in the building. Yet, the data availability may vary from one building to another. Therefore, two common situations with data availability were considered. Situation 1 assumed that only information from the historical DHW heat use might be used for prediction. Situation 2 demonstrated more favorable conditions, where also additional variables that affect DHW heat use were included in the model. These variables were determined using the Wrapper approach. The Wrapper approach showed that factors related to the guest presence have the most significant influence on the DHW heat use in the hotel. Nevertheless, daily data about the number of guests booked at the hotel did not appear to be informative enough for precise hourly modeling. Therefore, to improve the accuracy of the prediction, it was proposed to use an artificial variable. This artificial variable is identified based on the coefficient intensity of the guests DHW use according to the method presented in Section 4.2.1 and Paper V. The coefficients for a given day and the day before are shown in Fig. 12 and Fig. 13. They allowed us to reflect the hourly habits of the DHW use in the hotel.

For more precise prediction, the variation of the DHW heat use in different periods of time should be taken into account in Situation 1. The descriptive statistical analysis and box plots of DHW heat use in the hotel clearly showed that parameters such as hour, day of the week, and month should be included in the model. Accordingly, in Situation 1, the retrospective time series of the DHW heat use and the hour, day, and month were used as inputs for different prediction techniques.

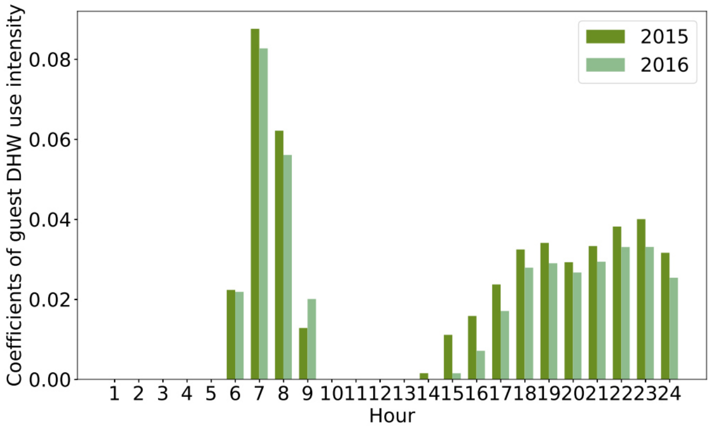


Fig. 12 Coefficients of the guest DHW use intensity based on the booking in the given day in the hotel in 2015-2016

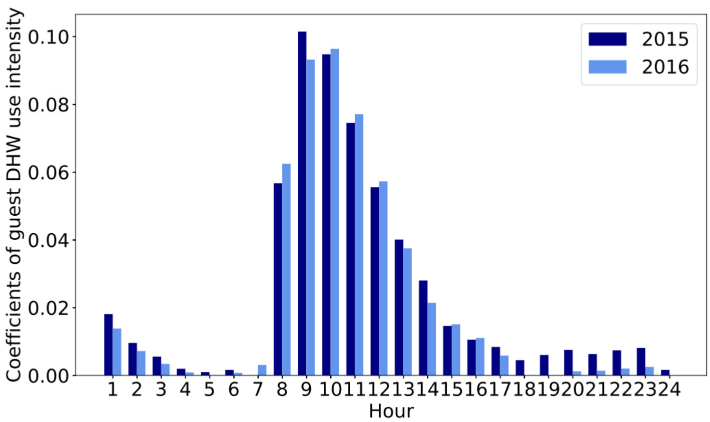


Fig. 13 Coefficients of the guest DHW use intensity based on the booking one day before in the hotel in 2015-2016

The classical time series modeling techniques, ES and ARIMA, showed poor accuracy of prediction with the high values of MAE and MSE, and R2 less than 0.6. The NN, Prophet, and XGBoost techniques showed better outcomes. Among the models considered for Situation 1, the Prophet had the best accuracy for the hourly DHW heat use modeling, as shown in Fig. 14.

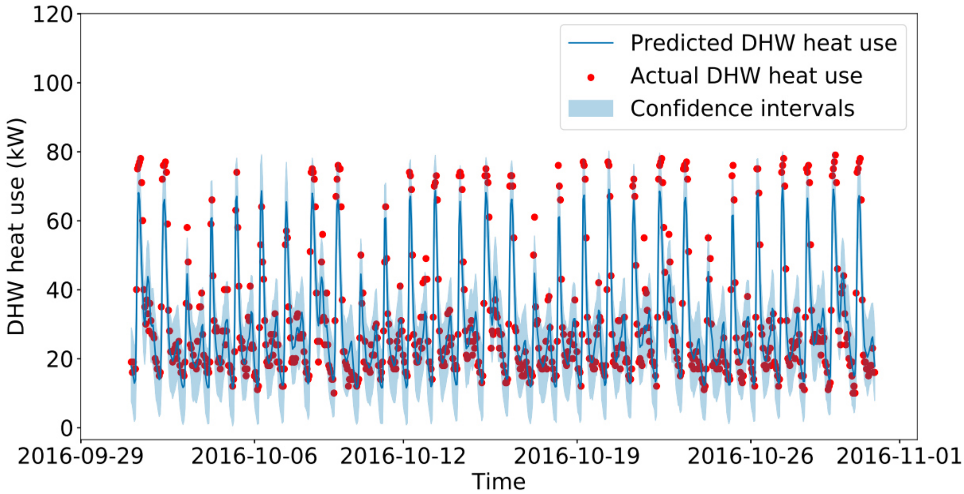


Fig. 14. Hourly modeling of DHW heat use based on the Prophet method in Situation 1

In addition, the Prophet model stayed robust. The R2 remained equal to 0.76 for both the training and the testing set. The analyses indicated that most of the actual values for the DHW heat use lay within the confidence intervals [103] for the model. This means that the Prophet model developed for Situation 1 may be used for predicting the DHW heat use in the hotel. However, despite this fact, the model may be improved. For this purpose, additional variables that affect the DHW heat use were considered in Situation 2.

As a part of the investigation for Situation 2, the feasibility of using different variables for the DHW heat use modeling was tested. Initially, the study looked at the same set of variables as in Paper IV. In addition, to take into account the daily variation of the guest presence and improve the prediction, the artificial variable Gst_{art} was used. Gst_{art} was calculated according to the method in Section 4.2.1. Different modeling techniques with and without application of artificial variable Gst_{art} were tested to determine the most accurate model.

The Wrapper algorithm was applied to categorize the best set of influencing variables. It was found that the most influencing parameters for all the models are related to the guest presence in the building. Gst and Gst_{Lag1} showed the best result for the models created only based on measured data, and Gst_{art} for the models where this artificial variable was applied. These three parameters allowed us to receive quite reliable models for the DHW heat use in the hotel. This fact shows the importance of taking into account the occupancy for DHW heat use modeling.

In the same manner as in the case of daily prediction (See Section 6.4), application of the mean wind speed (*Ff)* and the atmospheric pressure (*Pa)* in the hourly models did not increase prediction accuracy. In this regard, these parameters also should be excluded from hourly modeling. When the relative humidity (*Rh)*, was used, only a few models showed insignificant improvement. Thus, the application of *Rh* is usually not reasonable. The outdoor air temperature (*T)*, and energy use (*Eon)*, for other needs improved the models, but just slightly. For example, when adding these parameters to certain models, *R2* coefficient was increased by several percent.

The parameters hour (*H)*, day of the week (*DoW)*, and month (*Mth)* represented changes in the DHW heat use in different periods of time. In complex and accurate models such as Prophet, NN, and XGBoost, applying these parameters gave us good effects. However, simple models were unable to extract useful information from *H*, *DoW*, and *Mth* for the DHW heat use prediction.

Generally, two sets of influencing variables showed the best outcomes:

a) the set of variables without using the artificial variable Gst_{art}: *Gst*, Gst_{Lag1}, *T*, *Eon*, *H*, *DoW*, and *Mth;*

b) the set of variables with using the artificial variable Gst_{art}: Gst_{art}, *T*, *Eon*, *H*, *DoW*, and *Mth.*

In order to select the most accurate DHW heat use prediction model, nine different prediction techniques were tested. When the set of the variables without Gst_{art} was used, only the Prophet, the NN, the XGBoost, and the GMDH models showed satisfactory results of prediction. On the contrary, the application of the artificial variable, Gst_{art}, allowed us to improve the accuracy of prediction. Therefore, more models met the minimum acceptable criteria with R2>0.65. In general, when the artificial variable Gst_{art} was added into consideration, the models showed better outcomes. However, for advanced and complex prediction techniques, the effect of the application of Gst_{art} was less evident. These consequences can be explained by the fact that the Prophet, the NN, the XGBoost, and the GMDH models may better reflect hidden relationships in explanatory variables than the other models. Accordingly, these models may give us a quite reliable forecast based on both sets of variables, both with and without the application of Gst_{art}.

The Prophet and the NN were the best models for hourly prediction DHW heat use in the hotel. The NN model showed better performance on the training set, while Prophet on a testing set. For the NN model, R2 calculated on the training set was 0.89. Nevertheless, for the testing set, this criterion was reduced to 0.8. Such changes of R2 may indicate a tendency of the given model to overfitting.

Compering to the NN model, the Prophet model allowed us to obtain more robust results with minor changes in R2, MAE, and MSE. For this reason, the Prophet method was selected as the best model for the DHW heat use prediction in the considered hotel. This model is shown in Fig. 15.

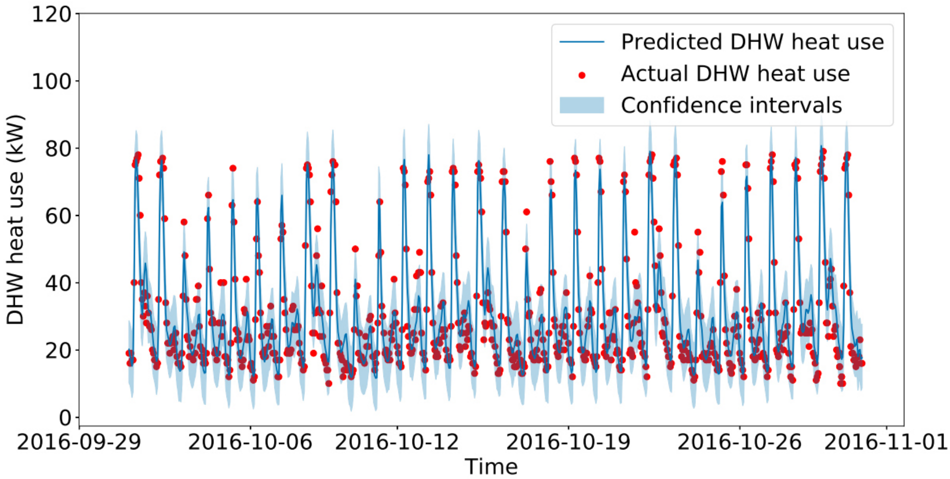


Fig. 15. Hourly DHW heat use model based on the Prophet method in Situation 2

The study confirmed that by means of easily accessible data, it is possible to obtain a fairly accurate model for the DHW heat use prediction for a hotel. Comparing the results in Situation 2 with the model that uses only the historical DHW heat use data (Situation 1), the application of additional variables (Situation 2) allowed us to improve the accuracy of prediction. For example, R2 was increased from 0.76 to 0.83 in the testing set, if using an artificial variable. For all the considered cases, the Prophet model proved to be an accurate and reliable model that may reflect periodical changes in DHW heat use. The developed models are useful for the DHW heat use modeling for other hotels under similar conditions.

6.6. Analysis of DHW energy use profiles for energy simulations in a hotel located in Norway

Section 6.6 explores the influence of DHW heat use profiles on building energy simulations. In more detail, this problem and the results of the investigation were described in Paper VI.

Dynamic simulation tools are widely applied for assessing the energy performance of buildings. The majority of simulation tools use DHW heat use profiles as a basis for estimating DHW energy needs. The case study for this investigation was a large hotel located in Eastern Norway. For this type of building, the EnergyPlus simulation model was developed. The model followed Norwegian building codes and requirements.

The DHW heat use profiles obtained based on measurement in the real hotel, profiles derived from the international standard “ISO 18523-1:2016: Energy performance of buildings” [104] and the national standard “SN/TS 3031:2016: Energy performance of buildings. Calculation of energy needs and energy supply” [105] were used as an input in the simulation model.

The simulated and the real yearly DHW energy use in the hotel is shown in Fig. 16. The results from EnergyPlus revealed the drawbacks of simulations when considering the standard values. For example, the difference between the annual DHW heat use simulated with the hourly profiles obtained from the measurements and the real total DHW energy use was approximately 10%. The SN/TS 3031:2016 profiles do not consider the circulation losses in the DHW system. For this reason, their application led to 32% underestimation of the annual DHW energy use. However, the standard ISO 18523-1:2016 overestimated the DHW heat use for 2.3 times. Consequently, when applying the standards, the energy balance obtained as a result of simulations was inaccurate.

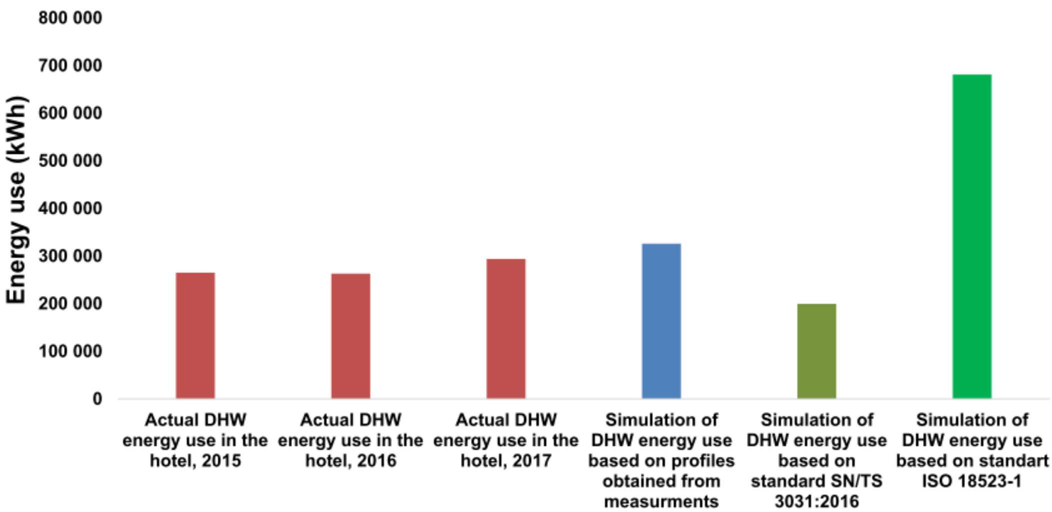


Fig. 16 Simulated and real yearly DHW energy use in the hotel

The investigation showed the need for improving the existing DHW heat use profiles given in the standards. The modern profiles should be based on accurate and up-dated statistical data obtained from real buildings.

6.7. Energy use for domestic hot water in Norwegian hotels and nursing homes

Section 6.7 and Paper VII discuss the results from a measurement campaign in Norwegian hotels and nursing homes. In this study, three hotels and nursing homes were involved. Heat use, water flow rates, and temperatures were measured on the DHW production systems in each building. At each location, the measurement equipment was installed for approximately six weeks period. Flow rates and temperatures were measured with an interval of 1 second, and then averaged to 2 seconds before the analyses. For the DHW heat use analyses, the data are averaged to hourly time step.

For comparison of the DHW heat use profiles and distribution efficiencies between the buildings, the average daily heat use was calculated, assuming that the measurement period was representative for the whole year.

Within this research, several parameters that may explain the variation of DHW heat use in different hotels were analyzed. In order to compare these parameters, the hourly DHW heat use profiles per heated floor area, per room, and per overnight number of guests were developed. The analysis of the DHW heat use for three hotels showed that all of these profiles have a similar shape, with a large peak in the morning. However, the number of rooms or number of guests were better parameters for describing the variation of DHW heat use than the floor area, which was commonly used in standards and normative documents.

A similar analysis was performed for the nursing homes. The shape of the DHW profiles showed that the nursing homes had similar routines when it comes to the DHW use, linked to morning routines and scheduled meals. As in the case of hotels, the comparison of profiles indicated that the heated area was not the best parameter to describe the hot water use.

The measurements showed a large variation in circulation heat losses for considered buildings. For instance, for the three hotels, the shares of circulation losses were 15%, 19%, and 25% of the DHW heat use. In nursing homes, these losses constituted 11%, 37%, and 39%. The malfunctioning and differences in types of the circulation system might explain such a diversity.

A comparison between the measurement data and the Norwegian standard "SN/TS 3031:2016: Energy performance of buildings. Calculation of energy needs and energy supply" [105] was performed. For the nursing homes, the normative numbers in the standard are the same as for the hotels, while the measurements showed a significant difference between these two building types.

Compared to the normative values, the actual measurements deviated significantly. These deviations may have a significant impact on the design of the building energy system. The conformity of the profiles obtained in this work indicated that they better reflect a variation of DHW heat use than normative values in the standard. However, for further improving the daily and the monthly variation of the DHW heat use profiles should be considered.

6.8. Development and analysis of hourly DHW heat use profiles in nursing homes in Norway

Section 6.8 focuses on improving the existing methods for DHW heat use profiles development and analysis. More detailed study outcomes were presented in Paper VIII, which analyses the hourly DHW heat use profiles in nursing homes. The investigation was based on one-year hourly data obtained from the three nursing homes in Norway.

The initial analysis showed a strong negative correlation between the monthly DHW heat use and the outdoor temperature. In nursing homes, it is expected that the routines for the

DHW use are similar around the year, and the variation of the monthly heat use for DHW may be described by the variation in cold water inlet temperature [74]. To consider the variation of the DHW heat use in the nursing homes over a year, the seasonality was investigated. The number of seasons during the year and the months associated with each season were identified based on the average daily DHW heat use for nursing homes in different months, applying the method described in Section 5.3. Using the Student's t-test, the months of the year were divided into two groups with substantially different mean values of the heat use within each group. The groups represent the cold and warm seasons. The cold season included the following months: January, February, March, April, May, November, and December. Meanwhile, June, July, August, September, and October were assigned to the warm season. Finally, for these seasons, separate profiles of DHW use were developed, as shown in Fig. 17.

At the next step of the investigation, the days of the week were assessed for similarity. According to the method in Section 5.1, the days of the week in nursing homes that have statistically similar profiles were identified:

- The first group: 1) Monday, Tuesday, Wednesday, Thursday and Friday,
- The second group: 2) Saturday and Sunday.

Further, the application of the method presented in Section 5.2 allowed us to determine the following borders of time zones:

1) The peak heat use of the DHW heat use occurred when the heat use was higher than 0.19 kWh/room for Monday-Friday in the cold season, 0.168 kWh/room for Saturday-Sunday in the cold season, 0.147 kWh/room for Monday-Friday in the hot season, and 0.137 kWh/room for Saturday-Sunday hot season;
2) The minimum heat use of the DHW heat use occurred when the heat use was less than 0.066 kWh/room for Monday-Friday in the cold season, 0.065 kWh/room for Saturday-Sunday in the cold season, 0.053 kWh/room for Monday-Friday in the hot season, and 0.052 kWh/room for Saturday-Sunday in the hot season;
3) The average heat use of the DHW heat use occurred when it was between 0.066 kWh/room and 0.19 kWh/room for Monday-Friday in the cold season, between 0.065 kWh/room and 0.168 kWh/room for Saturday-Sunday in the cold season, between 0.053 kWh/room and 0.147 kWh/room for Monday-Friday in the hot season, and between 0.052 kWh/room and 0.137 kWh/room for Saturday-Sunday in the hot season.

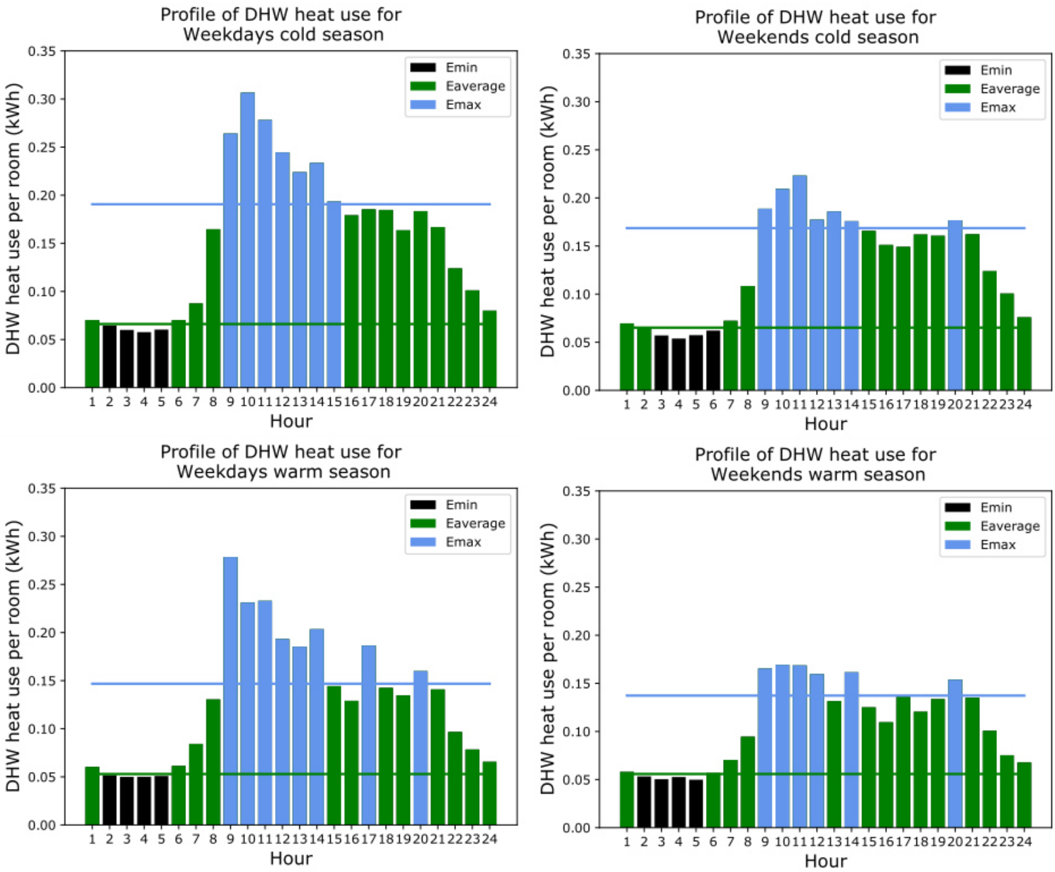


Fig. 17 Profiles for the DHW heat use in the nursing homes divided by day of week and seasons

Profiles of the DHW heat use in the nursing homes divided by day of week and seasons are shown in Fig. 17. For the nursing homes, the profiles obtained by seasons showed that the DHW heat use in the cold season was higher than in the warm season. In addition, nursing homes used less heat for DHW on the weekends than on the working days. The maximum DHW heat use in nursing homes usually occurred from 9:00 o'clock to 11:00 o'clock, and minimum from 2:00 to 5:00 o'clock.

Finally, the DHW heat use profiles obtained from the measurements in the nursing homes were compared with profiles from national standard SN/TS 3031:2016 and international standard NS-EN 12831-3:2017 [106]. The comparison showed that the European standard, NS-EN 12831-3, overestimated the daily DHW heat use by 1.65 times, and the Norwegian standard, SN/TS 3031, overestimated it by 3.5 times. The magnitude and timing of the peak heat use in the buildings were also different from the standards. The European standard explains much better the actual DHW heat use in the nursing homes than the Norwegian standard. For practical application and relevant decisions related to building energy supply systems, preference should be given to profiles obtained based on statistical data collected in real buildings.

6.9. Identifying typical hourly DHW energy use profiles in a hotel in Norway by using statistical methods

Unlike Section 6.8, Section 6.9 is focused on the development and analysis of the DHW heat use profiles in hotels. The hotel reviewed as a case study have typical characteristics for Scandinavian conditions, and well aims to reflect the trends of DHW tap energy use in similar types of buildings. Paper IX gives the overall description of the methods and outcomes of this study.

In the hotel, the DHW heat use constituted 19.5% of the total heat use in 2016 and 23% in 2017. The annual trend of the DHW heat use was analyzed by calculating the Centered Moving Average. The trend showed that over a year, the DHW heat use in the hotel varies a lot more. Therefore, it was necessary to identify the number of seasons of DHW energy use in the year, the months included in each season, and finally, develop separate profiles of DHW for each of these seasons. Seasons were identified by using the average monthly DHW heat use data for the last three years, as described in Section 5.3. Based on the t-criteria, the months of the year were divided into two groups. The groups represented the cold and the warm seasons. The warm season includes the months May, June, July, August, September, and October. January, February, March, April, November, and December might be assigned to the cold season.

At the second step of the investigation, the days of the week were assessed for similarity. Based on the method presented in Section 5.1, the groups of the days with the similar profiles were identified: 1) Monday, 2) Tuesday, Wednesday, Thursday, Friday, 3) Saturday, Sunday.

Afterward, the method explained in Section 5.2 was applied and it allowed us to determine the borders of time zones for the hotel. The profiles of DHW energy use in the hotel divided by month and season are shown in Fig. 18.

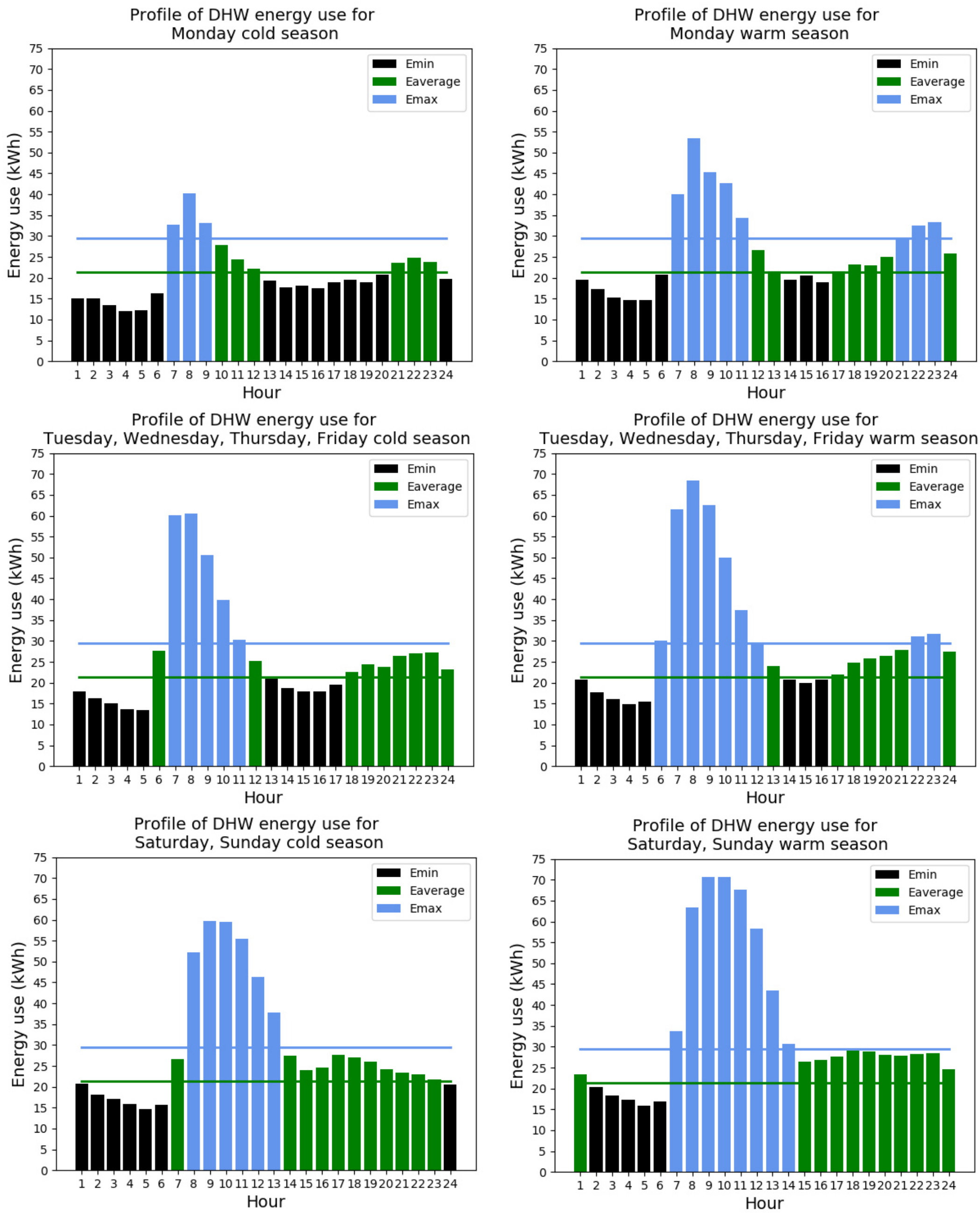


Fig. 18 Profiles of DHW energy use in the hotel divided by seasons and days

The profile analyses showed that the DHW heat use on Mondays was much lower than in the other days. For instance, the maximum heat use on Monday in the cold season was 40 kWh and 55 kWh in a hot season, while on the other days it was 60 kWh and 70 kWh, respectively. A smaller number of visitors of the hotel on Mondays compared to other days of the week might explain these results

The maximum DHW heat use on working days usually occurred from 7:00 o'clock to 9:00 o'clock. From 9:00 o'clock to 12:00 o'clock, the DHW heat use tended to decrease, although it still remained quite high and corresponded to the pick DHW heat use. The small spikes of DHW heat use may also be observed in the hot season in the evening time from 21:00 o'clock to 23:00 o'clock. However, in the cold season, there were no peaks in the DHW heat use in the evening. The minimum DHW heat use may be observed at midday and at night.

The peak DHW heat use in the weekends was shifted by one hour ahead compared to the working days. The maximum DHW heat use on weekends occurs from 9:00 o'clock to 11:00 o'clock.

In general, this study, presented in Paper IX, demonstrated that dividing the DHW heat use profiles by the seasons and the days of the week was reasonable for hotels.

6.10. Analysis of monthly and daily profiles of DHW use in apartment blocks in Norway

Section 6.10 presents the results related to the DHW use in apartment blocks. The detailed description of methods and the results of this investigation are given in Paper X, which analyzed the monthly and hourly profiles in apartment blocks in Norway. For this purpose, two data samples were used. Due to data availability, these data samples were obtained from different sources, nevertheless for similar apartment buildings. The first data sample contained data of the monthly DHW use in 49 apartments in Norway. The second data sample included hourly data on the DHW and the heat use in four apartment buildings. Two of these buildings belong to social housing and the other two to a housing cooperative.

The monthly profiles in 49 apartments were used to obtain useful information on the structure of the DHW heat use, expected volumes, and influencing variables.

The structure of monthly DHW use was estimated based on separate measurements in kitchens and bathrooms. The data revealed that approximately 30% of DHW was used in kitchens, and the rest 70% in bathrooms. The investigation of DHW use in Swedish apartments shows a different share of DHW use, with 60% DHW use in bathrooms and 40% in kitchens [60]. The measured profiles of DHW heat use in apartments in Norway and Sweden were also compared in Paper II. Despite the similar living standard and weather conditions, the comparison showed significantly higher DHW heat use in Norway. This fact indicates a substantial possibility for improvement of DHW heat use in residential buildings in Norway.

In order to estimate the influence of apartment sizes on the DHW use, the box plots for average DHW use for apartments with 33 m^2, 51-52 m^2, and 68-72 m^2 floor areas were developed, as shown in Fig. 19. Apartments with 33 m^2 floor area showed the highest average DHW use of 2.76 liters per m^2 per day, while the average in the 51-52 m^2 apartments was 1.78 liters per m^2, and the average in the 68-73 m^2 apartments was 2.5 liters per m^2.

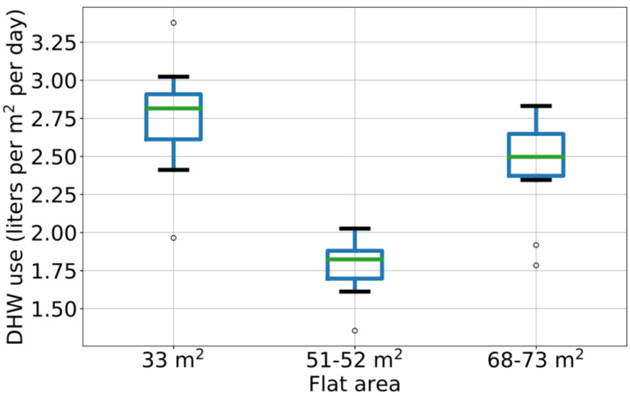


Fig. 19. Box plot for the average monthly DHW use for different apartment sizes

The analyses revealed that even though the floor area was an essential parameter, it could not entirely explain the variation of DHW use in different apartments. The number of inhabitants may better explain this variation, especially for apartments that have similar sizes. However, for apartment blocks, information about the number of people who live in each apartment usually are not disclosed. Therefore, it was proposed to find groups of apartments that have similar levels of DHW use based on the cluster analysis. The assumption was that each of these clusters should represent DHW use in a group of apartments with a similar amount of people. The clustering method showed the three main clusters of the DHW use. Cluster 1 and Cluster 2 mainly contained apartments with 33 m^2 and 51-52 m^2 floor area. Cluster 3 included all the apartment types. The average DHW use in apartments within Cluster 1 was equal to 31 liters per day, while Cluster 2 – 76 liters per day, and Cluster 3 – 167 liters per day. The standard “NS-EN 12831-3:2017: Energy performance of buildings”

[106] and the paper [12] give the reference values for the daily average DHW use per person. These values are equal to 30-40 liters per day. By using these values to estimate the number of residents in the apartments, Cluster 1 might consist of apartments with only one resident, Cluster 2 apartments with two residents, and Cluster 3 families with three or more residents.

Both monthly profiles for the DHW heat use per floor area and for a different number of inhabitants displayed seasonal variation of the DHW heat use, with lower heat use from April to July. The significant decrease in the DHW use in the spring/summer months could be explained by the increased cold-water inlet temperature and vacation time in Norway.

The hourly profiles in two multi-family social housing and two housing cooperatives were used to study the effect of ownership type on hot water use, as well as daily and weekly variations, and peaks in the DHW heat use. The average hourly DHW heat use for social housing and housing cooperative is shown in Fig. 20.

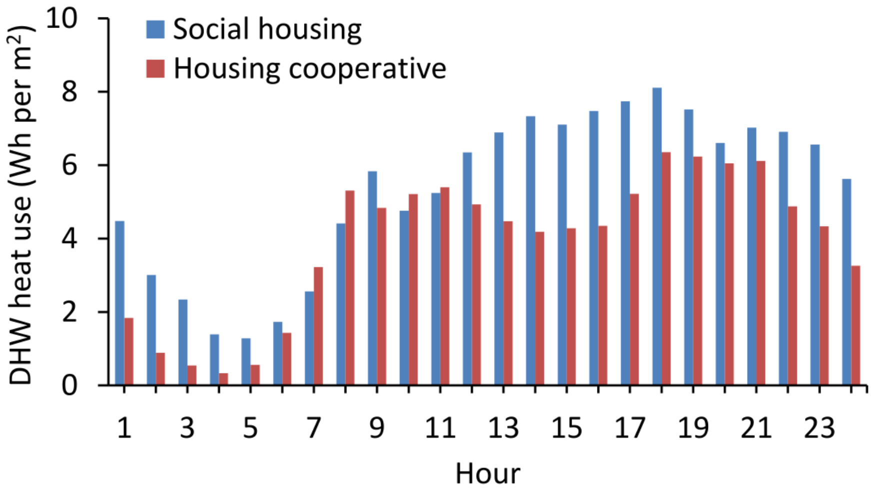


Fig. 20. Average hourly DHW heat use for social housing and housing cooperative

Social housing buildings are owned and managed by the state to provide affordable housing for people who need it. In housing cooperatives, people typically own their apartments, representing a regular type of ownership in Norway. The profile of the DHW heat use in housing cooperative has a typical shape with the morning peak from 8:00 o'clock till 11:00 o'clock, reduction of the DHW heat use from 13:00 o'clock to 16:00 o'clock, and evening peak occurred from 18:00 o'clock until 21.00 o'clock. Unlike a housing cooperative, the DHW use profile for the social housing was more even through the day and with a morning peak, about one hour later than in the housing cooperative. The social housing profile had an increased DHW heat use in the daytime, from 13:00 to 16:00 o'clock. The evening peak in the social housing took place before 20:00 o'clock. In general, social housing consumed more heat for DHW. An explanation of this might be that a larger share of the residents in social housing was staying home during the daytime. Both the social housing and the housing cooperative showed a weekly variation of the DHW heat use, with higher DHW use during the working days.

The profiles of the DHW heat use for the social housing and the housing cooperative were compared with the reference profile presented in the national standard SN/TS 3031:2016 [105]. SN/TS 3031:2016 provides valuable information about the peak values for the DHW heat use. However, compared to the four apartment buildings analyzed, the standard profile was not accurate enough and should be modified. In addition, it may be relevant for the standards to consider the difference between the social and the regular housing.

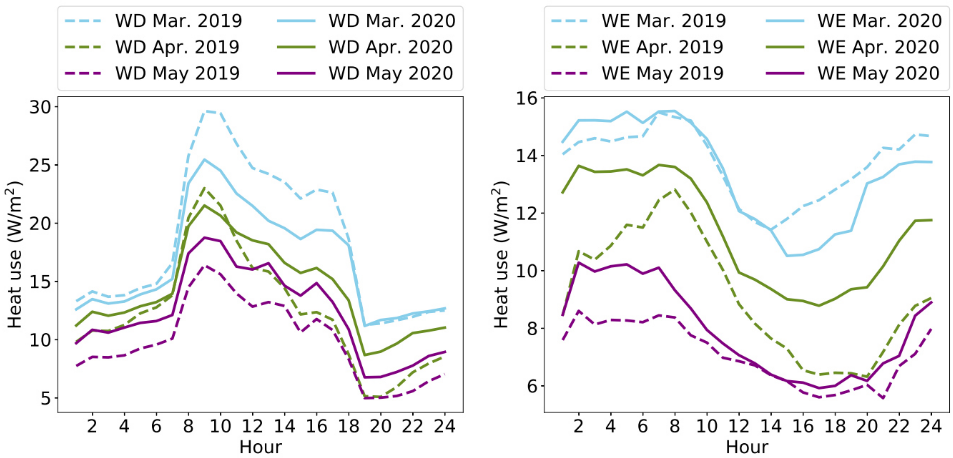
6.11. Analysis of heat use profiles in Norwegian educational institutions in conditions of the COVID-lockdown

Section 6.11 investigates the heat use profiles analyses and scenario-based modeling for Norwegian educational institutions in normal conditions and during the COVID-lockdown. The more extensive outcomes of this investigation were presented in Paper XI.

In order to avoid unnecessary energy use and ensure the proper functioning of buildings, it becomes essential to have a better understanding and planning of heating use for a different type of building. This problem was especially important during the COVID-19 pandemic when most countries have imposed a partial or full lockdown that aims to stop the spreading of the infection. Many people were compelled to avoid gatherings and crowds, stay at home and work remotely. Such drastic changes in the behavior of energy users have a significant impact on energy use in buildings and lead to substantial problems in the energy sector.

The negative influence of the COVID-19 pandemic on the energy sector may be mitigated by ensuring the energy efficient operation of buildings, better energy planning, quick adaptation to new conditions, and introduction of proper operation measures. SH and DHW heat use profiles and scenario-based models provide us with valuable insights to analyze changes in energy use in buildings and take actions to respond to these changes. The study presented in this section aimed to improve the existing knowledge about heat use in educational buildings in Norway in normal conditions and during the period of the COVID-19 pandemic. The research was based on heat use data obtained from eight kindergartens, twelve schools, and buildings at the university campus located in Trondheim, Norway. Unfortunately, in considered educational buildings, the only one heat use meter for both SH and DHW was available. Subsequently, this PhD study had shown that this state of affairs is typical for many buildings in Norway and significantly complicates the analysis of the DHW heat use in such buildings.

First, in this investigation, the profiles of heat use in buildings during the COVID-lockdown and the previous year were compared. An example of the developed heat use profiles for kindergartens is shown in Fig. 21. For the other educational building, the profiles had a similar shape.



a) b)

Fig. 21 Heat use profiles for kindergartens, where: a) profiles for weekdays, b) profiles for weekends

Many publications assume that during the lockdown, the operation of educational institutions would follow the weekend patterns. The investigation in this study found that the shape of the heat use profiles on weekdays before and during the pandemic remains almost unchanged and differs significantly from the weekend profiles, see Fig. 21. The profiles revealed that in March 2020, the heat use was lower than in the same period of 2019. In April 2020, the heat use was slightly higher than in April 2019. Differences between the profiles in March and April were mainly influenced by changes in the outdoor temperature, instead of changes in the heating system settings. The type of the heating system did not affect this state of affairs. The heat use profiles in buildings with electric heating systems had similar behavior to profiles for buildings using district heating.

The results showed that some primary educational institutions might have operated during the COVID-lockdown. In order to support parents who are working in critical positions such as health care, transportation, police, and others, some kindergartens and junior schools remained open during the pandemic. Our analysis also showed that all considered educational buildings did not reduce heat use, regardless of the transition to distance learning. The policy for reducing the heat use during the lockdown in educational institutions has not been developed. Therefore, it may be stated that during the COVID-lockdown, the energy system in many buildings was operated inefficiently.

After the educational buildings were reopened in May 2020, the profiles showed an increase of the heat use. Such an increase might be explained by changes in DHW heat use due to the introduction of strict requirements for regular buildings' disinfection and personal hygiene.

For better heat use planning, this study suggested scenario-based modeling for possible settings of the heating system. The following scenarios were developed for educational institutions: 1) Scenario 1 − Modeling based on the settings for a normal year, 2) Scenario 2 − Modeling in accordance with night settings of heat use, 3) Scenario 3 − Modeling based on settings that were used during the lockdown. The scenarios were developed based on the application of ESC method, as introduced in Section 3.1, and adjustment with the outdoor temperatures of the typical cold and warm years. The detail explanation of the methods that were used in this investigation is given in Paper XI. It should be noted that since scenarios were developed based on a short-term lockdown, the study had some limitations. These limitation were presented in Paper XI.

The methods showed high accuracy in modeling Scenarios 1 and 2. Scenario 3 was developed by monthly variation factors of the heat use. These factors were used in order to project the seasonal variations of the SH and DHW heat use in the COVID-lockdown conditions. The results for the scenario-based analysis for heat use in kindergartens are shown in Fig. 22.

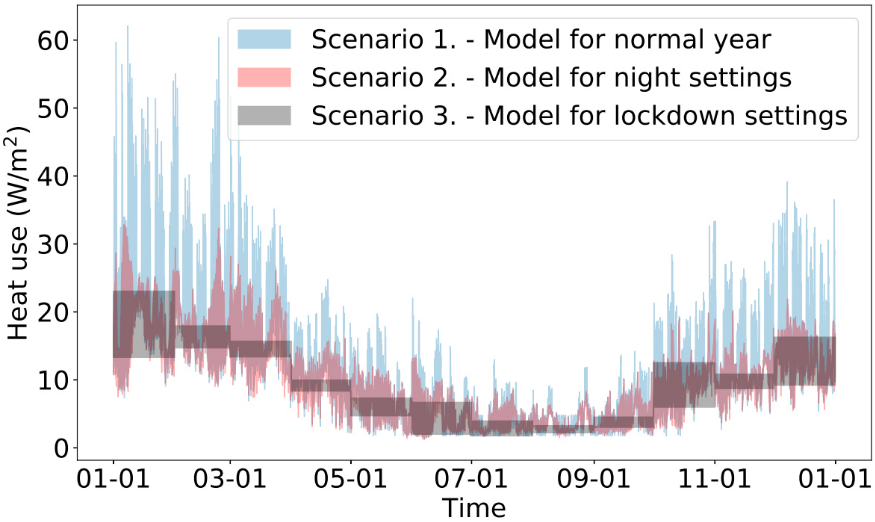


Fig. 22 Heat use in kindergartens based on the scenario analysis

The proposed scenarios can be used for planning the heat use and estimating the potential energy savings. For example, the analysis showed that application of night settings as in Scenario 2 during the lockdown in March might allow us to save 79 Wh/m^2 per day for kindergartens, 72 per day Wh/m^2 for schools, and 80 Wh/m^2 per day for university building. In normal condition, the specific annual heat use in kindergartens was 102 kWh/m^2 per year, in schools 63 kWh/m^2 per year, and in university 123 kWh/m^2 per year. Therefore, if annual heat use is considered, for kindergartens, the application of Scenario 2 may save 20.2 kWh/m^2 per year, for schools –17.7 kWh/ m^2 per year, and for university building 21 kWh/m^2 per year. However, without having separate measurements for DHW heat use, it is difficult to say how DHW affected the total heat use in considered buildings. Therefore, the investigation in this work showed that the separate consideration of SH and DHW heat use in buildings is essential for better heat use planning and analyses.

6.12. Discussion

This section summarizes the results of investigations presented in the selected publications and links them to research questions from the PhD study (See Section 1.2).

The literature review showed that the proper implementation of sustainable and energy efficient solutions for DHW systems requires the application of advanced data analyses, which includes the development of accurate and representative profiles, prediction and simulation models for DHW heat use in buildings. Therefore, the research questions in Section 1.2 reflect the most critical aspects related to data analyses of DHW heat use in buildings in Norway. In more detail, these questions and their connection to the publications will be discussed below.

The first research question was related to data preprocessing for DHW heat use analysis. The studies presented in Papers I-XI showed that the completeness and data quality on DHW heat use differ from one building to another. In some buildings in Norway, accurate data of hourly or monthly DHW heat use are measured regularly. However, for many buildings, DHW data are of poor quality or not measured separately from SH. Unfortunately, the last situation is very common for Norwegian buildings. For this reason, data preprocessing should be approached on a case-by-case basis, with particular attention to proper data synchronization, removal of outliers and incorrect data, and filling information gaps by using statistical methods.

The second research question was dedicated to restoring DHW heat use information from measurements of the total heat use in buildings. Solving this problem may allow us to analyze DHW heat use in buildings with only one energy meter that measures the total SH and DHW heat use. Papers I-III explore various methods for solving this problem. The research showed that ESC and SSA methods allow us to split total heat use into SH and DHW components. In such a way, the hourly DHW heat use data may be restored. However, the restored DHW heat use data are less accurate than measured. For this reason, it is suggested to use the restored data as a temporary solution. At the same time, the gradual installation of DHW energy meters should be promoted in Norwegian buildings.

The third research question considered the factors that influence the DHW heat use in buildings. The influence of different factors on the DHW heat use was investigated in Papers IV-X. These papers showed that the building type and its operating modes significantly affect DHW heat use. A comparison of DHW heat use in the social and the regular housing in Paper X revealed that the ownership form might also influence DHW heat use. The DHW system type, the floor area, and the number of people residing in buildings proved to be essential parameters that may be used to explain the variation of DHW heat use in different buildings. It was also found that DHW heat use varies depending on the hours of the day, days of the week, and seasons. Therefore, for DHW heat use analysis, it is essential to take into account these variables. The Papers IV-V showed that the guest presence is an important factor influencing the DHW heat use in hotels.

The fourth research question was dedicated to the prediction of DHW heat use. This issue was covered in Papers IV-V. The study confirmed that by means of easily accessible data, it is possible to obtain fairly accurate DHW heat use prediction. These data are retrospective time series of DHW heat use, information about the hour of the day, day of the week, and month. In addition, including information about the people presence and other parameters mentioned in Papers IV-V may significantly improve the accuracy of DHW heat use prediction. The statistical prediction method called the Prophet model showed the best accuracy and robustness for the DHW heat use prediction among various time series and machine learning prediction models. Therefore, this model is recommended for predicting the DHW heat use in buildings.

The fifth research question considers the problem of developing and analyzing DHW heat use profiles. Different aspects of this problem were explored in Papers VI-X. The studies revealed that the commonly used standards in Norway could not correctly explain the timing and variation of DHW heat in buildings. In order to cover the drawbacks of standards, the representative profiles of DHW heat use should be developed based on the statistical data collected in real buildings. Therefore, in this study, the methods for developing unified profiles for the months and days of the week with similar characteristics of the DHW heat use were suggested. In addition, the method that allowed us to recognize the timing of the peak, average, and low heat use was proposed. In Papers V-X, the analysis and development of DHW profiles were performed in such a way that specific features of the considered buildings and available data were taken into account. Accordingly, the representative profiles of DHW heat use were obtained for different types of residential and non-residential buildings in Norway.

The sixth research question and Paper XI explores the issue of heat use modeling in educational institutions during the COVID-lockdown. During the lockdown, the educational buildings are closed, and the employees have limited access to these buildings. The need for heating and DHW in buildings in this period reduces. Consequently, the heating system's exploitation in a way as before the lockdown, becomes excessive and inefficient. However, the analysis of actual heat use profiles showed that heat use before and during the lockdown in buildings remained the same. Unnecessary energy use can be avoided by applying the proper settings to the buildings' heating system in adjustment to the demand changes. In order to select proper settings and estimate the benefits of their implementations, scenario-based modeling was proposed in Paper XI. In addition, the potential for energy savings were assessed by comparing a scenario that represents the behavior of heating use under normal conditions with alternative scenarios for the lockdown period.

7. Conclusion

The main objective of this PhD research was to improve the methods for performing data-driven analysis of the DHW heat use and achieve a deeper understanding of DHW heat use in buildings in Norway. This PhD study addressed the following issues: data analysis of the DHW heat use, splitting the total heat use in buildings into the DHW and the SH heat use, identifying variables that affect the DHW heat use, developing the accurate models for the daily and the hourly DHW heat use prediction, creating representative profiles for the DHW heat use for different building categories. The most important findings of this PhD study are presented below.

The data collected within the PhD research showed that in Norwegian buildings, even modern passive houses, often only one heat meter is installed to measure the total heat use. Such measuring systems cannot quantify the SH and DHW heat use separately. The research work within this PhD study revealed that the regimes of work and the influence of different factors for SH and DHW systems did not coincide. Therefore, for the corresponding conditions, a method that will allow us to analyze the DHW and SH heat use individually is needed.

The models for the TD and the TI parts of the total heat use in a passive school were developed. The consideration of the TI total heat use was useful for the DHW heat use analysis. However, it could not fully explain the variation of the DHW heat use in a building. For this purpose, the methods for restoring the DHW heat use from the total heat use are required.

The methods for restoring the DHW heat use profiles from the total heat use were investigated. The widely used seasonal and the ES methods were compared with their modification - the HSM-ES method. The hybrid summer signature method had the resulting profiles, which were the most similar to the typical profiles obtained from the actual measurements. However, all the three methods tended to overestimate the DHW heat use. Their application was more suitable for planning the maximum DHW heat demand rather than the average DHW heat use.

Splitting the total heat use into the SH and the DHW heat use on an hourly basis was more beneficial than restoring the typical DHW heat use profiles. The method for splitting the hourly DHW and SH heat based on the ESC and the SSA was proposed. The application of this method showed that the restored models for the hourly SH and the DHW presented well the general trends of the heat use for most of the year. However, overestimation of the DHW heat use was observed for the summer months.

The analyses indicated that the accuracy of the methods for the DHW heat use restoring might be affected by the unjustified SH heat use in the non-heating season. The SH heat use in the warm season occurs due to incorrect sizing and operation of the SH system in buildings. Despite inaccuracy, the proposed method in this PhD work for restoring the SH and the DHW heat use was useful for obtaining the valuable information for estimating the performance of the SH and the DHW systems, developing prediction models, and profiles. Nevertheless, the application of the methods for restoring the SH and DHW heat use is not an ultimate solution. For a more precise analysis of the heat use in buildings, it is recommended to use the DHW and SH data collected from the two separate meters.

The literature review indicated that the data-driven prediction of the DHW heat use in buildings is not studied well enough, especially for non-residential buildings. The prediction modeling of the DHW heat use was carried out using hotels in Norway as a case study. In order to make the developed models and data processing techniques applicable to other categories of buildings, two situations with different input variables were studied. For Situation 1, the prediction was based only on data obtained from historical measured DHW heat use. For Situation 2, additional variables that affect DHW heat use were applied.

The Wrapper approach showed its high efficiency in determining the variables that affect the DHW heat use and should be included in the prediction model. This approach indicated that the main factors that influenced the DHW heat use in the hotel were the number of guests booked in the hotel on the given day and the day before. Nevertheless, the number of guests was collected on a daily basis, which made them less efficient for hourly modeling. Therefore, to improve the accuracy of the hourly model, the introduction of an additional artificial variable that explained the hourly intensity of the guests DHW use was proposed.

Identifying the DHW heat use model requires a comparison of various prediction methods. Selection of the best method among those considered should be based on the criteria of model adequacy. Among considered methods, the Prophet model showed the best accuracy and robustness for the DHW heat use prediction for both Situation 1 and Situation 2. The obtained models can be used to solve energy saving problems, as well as to build predictive profiles for the DHW heat use.

The DHW heat use profiles obtained from the measurements in the nursing homes, the hotels, and the apartment blocks were compared with profiles from national standard SN/TS

3031:2016 and international standard NS-EN 12831-3:2017. The comparison revealed that the standards are not accurate enough. The magnitude and timing of the peak heat use for all building types were different from the values proposed in the standards. The analysis showed that using profiles from the national and the international standards caused significant deviation between the simulated and the real DHW heat use. At the same time, profiles that are based on the actual measurements allowed us to obtain more accurate simulation results. Therefore, for simulation purposes, practical applications, and decisions making related to DHW systems, the preference should be given to the DHW profiles obtained based on the statistical data collected in real buildings.

Within the PhD research, several parameters that may explain the DHW heat use variation in the different buildings were analyzed. The analyses of the DHW heat use showed that the number of rooms or number of people who reside in the building were better parameters for describing the variation of DHW heat use than the floor area, which is commonly used in national regulations in Norway.

The analyses of the time series for the DHW heat showed significant monthly and daily variating of DHW heat use. The statistical methods to assess the similarities of the profiles by days of the week and seasons were proposed. These methods were tested using data for the DHW heat use in the nursing homes and the hotels. By using the Student's t-test, the months of the year were divided into two groups with substantially different mean values of the heat use within each group. These groups represented the warm and the cold seasons. Further, the days with similar profiles were identified. In nursing homes, the DHW heat use was different on weekdays and weekends. Whereas for the hotels, the profiles on Mondays differed from the profiles on both weekends and weekdays. According to these results, unified profiles for the months and days of the week with similar characteristics of the DHW heat use were developed for hotels and nursing homes. Afterward, the method for statistical grouping of the DHW hourly heat use was proposed for recognizing the timing of the peak, the average, and the low heat use.

Due to specific features of the apartment buildings, they were considered separately from the non-residential buildings. For apartment buildings, the monthly and the hourly DHW heat use profiles were investigated. In the considered apartments, nearly 30% of DHW was used in kitchens and the rest 70% in bathrooms. The box plot method showed that the size of apartments affected the DHW heat use. However, without considering the occupancy, the size of apartments could not entirely explain the variation of the DHW heat use in different apartments. For many residential buildings, the information about number of inhabitants in a particular apartment was not known. The PhD study showed that the hierarchical cluster analysis could be used to identify the groups of apartments with similar numbers of residents and the approximate number of residents in each of these groups. The obtained monthly profiles demonstrated the monthly variation of DHW heat use with a noticeable reduction in the summer. More detailed hourly profiles in apartment blocks showed that the property ownership type had an impact on the DHW heat use. The shapes of the profiles in the social housing and the housing cooperative had a noticeable difference, with a higher DHW heat use in the social housing. Therefore, it was recommended to use the individual profiles for these types of apartment blocks. In addition, for both the social housing and the housing cooperative, the DHW heat use profiles for working and non-working days should be considered separately.

The methods proposed in this PhD thesis for the DHW heat use analyses, prediction models, and profiles helps to form a basis for the proper implementation of energy saving measures and increasing the efficiency of DHW heat use in different types of buildings in Norway.

8. Limitations and recommendations for further work

This project was limited to only several buildings categories located in Eastern Norway. The influence of the location on the DHW heat use requires additional consideration. For this reason, in the future work, the appropriate analyses for a larger number of buildings located in different parts of Norway should be performed. Furthermore, it is suggested to investigate the DHW heat use in those types of buildings that were not covered in the current study.

The proposed method in this PhD study for restoring the hourly DHW heat use from the total heat use in the buildings has some limitations. This method was dedicated to the case when one meter measured the total heat use, which includes both DHW and SH. The restored DHW heat use for the summer months was less accurate than for the rest of the year. For this reason, the ways to modify the proposed approach and improve the model for DHW heat use will be investigated in the future work.

The research showed that occupancy had a significant impact on the DHW heat use in buildings. However, due to many reasons, the data about occupancy were not easily accessible for regular buildings. Therefore, in this work, for the DHW heat use prediction modeling, only daily data about occupancy were used. In smart buildings, the occupancy may be identified in more detail, up to the location of a particular person. This information gives the basis for a more in-depth analysis of the DHW heat use. Thus, it would be interesting to evaluate how better knowledge about occupancy could be used to improve the developed models and profiles.

The analysis of the heat use in considered buildings pointed out that circulation losses constitute a significant share of the DHW heat use. In order to improve energy efficiency in DHW systems, it is desirable to conduct a more detailed study of the technical aspects associated with circulation losses. The special attention should be paid to heat losses detection in DHW systems.

The COVID-lockdown in educational institutions in Norway lasted for about two months. In this regard, the amount of data collected over this period was limited for a comprehensive analysis. Due to the lack of data, it is challenging to perform accurate heat use planning for the entire year. Furthermore, due to restrictions that were gradually imposed, the patterns of the heat use may be changed several times during and after the lockdown. Therefore when additional data will be collected, further work shall be performed for improving scenarios of heat use in buildings In addition, it would be highly beneficial to study the changes in DHW heat use during the COVID pandemic relying on actual measurements.

The prediction models and profiles may find practical applications for the integration of sustainable and energy efficient solutions in buildings in Norway. The development of such solutions based on the obtained DHW heat use models and profiles will be the main topic for future work. The following solutions are of particular interest for my further investigations: 1) better utilization of solar-assisted DHW water heating systems, 2) optimal operation and design of DHW systems based on dynamic energy prices, 3) using the DHW heat systems for grid congestion management via demand-side flexibility markets.

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Selected papers

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Analysis of energy signatures and planning of heating and domestic hot water energy use in buildings in Norway

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Abstract. Widespread introduction of low energy buildings (LEBs), passive houses, and zero emission buildings (ZEBs) are national target in Norway. In order to achieve better energy performance in these types of buildings and successfully integrate them in energy system, reliable planning and prediction techniques for heat energy use are required. However, the issue of energy planning in LEBs currently remains challenging for district heating companies. This article proposed an improved methodology for planning and analysis of domestic hot water and heating energy use in LEBs based on energy signature method. The methodology was tested on a passive school in Oslo, Norway. In order to divide energy signature curve on temperature dependent and independent parts, it was proposed to use piecewise regression. Each of these parts were analyzed separately. The problem of dealing with outliers and selection of the factors that had impact of energy was considered. For temperature dependent part, the different methods of modelling were compared by statistical criteria. The investigation showed that linear multiple regression model resulted in better accuracy in the prediction than SVM, PLS, and LASSO models. In order to explain temperature independent part of energy signature the hourly profiles of energy use were developed.

1 Introduction

Prediction of building's heat energy use is a complex task. Particularly, this issue becomes challenging for district heating (DH) companies when heat energy planning is considered. Traditionally, the DH energy load include energy need for heating and domestic hot water (DHW).

These days low energy buildings (LEBs) such as passive houses (PHs) and zero emission buildings (ZEBs) are set as a national target for achieving energy efficiency and increase in primary energy savings. Simultaneously, characteristics of energy use in these types of building and their interactions with energy system are not fully investigated. The introduction of newly constructed LEBs and renovation of existing buildings to LEB standard brings additional volatility to heat demand in energy system.

DH production planning and operation involve decision making under uncertain conditions. Hence, accurate forecasting of daily and hourly heat loads is an important task in DH sector [1]. The need in advanced prediction technique arises, since load profiles of LEBs show variation in terms of energy use and duration of heating hours.

Energy signature diagram is a widely used instrument for analysis and prediction of energy use in the buildings. Energy signature diagram estimates energy use for DHW and DH as a function of outdoor temperature and may include other parameters. In most cases, the task of DH energy use is forecasting in the buildings that results in development of an accurate and representative energy signature diagram.

Two main approaches are available for modelling of DH energy use, which are physical modelling and data-driven approach.

Physical modelling is also called engineering approach, which employs physical principles to calculate thermal dynamics and energy behaviour on the whole building level and sub-level components [2]. A great example of physical modelling is software tools that were developed for energy use evaluation. Such simulation tools like EnergyPlus, ESP-r, IDA-ICE, BLAST, DOE eth. are well known and are mentioned in a number of research papers. The main drawback of mentioned above simulation tools that they require detailed input data for high quality modelling. To obtain these data is not always possible and economically reasonable.

On the contrary, in a data-driven approach, building energy behaviour is analysed by defining its statistical relationships with one or more different driving forces or parameters [3]. This approach got a lot of attention during recent years and is used for many applications. In particular, Machine learning techniques are widely applied for solving practical tasks in DH modelling and demonstrate high level of accuracy.

The widely used methods for energy use prediction are: Linear Regression, Support vector machine (SPV), Artificial neural networks (ANNs), Decision threes and other algorithms for development of linear and non-linear models. It should be noticed that mentioned methods are considered as advanced techniques. Some of them are quite sophisticated and may require application of special software, considerable amount of detailed input data, expert work and long computation time. In addition, these methods are not always applicable for utility companies.

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Nevertheless, prediction based on energy signature diagram, applying regression analysis is one of the most popular methods that is employed by a number of companies.

Regression analysis is statistical tool, which allow us to describe the variation of energy use in the building by the changes in influencing variables [2]. The goal of the regression analysis is to find an appropriate mathematical model and to determine the best fitting coefficients of the model from the given data [4].

Employment and comparison of algorithms based on multiple linear regression (MLR) analysis, general linear regression (GLR), ordinary least squares regression (OLS), autoregressive (AR), autoregressive integrated moving average (ARIMA), Bayesian regression, polynomial regression (poly), exponential regression, multivariate adaptive regression splines (MARS), case-based reasoning (CBR), and k-nearest neighbours (kNN) for building energy use prediction is given in [5]. Some applications of regression algorithms are described further. The study performed in [6] has proven that regression based prediction can be efficiently used as a tool for long-term energy use prediction. The modelling of monthly heating demand for residential buildings is investigated in [7]. The comparison of energy signature method and Eta method based on statistical regression model can be found in [8]. The authors found high degree of predictability for both heating and cooling loads treating them simultaneously. Aranda et. al [9] apply regression models to predict the annual energy use in the banking sector. Multiple regression model for fast prediction of heating energy demand with application on residential multifamily building is done in [4]. Prediction of annual energy use for office building from heating and cooling perspective is investigated in [10]. Hence, it can be concluded that the regression algorithm is widely used due to its simplicity and accuracy. Therefore, this paper describes improved methodology for planning and analysis of heating and DHW energy use by means of energy signature method with application of advance regression techniques.

The main objective of this study is to support heat and DHW energy planning that involves LEBs by providing rapid and simple solution of energy demand assessment with high level of accuracy.

2 Methodology

2.1 Low energy school building

The analysis performed in this work aimed to improve a degree of predictability of energy prediction tool. Due to increasing share of LEB in a building stock it is important to have a tool able to work on every building type and category. For this reason, a passive school was introduced as a source of energy use data. The school was constructed in 2010 in Oslo and has 6 454 m^2 heated area. Specific heat use calculated in 2011 was 31.76 kWh/m^{2}a. The energy signature diagram is shown in Fig. 1. The characteristics of the mentioned passive school building are typical for Norwegian conditions and energy use threshold was found in the range with other similar buildings in Norway.

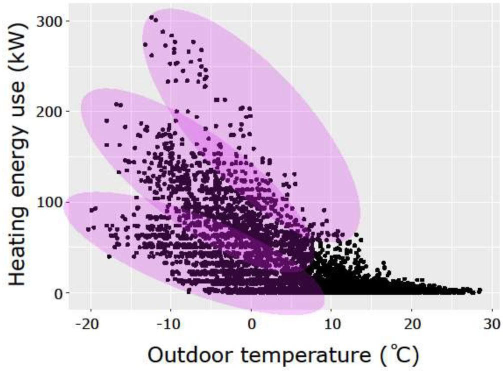

Fig. 1. Energy signature diagram of analysed building

Obtained data samples from school building were hourly based with one year duration. The building monitoring system sampled data that included various categories explained in Table 1. From Fig. 1 it can be noticed that there is no a clear pattern in energy use while the outdoor temperature is below zero. Simultaneously three-tailed pattern in the left part of Fig. 1 can be distinguished. The reason for this is unknown and may be caused by various reasons. Some of them could be due to applied control strategies or operation regimes in analysed building. Therefore, the aim of energy predictor is to capture shown volatilities in energy use data and provide reliable model that would be capable to identify them under various conditions in different types of buildings.

2.2 Regression model

In the most cases, analysis of energy signature diagram is based on using simple regression models in order to describe the behaviour of energy use in the building. Considering that energy signature diagram is dependent in terms of start and end of heating season, the division on temperature dependent and temperature independent parts that could be found in many publications is usually explained by the following equations:

If T_t < CPT:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \varepsilon \quad (1)$$

If T_t > CPT:

$$Y = \beta_0 + \varepsilon \quad (2)$$

where, ε is random error. β_0, β_1,…, and β_p describes the expected change in the predicted variable Y in response to a unitary change in x_i when the rest of predictors remain constant. The x_i is explanatory variables, such as wind speed, temperature, eth. CPT is change point temperature, with physical meaning of start and end of heating season. This means that temperature dependent part considers space heating and domestic hot water (SH+DHW), while temperature independent part considers DHW only.

In order to solve the introduced above equations, traditionally the least squares method is applied separately

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to each segment of the model. This lead to composition of two regression lines that fit the data as closely as possible, while minimizing the sum of squares of the differences (SDD) between observed and calculated values of dependent variable. The reasonable modification of the method of energy signature modelling is proposed in the article of Lindberg et. al [11]. The authors of this work introduce a temperature moving average (TMA) of last 24 hours as additional explanatory variable in the model in order to take in account building inertia in the model. Also in the article the change point temperatures, as well as, models are identified for each hour of day.

Despite the relative simplicity, there are many drawbacks and unsolved issues in considered methods. For example, the question of identifying exact value of CPT is usually not considered. Moreover, in a number of publications, selection of CPT is relies only on intuition and experience of researches. In addition, the possibility to increase the accuracy of the energy signature model by using advanced modelling techniques has not been studied sufficiently. Therefore, the improved approach of energy signature analysis is proposed in this article.

The analysis of energy signature proposed to conduct in the following way. First, the available statistical data should be pre-processed by division in two samples related to (SH+DHW) needs and related to DHW needs. This was done by a piecewise regression method combined with additional conditions related to month of the year. The piecewise regression allows us automatically to figure out the exact value of CPT in energy signature diagram. In such way, two regression lines are used to fit the data set as closely as possible. This minimizes the sum of squares of the differences (SSD) between the observed and the calculated values of energy use in different segments of energy use diagram.

When there is only one breakpoint, at x = CPT, the model can be written as follows [12]:

$$\begin{aligned} y &= a_1 + \beta_1 \mathrm{x} \qquad \text{for } \mathrm{x} \le \mathrm{CPT} \\ y &= a_2 + \beta_2 \mathrm{x} \qquad \text{for } \mathrm{x} \ge \mathrm{CPT} \end{aligned} \tag{3}$$

In order for the regression function to be continues at breaking point, the two equations for y need to be equal at breakpoint (when x = CPT):

$$a_1 + \beta_1 \mathrm{CPT} = a_2 + \beta_2 \mathrm{CPT} \tag{4}$$

Solving for one of the parameters in terms of the others by rearranging the equation above:

$$a_2 = a_1 + CPT(\beta_1 - \beta_2) \tag{5}$$

Then by replacing a_2 with the equation above, the result is a piecewise regression model that is continuous at x = CPT:

$$\begin{aligned} y &= a_1 + \beta_1 \mathrm{x} && \text{for } \mathrm{x} \le \mathrm{CPT} \\ y &= a_1 + CPT(\beta_1 - \beta_2) + \beta_2 x && \text{for } \mathrm{x} \ge \mathrm{CPT} \end{aligned} \tag{6}$$

where: β_1 and β_2 are regression coefficients, which indicating the slope of the line segments; a_1 , a_2 are regression constants, which indicates the intercept at the Y-axis.

In this study the CPT was defined by computational means applying Python software. Temperature dependent heating energy use was explained via multivariable regression models. In order to obtain reliable models that considers the variety of data points, energy use data were separated in four sample groups: 1) weekends, 2) working days – working hours 3) working days – non-working hours 4) non-typical energy use. Untypical energy use data were investigated based on confidence intervals to regression models. For each group of samples, separate models were obtained. In order to choose the best model that explains energy signature diagram, several advanced models like: support vector machines (SPV), partial least square regression (PLS), least absolute shrinkage selector operator (LASSO) were compared applying statistical criteria. The final model is a combination of four sub-models separated by four sample groups and used to generate prediction output. The testing and training sets were defined and model was tested.

Instead of considering values of temperature independent energy use as an intercept shown by Eq.(2), it is suggested to present them by means of energy profiles with division on months, working and non-working days.

The statistical analysis and model development of energy signature diagram for LEBs was implemented with software tools like R and Python.

3 Results

The results given in this section show workflow how the analysis on model was done and improvements were introduced. The results are divided in several sections with specific tasks to analyse.

3.1 Correlation analysis

One of the most important tasks in prediction of building energy use is selection of input variables. A number of studies dealing with parameter evaluation could be found in literature. Several studies show that solar irradiation has impact, others that wind speed effects energy use [13, 14]. In addition, the day of the week or working hours correlate a lot. In order to figure out which variables have the highest impact, a correlation analysis was introduced in this study. A correlation analysis is a simple way to select the input variables and see the degree of linear relationship between them. Quite often, it is not always possible to collect all the variables when it comes to real operation, therefore, correlation analysis aimed to identify factors that have the highest impact on analysed parameter and to reduce the total number of components. In such way, the most insignificant parameters are eliminated. The building monitoring system sampled various data categories shown below, together with energy signature diagram shown in Fig. 1 the correlation analysis was conducted. The correlation analysis aimed to find out how various factors effect heating load when system is operated under temperature dependent (SH + DHW) and temperature independent (DHW) modes. A correlation matrix was created and the results are shown in Table 1.

Table 1. Correlation matrix results

Component	SH+DHW	DHW
Month	-0.370	-0.070
Weekend day	-0.235	-0.167
Working day	-0.362	-0.058
Day of the week	-0.202	-0.127
Hour	0.021	0.012
Outdoor temperature	-0.516	-0.237
Medium outdoor temperature during 24 hours	-0.554	-0.426
Wind	-0.006	0.270
Medium wind during 24 hours	-0.160	0.292
Season	-0.364	-0.455
Electricity use	0.595	0.431

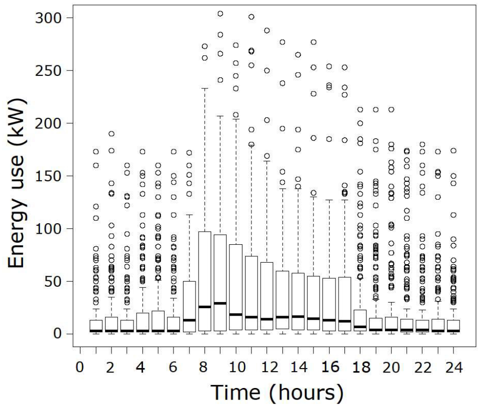
To recall, the correlation coefficient measures strength and direction of a linear relationship between the variables. The week positive or negative correlation starts from value of ±0.30.

From Table 1, it can be noticed that SH+DHW heating load shows low correlation with wind, medium wind, and hour of the day. Hour of the day and wind are below significance level, while medium wind has low correlation with heating load. The weak correlation was observed for parameters like weekend/weekday, month and season. The correlation is negative for all parameters and this can be explained as all these components are similar in terms of time factor. The highest negative correlation was found for outdoor temperature and medium outdoor temperature. This indicates that heating load increases while temperature decreases. The electricity use has moderate positive correlation with heating. It might be that some school areas are heated up with electricity panels and this is the reason of positive correlation. The analysis of temperature independent part (DHW) shows moderate correlation with medium outdoor temperature, season and electricity use. This is reasonable, because energy use in DHW part would be different due to seasonality, e.g. summer vacation, Easter holidays or beginning of school season.

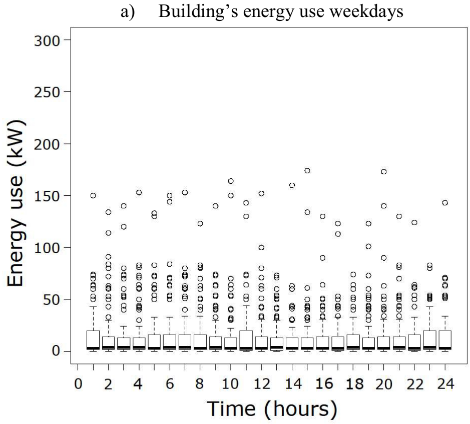
3.2 Building's energy use profile

The analysis of energy signature diagram is key to understanding of future energy use for a particular building type and a building category. Therefore, it is important to figure out the reasons for typical and untypical energy use patterns that were found in Fig. 1. The tailed data shown in left side of Fig. 1 were investigated by separation of existing data points on hourly basis intervals. The idea behind this was to find cluster formations that could explain tails.

Unfortunately, hourly data distribution could not provide clear explanation about energy use extremes. In order to see more clearly energy use pattern, the boxplot was established and is shown in Fig. 2. The spikes in data were observed practically during each hour of the day. However, it can be noticed that energy use increases drastically starting from 7 AM and decreasing by 5 PM (17 o'clock in Fig. 3). Before that time energy use showed maximum at 150 kW, but later increased up 250-300 kW.



a) Building's energy use weekdays



b) Building's energy use weekends

Fig. 2. Hourly energy use

The boxplot depicts data for weekdays and weekend days. The maximum, median and minimum energy use and density of data points are shown. In addition, outliers and suspected outliers that are not typical to the analysed data range are shown. The suspected outliers are shown as dots with higher density, while outliers are randomly distributed dots far beyond of suspected outliers. Fig. 2 shows that the building energy use has clear visible pattern, showing increase during working hours in the period between 7–17 o'clock. The weekend profile shows pretty smooth energy use pattern without sudden peaks and drops during the day.

3.3 Analysis of temperature lag

As it was mentioned before, TMA of last 24 hours has to be introduced in order to consider building inertia in the

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model, see [11]. The analysis on TMA aimed to figure out how lagged outdoor temperature in terms of hour of the day effects on building energy. It is known that building it a subject to thermal inertia. Depending on building constructions, some buildings can accumulate more heat and use it afterwards to improve indoor thermal comfort. In order to figure out to which extent temperature lag has effect on energy use, the outdoor temperature was shifted by each hour for 48 hours see correlation between mentioned parameters. Fig. 3 shows correlation between TMA and heating energy use.

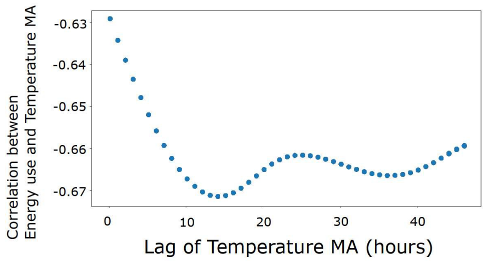


Fig. 3. Effect of temperature lag on energy use of building

Fig. 3 shows that if the correlation factor has a bigger absolute value, this indicates better fit between TMA and heating energy use. This is a good indication that thermal inertia in the building takes place, because better correlation was achieved when the TMA was shifted. The largest correlation for TMA was found for 14 hours. This shows that lag of 24 or 48 hours that are commonly used for model definition and description of building inertia is misleading. The found results showed that value of this parameter is dependent on building's construction type and time constant parameter.

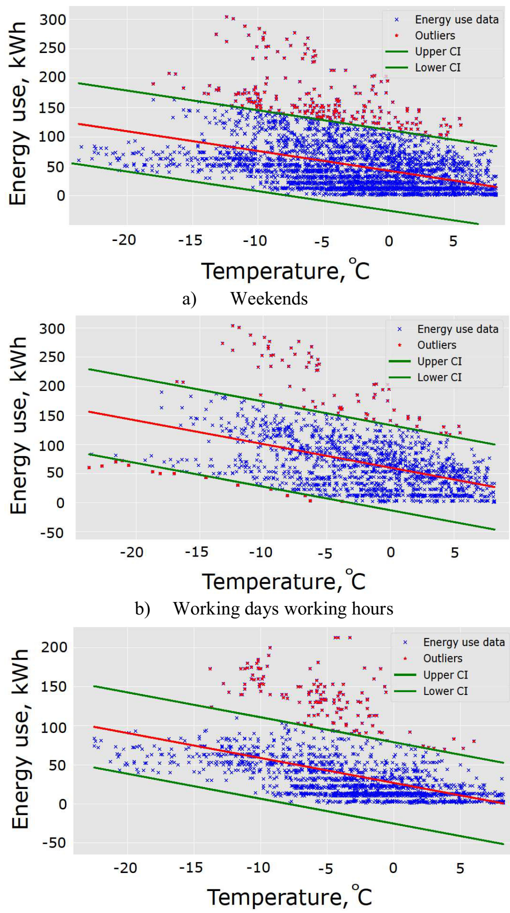
3.4 Model formulation

Next step of the analysis aimed to check if cluster formations could be distinguished among available data. Therefore, several clustering algorithms have been tested. The main focus here was on temperature dependent part (SH+DHW), due to high variety in data points. The tests were conducted with the following algorithms: k-means clustering, hierarchical clustering, density based clustering, and model based clustering. In spite of different approach used in each method, most of the them did not show a good degree of clusterization. The cluster formations did not follow specific pattern that would explain tailed data. For this reason, the decision was made to apply techniques that would allow to separate untypical data points in existing data range. Hence, confidence interval (CI) was applied to analysed data. The CI was calculated by next equation [15]:

$$\text{C.I}= \hat{Y}_i \pm S_e \times t\left(1-\frac{\alpha}{2}, f_e\right) \times \sqrt{1+\frac{1}{n}+\frac{(X_i-\bar{X})^2}{(n-1){S_x}^2}} \tag{7}$$

where, $\hat{Y}_i$ is predicted value of energy use; $t(1-\alpha/2, f_e)$ is Student's criteria, which depends on probability α and f_e degrees of freedom; n is the sample size; S_e is the residual standard deviation of actual energy about the regression line; $\bar{X}$ is the mean value of independent variable; X_i actual value of independent variable; S_x is the standard deviations of the of independent variable.

Fig. 4 show regression model with upper and lower bounds of the confidence interval. This step aimed to separate data that did not fit in typical model population. The shape of many sample distributions can be approximated by a normal distribution. A convenient aspect of normal population distribution is that we can apply 95% confidence interval to describe desired population range. The confidence interval was created for each group of dataset described in Section 2.1, weekends, working days – working hours and working days – non-working hours. The results are given in Fig. 4.



a) Weekends

b) Working days working hours

c) Working days non-working hours

Fig. 4. Regression models with confidence interval

The accuracy of all models was evaluated by few statistical criteria: multiple determination coefficient (R^2), mean absolute error (MAE), and mean square error (MSE). The mathematical formulation of statistical criteria is shown below.

$$R^2 = \frac{Var(y_i')}{Var(y_i)} = 1 - \frac{Var(\mathrm{e})}{Var(y_i)} \quad (8)$$

$$MAE = \frac{\sum_{i=1}^{n} |y_i - y_i'|}{n} \quad (9)$$

$$MSE = \frac{\sum_{i=1}^{n} (y_i - y_i')^2}{n} \quad (10)$$

where, y_i is the predicted output variable and y_i' is the actual output variable for i^{th} entry in the analyzed database, and n is the number of samples in training subset. e is error term. The results are summarized in Table 2 and Table 3.

Table 2 and Table 3 shows prediction results for testing and training sets for different predictive algorithms under various statistical criteria. To recall, R^2 criteria means the better model when it is closer to 1, for MAE and MSE, the lower value, the better model.

Table 2. The accuracy of main models

№	Model type	R^2		MAE		MSE	
		Training set	Testing set	Training set	Testing set	Training set	Testing set
1	Linear regression	0.834	0.832	7.71	7.84	202.18	208.09
2	SVM	0.828	0.829	7.26	7.60	208.41	209.71
3	PLS	0.833	0.829	7.59	7.80	200.92	206.80
4	LASSO	0.834	0.831	7.29	7.49	185.41	189.04

Table 3. The accuracy of outliers' model

№	Model type	R2		MAE		MSE	
		Training set	Testing set	Training set	Testing set	Training set	Testing set
1	Linear regression	0.814	0.725	14.94	17.14	485.48	661.21
2	SVM	0.801	0.709	14.26	17.50	514.37	706.05
3	PLS	0.773	0.657	15.35	18.36	461.16	644.74
4	LASSO	0.717	0.554	13.20	18.89	351.20	497.96

From Table 2, it can be noticed that obtained regression model shows good prediction ability to explain heating energy use. Both training and testing results scores were found in the same range for all statistical criteria. It can also be noticed that more advanced algorithms resulted in close values to regression model. This shows that improvements introduced to regular regression model resulted in good explanation degree of analysed energy use data of school building. The results for outliers' model that are shown in Table 3 were found as less accurate. This can be explained by sparse data and occasion occurrence of it. In general, it can be concluded that improvements made to regression model led to better prediction capability. This is valuable information, since in such way the prediction done by utility companies become more reliable and security of supply increases.

3.5 Analysis of outliers

The analysis of data points separated as outliers from Fig. 4 was investigated. The total number of identified points was 2.6% of total annual data points, which corresponds to 17% of total heating energy use. The analysis showed that the occurrence of outliers mainly appeared in two consecutive months such as January and December. The distribution of these points showed random pattern without clear cluster formations except Thursday. During that day energy use cluster was identified between 18–22 o'clock (6-10 PM). This is particularly relevant for January. The reason for this could be that the building was used for purposes other than education. It is quite common that in Norway schools are booked for Christmas celebration by local companies. Other reasons could be particularities in the in operation of the heating and ventilation system in the building. Unfortunately, analysed data were received without any explanation about equipment installed inside the building and therefore, it was hard to conclude something about its operation. During other months the number of outliers was negligible and this information was considered as insignificant.

3.6 Analyses of temperature independent part of energy signature

As has been mentioned above, energy signature consists of two different parts – temperature dependent (SH+DHW) and temperature independent (DHW) energy use. These parts are separated by CPT and the additional condition related to the month of the year. The analysis of temperature independent part showed that statistical data covered months from April to October. It was found that occasionally temperatures lower than CPT were observed during this period. Nevertheless, analysis shows that these temperatures do not last for a long time and the need in SH does not occur. Therefore, it can be concluded that temperature independent energy use can only be observed within considered months.

DHW energy use profiles is the primary instrument for understanding people behaviour and their effect on DHW use in buildings. Analysis of DHW profiles showed changes of energy use under different time intervals. Primarily, DHW energy use depends on a number of people who are present in a building. However, information about people presence is usually not available. The month of the year and the day of the week are factors that have direct influence on building attendance and, consequently, DHW energy use. Statistical analysis showed that unlike SH, DHW energy use has no other important explanatory variables. Therefore, an approach that differs from regression analysis should be used to explain temperature independent part of energy signature. The profiles found for working days and weekends are shown in Fig. 5 and represent average values in selected period.

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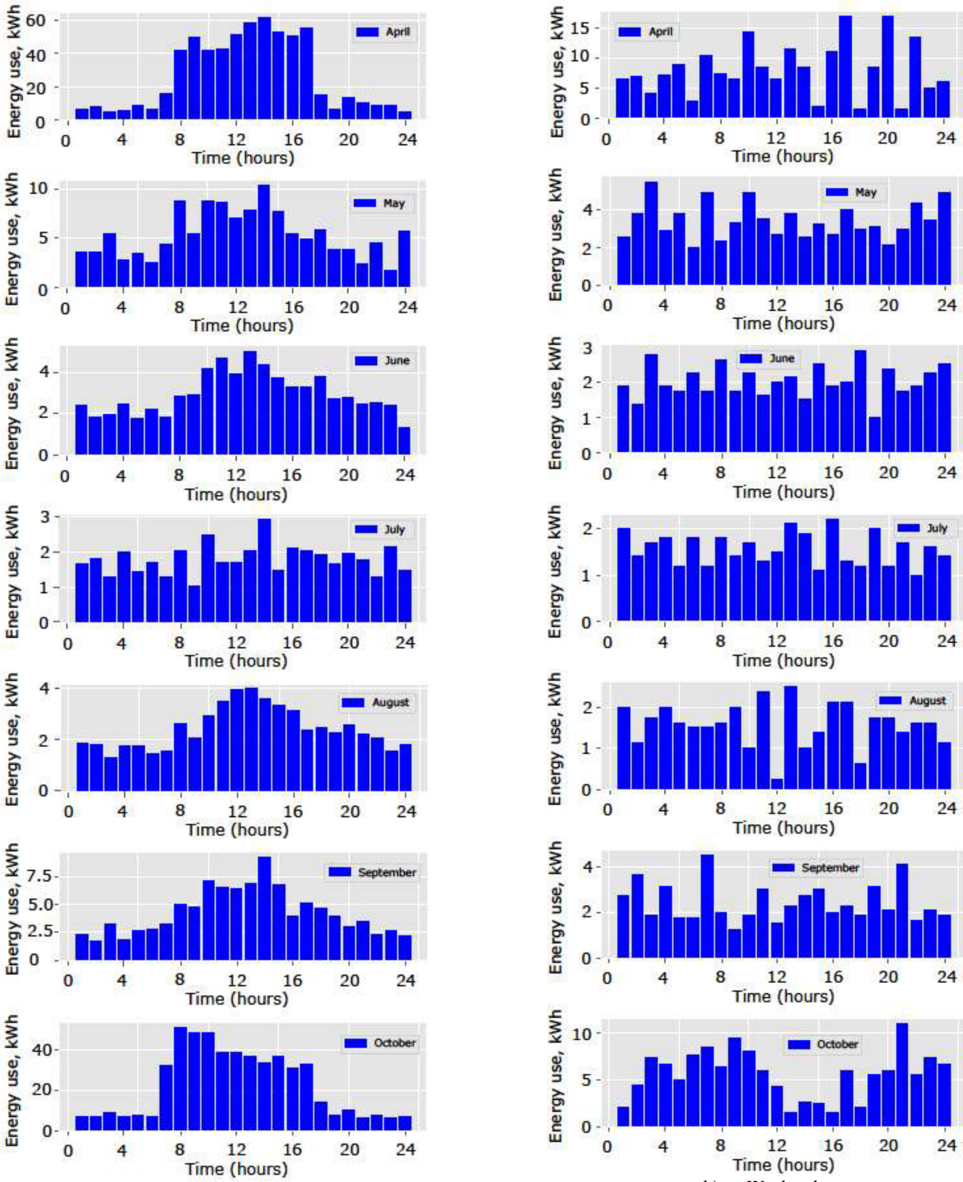

a) Working days

b) Weekends

Fig. 5 Profiles of temperature independent part of energy signature

The value of R^2 showed that the proportion of total variation of outcomes explained by the profiles was equal to 0.71. This value of R^2 justified the expediency of using profiles. Moreover, the profiles obtained in this way were quite informative and allow us retrieve additional information about DHW energy use in buildings.

As we can see from Fig. 5 the energy use in April and October are higher than in other months. This is due to the fact that in these months the school building was fully occupied by students. In addition, the outdoor temperature was lower and could induce to extra energy use. The smallest DHW energy use was in June, July, and August when there was no classes in the school and most of employees were on vacation. Further, DHW energy use is oscillating along zero line during the summer time, the reason for this could be that hot water circulation (bypass) took place to keep the system in operation. The energy use in working and non-working days was different. In working days the maximum value was higher, as well as variation of energy use in general. Finally, it can be concluded that information retrieved from profiles is very useful to understand occupant behavior and will be used in further research.

4 Conclusions

This paper aimed to improve prediction of heating energy use by introducing changes to general regression model algorithm. The analysis was done on the passive school on hourly data resolution. The model was divided into the sub-models that helped to separate untypical energy use data from typical energy data range points. The correlation analysis was performed and most influential variables were selected for model formulation. The results showed that introduced improvements resulted in high accuracy in comparison with more sophisticated algorithms like SVM, PLS, and LASSO. This is a good observation, because regression algorithm does not require sophisticated knowledge, high computational time, or expert work for its implementation. Further, the analysis of the temperature lag showed that it is misleading to introduce lag of 24 hours and 48 hours that could often be found in the literature. The reason for this is due to differences in thermal inertia of building types. The analysis of outliers showed some degree of clusterization during January and this could be explained by non-educational activities in the analysed building and operation particularities. The temperature independent part of energy use was analysed and hourly profiles were developed. In general, it can be concluded that improvements made to regression model led to better prediction capability. This is valuable information, since in such way the prediction done by utility companies become more reliable and security of supply increases.

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Domestic hot water decomposition from measured total heat load in Norwegian buildings

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Abstract

In Nordic climates, the energy use in buildings is dominated by space heating (SH) and domestic hot water (DHW). Heat load measurements with hourly resolution from smart meters are now becoming the standard. However, in most cases, only the total heat use in the building is metered, without separation into DHW and SH use. The analysis performed in this work is aimed at comparing and verifying different methods for estimating typical DHW load profiles by decomposition of heat load measurements into SH and DHW. Three methods have been used for the decomposition of the same set of measurements of the heat load from 78 buildings comprised of apartments and hotels: the seasonal method, the energy signature method and hybrid summer-signature method. All three methods have limitations, but in this article it is shown that the hybrid-summer signature method, which is a new method that is proposed in this article, has the closest similarity to measurements of DHW energy use from similar buildings.

Introduction

The building stock is the most energy demanding sector in Norway. According to (Abrahamsen and Bergh, 2011), it accounts for about 40% of the total energy consumption. A characteristic feature of energy use in buildings in Norway is a high demand for space heating (SH) and domestic hot water (DHW) (Unander et al., 2004). For this reason, a huge potential for increasing energy efficiency in buildings in Norway can be gained through better design and operation of SH and DHW systems.

Analysis of energy use in existing buildings is a powerful instrument for achieving energy savings in buildings, performing better design and dimensioning of the energy systems, as well as introducing energy planning and demand-side management. The European Directive 2018/844 prescribes that energy analysis for building stock should include typical energy consumption for SH, DHW, and other technical systems in a building. However, the heat meter systems in most buildings are simplified and do not allow us to perform energy analysis in a proper way, and a significant share of buildings in Norway uses only a single heat meter for the total heat use. The readings from the meter are not separated into SH and DHW heat use. Experience shows that SH and DHW systems are technically detached. The factors affecting the energy performance in these two systems and are different (Tereshchenko et al., 2019). Accordingly, it is crucial to conduct the analysis of heat use in SH and DHW systems independently (Cai et al., 2018). Despite the obvious drawback of simplified heat metering systems, the measured total heat use still contains valuable information about the DHW and SH systems performance. However, to use this information correctly, the reliable and accurate method for extracting the DHW and SH heat use profiles from the total heat use should be applied.

Currently, there are no generally accepted recommendations on how to separate the SH Acknowledgment and DHW profiles from the total heat use. The several approaches for decomposing the SH and DHW profiles from the total heat use that can be found in scientific publications are discussed in the text below.

In the article (Tereshchenko et al., 2019), the energy signature curve (ESC) was used to find temperature-dependent and temperature-independent part of the heat use in a Norwegian school. The temperature-independent part in ESC represents the DHW heat use. Based on this assumption, the DHW heat use profiles for working days and weekends were found. When the DHW heat use profiles are known, the profiles for SH can be extracted from the total heat use.

The modification of the ESC approach that takes into account the monthly variation of DHW heat use in dwelling in the United Kingdom (UK) is proposed in (Burzynski et al., 2012). The authors in (Burzynski et al., 2012) consider the days when the outdoor temperature is higher than the base temperature (Tereshchenko et al., 2019) as only the DHW heat use in the building. Hence, the DHW heat use profiles for several warm months can be found. After that, the DHW monthly variation factors from the UK national standard "The government's standard assessment procedure for energy rating of dwellings" were used to extrapolate the DHW heat use from warm months to other months of the year (Burzynski et al., 2012).

Linear regression models were used to extract DHW heat use profiles from the total heat delivery in (Sørensen et al., 2019). A model for total heat delivery was built with using the outdoor temperature, separate hours of each day, weekdays and holidays as an input for the modelling. When estimating the DHW heat use, the authors set the outdoor temperature in the models equal to the break-point temperature, before calculating the DHW daily load profile with hourly mean values (Sorensen et al., 2019).

A time series method for extracting DHW heat use spikes from the total heat use is presented in (Bacher et al., 2016). The method uses the fact that the SH heat use changes gradually during the day due to changes in outdoor temperature and user behaviour. DHW heat use does on the other hand create short-lived spikes in the total heat use time series. In order to identify the slow changes of SH heat use, the authors in (Bacher et al., 2016) propose to apply a non-parametric kernel smoother. All heat use values which lie above the kernel smoother are considered to be DHW heat use spikes.

Another method for detecting the SH and DHW heat use profile is proposed in (Marszal et al., 2019). The method consists of the following steps: 1) the daily profile for the total heat use in an average summer day is identified; 2) the non-DHW use is calculated as a minimum of total heat use profile for an average summer day or average for hours from 0:00–04:00 o'clock; 3) the DHW profiles are calculated by deducting the non-DHW heat use from the value of the heat use at each hour of the day.

An investigation of SH and DHW heat load measurements is shown in (Riachi et al., 2014). Here, the authors propose to model the DHW heat use based on the volumetric DHW use, the building activity, and the type of DHW system within the building. The SH loads are estimated according to the changes in outdoor temperatures, the building setpoint temperature, the night setbacks, and days of the week.

An alternative modelling approach that couples of the behavioural, stochastic, and energy balance models is proposed in (Fischer et al., 2016). The SH model in this approach uses a simplified physical method with a behavioural model for standardised buildings. The characteristics of the DHW heat use is found as a result of the SH model.

The literature review shows that the issue of extracting the SH and DHW profiles from the total heat use is not solved yet. The methods described above require extensive knowledge about the characteristics of the DHW and SH systems, the monthly variation factors for DHW heat use and/or users behaviour in buildings. Usually, when an energy analysis is conducted on a group of buildings, this information is not available. Several of the methods described are not verified with actual measurements (Bacher et al., 2016). For this reason, the comparison and further investigation of methods for identifying DHW and SH profiles from the total heat use in buildings are required.

Methodology

The analysis performed in this work is aimed at comparing and verifying different methods for estimating typical DHW load profiles for different building types by decomposition of heat load measurements into SH and DHW. Three methods have been tested for the decomposition of the same total heat use data from measurements: measurements: the seasonal method, the energy signature method and the hybrid summer-signature method. The seasonal method and the energy signature method are classical methods. Meantime, the hybrid summer-signature is a new method proposed in this article The results from the decomposition with each method have then been compared against each other and against measurement of DHW heat loads, profiles from the national standard, as well as other studies conducted on decomposition and measurements of DHW in Norwegian buildings.

Measurements

DHW use is significantly influenced by user behaviour and the number of occupants in a building. For this reason, the analysis was performed on measurement data from a large number of buildings. In total, data from 78 Norwegian buildings have been used in this analysis. The buildings are comprised apartments and hotels. None of the buildings are considered to be passive houses or low energy buildings (very energy efficient). The measurements gathered for each building contain between 1-3 years of hourly data on the outdoor temperature and the total heat load (HtTot) in each building. The total heat load is assumed to be the sum of energy use for SH and DHW. The HtTot is covered by district heating in all buildings. The buildings are not registered with secondary heating and/or heat storage inside the buildings, however it is uncertain whether this is actually true for all of them. Table 1 shows an overview of the number of buildings within each building category that were analysed in this paper.

Table 1: Number of buildings sorted by building category.

Building category	Number of buildings
Apartment blocks	58
Hotels	20
Total	**78**

Decomposition method 1: Seasonal method (SM)

The seasonal method – which is sometimes referred to as the summer method - assumes that there is no demand for SH during the summer time (between June 1st and August 31st) in any of the buildings, and that the HtTot during the summer months is used only for DHW purposes. For each building, a typical DHW profile for workdays and weekends is created by extracting the average value for HtTot for every hour of the day during the summer period. SH is assumed to be zero in the summer. SH energy use for the rest of the year is identified as a difference between the measured heat load in the building and typical DHW profiles.

There are two approaches to treat holidays in seasonal method. The first approach ignores holidays when creating the typical DHW profile with the seasonal method. The second approach assumes that for a building there will be at least 30 days within each year when there will be little-to-no operation of SH and DHW systems due to the residents/users being away during the holidays. Most of these days will occur during the summer months.

Therefore, the way of identifying holidays is to mark the 30 days with the lowest heat load out of the warmest days within each year. These data should be eliminated from analysis to take effect of holidays into consideration.

Decomposition method 2: Energy signature method (ES)

In the energy signature method, an energy signature curve (ESC) is created for each building. The ESC shows the relationship between the total heat load in an observed building and the outdoor temperature, as shown in Figure 1. For a typical building, the ESC consists of two parts, divided by the change point temperature (CPT). The CPT is a critical temperature that indicates when the heating season ends. It is assumed that when the outdoor temperature is higher than the CPT, the SH system does not work and the heat use in the building is mainly related to the DHW use.

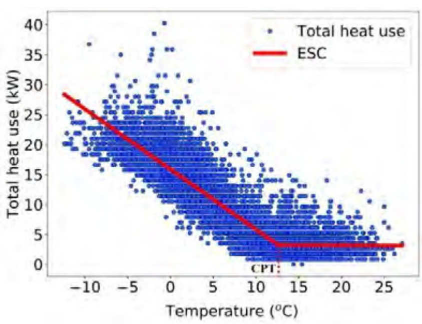

Figure 1: An example of the energy signature curve for the considered apartment building (Csoknyai et al., 2019).

The CPT can be identified by using the piecewise regression method. This method allowed us to find the CPT and construct separate models for the two parts of the ESC, as shown in Equation 1:

$$f(x) = \begin{cases} \beta_0 + \beta_1(x - CPT) + \varepsilon & If\ x < CPT \\ \beta_0 + \beta_2(x - CPT) + \varepsilon & If\ x > CPT \end{cases} \qquad (1)$$

where $f(x)$ is a model for the ESC, x is the outdoor temperature, $\beta_0, \beta_1, \beta_2$ are the coefficients of the piecewise model, and ε is the residual error.

Using Equation (1), the CPT values were determined for the considered buildings. After, based on the ESD, the heat use when SH system is not operating, and DHW is the main energy consumer in the buildings was identified. Finally, the DHW heat use profiles for each building and building categories were calculated.

Decomposition method 3: Hybrid summer signature method (Hybrid SM-ES)

In order to improve the existing methods for HtTot decomposition, the authors propose a hybrid SM-ES method that takes aadditional features of SH and DHW systems performance into account. Buildings with ventilation systems might have a heating demand for heating of ventilation air during the summertime in the hours when the outdoor temperature is low – such as in the night time, in the early morning hours and on particularly cold days. By simply extracting the average value for heat load for every hour of the day during the summer (as is done in the seasonal method and to a certain extent in energy signature method), heating of ventilation air may be faulty interpreted as heating of DHW.

When using the hybrid summer signature method, the summer values for the heat load (HtTot) and outdoor temperature (Tout) for every hour of the day are plotted with the Temperature at the X-axis and the heat load on the Y-axis (in an so-called Energy-Temperature-/ET-curve). Linear regression is then used to calculate the expected value for HtTot for the given hour at a given temperature, as shown in Figure 2. When the interpolation is done at higher temperatures it can be assumed that there will be no space heating in the building, and that the interpolated value for the heat load is used solely for DHW heating purposes. In Norwegian buildings, the heating of ventilation air stops at above 16°C. Therefore, the typical DHW profiles created with the hybrid summer signature method has been tested at 16°C, 18°C and 20°C.

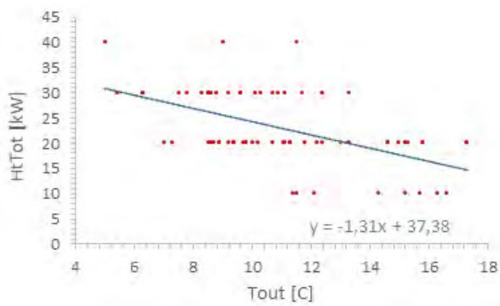

Figure 2 Tout and HtTot in one of the considered apartments on weekdays at 07:00.

In some buildings, the obtained value from the SM-ES method will become negative in some hours when the heat load is interpolated at higher temperatures, such as 20°C. When this occurs, the heat load is set to zero. In order to reduce the number of hours that get negative values for heating, whilst still aiming to reduce the effects of ventilation heating, the linear regression is performed at 18°C in this analysis.

Results

The test data (measurements of HtTot from the 78 apartments and hotels) have been decomposed into DHW and SH using three methods: the seasonal method (SM), the energy signature method (ES-1) and the hybrid seasonal signature method (Hybrid SM-ES).

The results have been compared to different reference data:

- An application of the energy signature method on a different set of measurements of HtTot (Lindberg, 2017) (ES-2)
- Actual measurements of DHW use from three different sources (REF-1 from (Walnum et al., 2019), REF-2 from (Bagge et al., 2015) and REF-3 from (ElDek, 2020)).
- Normative inout data for DHW energy use for building modelling from the national standard "SN-NSPEK 3031:2020: Energy performance of buildings. Calculation of energy needs and energy supply".

The reference data is collected from different sources with differences in methodologies, system boundaries and building types. An overview of the modelling and the reference data sources is given in Table 2.

Table 2 Overview of simulation and reference data.

		Description	#	Sirc. losses	Energy supply
Test data	SM-1	Seasonal method without (1) and with marking (2) of holidays.	58 apartment blocks, 20 Htl	Yes	DH
	SM-2				
	Hybrid SM-ES 18	Seasonal method with linear regression at 18°C			
	ES-1	Energy signature 1			
References	ES-2	Reference Energy signature values for apartments (Pedersen, 2007) and for hotels (Lindberg et al., 2019).	53 dwellings, 7 hotels	Yes	DH
	REF-1	Reference 1 from measurements. Flow and energy measurements on pipes in Norwegian hotels and apartments. (Walnum et al., 2019)	2 Apt. blocks 3 hotels.	Yes No	DH and EL
	REF-2	Reference 2 from measurements. Flow measurements on pipes in Swedish apartments, later converted into energy with a fix conversion factor. Individual metering for each unit. (Bagge et al., 2015)	4 apt. blocks with 1000 units.	No	NA
	REF-3	Reference 3, measurements of DHW energy use in single family houses. Energy measurement on socket (ElDek, 2020)	Unknown.	Yes	EL
	NORM	SN-NSPEK 3031:2020. Normative values of net energy demand for heating of DHW used in building modelling	-	No	-

Daily profiles

To evaluate the different decomposition methods, the typical daily profiles for DHW energy use in hotels and apartments have been created based on the test data. These daily profiles have been compared to the daily reference profiles for DHW energy use in apartments and hotels.

The reference daily profiles on DHW energy use from measurements in apartments are shown in Figure 3 (Weekdays) and Figure 4 (weekends). The reference measurements have been gathered from three different sources: REF-1 and REF-3 come from measurements of DHW energy use in Norwegian apartment buildings, while REF-2 is gathered from the measurement of DHW use in 1000 Swedish apartments. REF-2 is plotted in the figures with a spread from the lowest 10^{th} percentile to the highest 10^{th} percentile of DHW energy use from all of the apartment units, indicating a large spread in DHW energy use between different users. The apartment references indicate that usually during weekdays, apartment blocks will have a high morning peak and evening peak for DHW energy use, with a significant reduction in DHW energy use during the night time. On weekends, the references indicate that apartments typically will have a higher morning peak at a later time of day (compared to workdays), with higher consumption of DHW energy use throughout the day, but still with a low consumption during the night time.

Figure 5 and Figure 6 show the typical profiles for apartments created from the test data with the different decomposition methods, plotted against REF-2, the reference energy signature profiles (ES-2) and normative values for DHW energy consumption (NORM). The seasonal-method profiles (SM-1 and SM-2) and the energy signature profiles (ES-1 and ES-2) show higher values for most hours compared to the typical profiles obtained from measurements, with little reduction in energy consumption during the night time. The hybrid SM-ES 18 profiles are closer to the average profile from REF-2, and show a more significant reduction in the energy consumption during the night time, although the typical daily profile from the Hybrid SM-ES method creates a "flatter" daily profile for the apartments with less significant morning and evening peaks, compared to the other decomposition methods.

The typical daily profile for hotels (regardless of weekdays/weekends) from the test data and from the references is shown in Figure 7. All of the daily profiles for DHW energy consumption in hotels indicate a high morning peak, and a slight increase in DHW consumption towards the evening/night, with a decrease in energy use during the night. The Hybrid SM-ES method has a bigger decrease in energy use during the night compared to the other decomposition methods. The weekend and weekday DHW profiles are not plotted individually for hotels, as the reference values don't separate between different days in the typical profile. The test data does however indicate a later morning peak in hotels on weekends compared to weekends regardless of the decomposition method used.

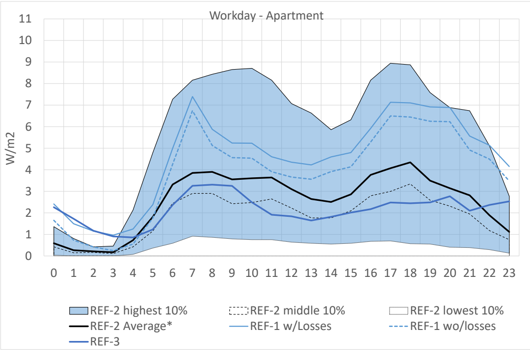

Figure 3 Reference measurements of DHW energy on weekdays in apartments.

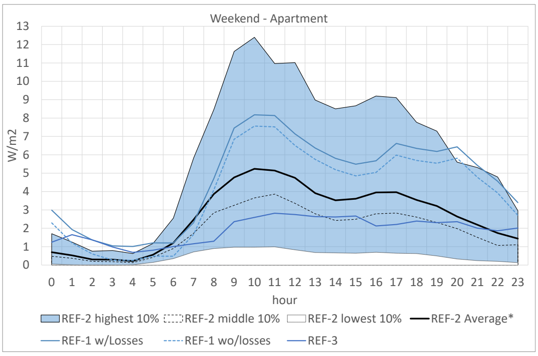

Figure 4 Reference measurements of DHW energy on weekends in apartment buildings.

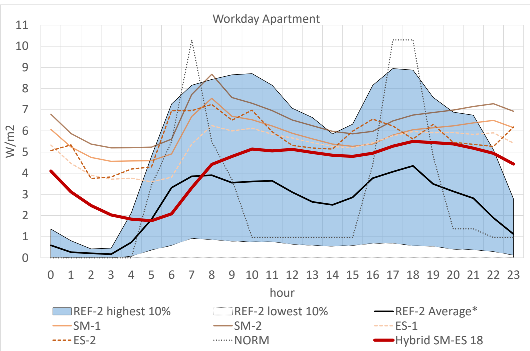

Figure 5 Average weekday profiles for DHW energy use in apartments created for the test buildings with different methods compared against REF-2 and NORM.

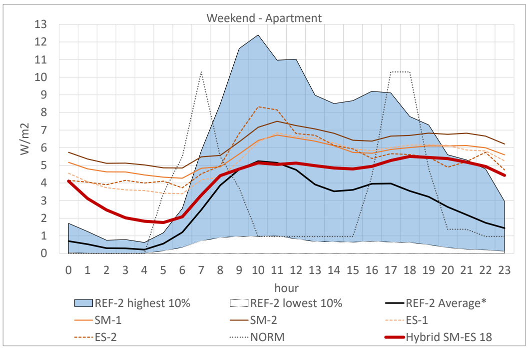

Figure 6 Average weekend profiles for DHW energy use in apartments created for the test buildings with different methods compared against REF-2 and NORM.

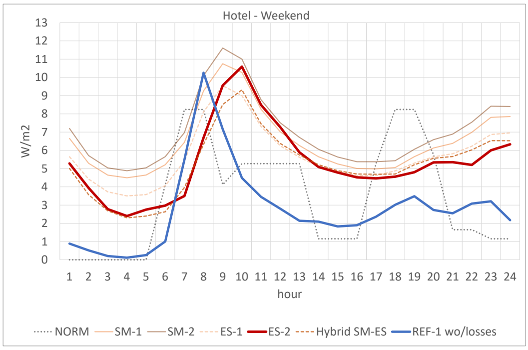

Figure 7 Average daily profiles for DHW energy use in hotels created for the test data with different methods compared against REF-1 and NORM.

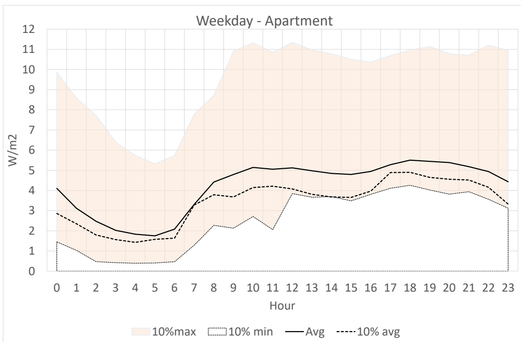

Figure 8 Variation in daily profiles for the apartment test data on weekdays created with Hybrid SM-ES method at 18°C.

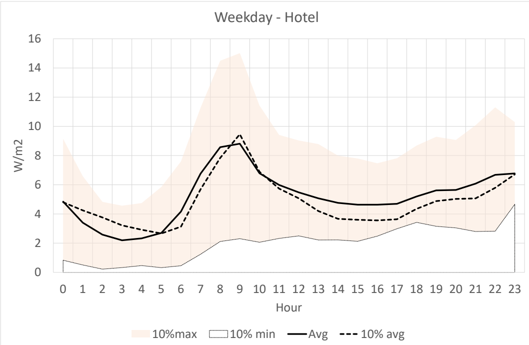

Figure 9 Variation in daily profiles for the hotel test data on weekdays created with Hybrid SM-ES method at 18°C.

The average daily profiles for DHW energy use in apartments and hotels created with the hybrid SM-ES-method has the resulting profile which is the most similar to the typical profiles obtained from actual measurements on the building category level. However, there is a large variation in the typical DHW energy consumption between all the buildings in the test data. Figure 8 and Figure 9 show the variation between the typical profiles created with the hybrid SM-ES method for the 78 apartments and hotels respectively, from the lowest 10th percentile to the highest 10th percentile.

Annual energy use for DHW

The different methods for extracting the DHW energy use give different results on the annual consumption of energy use for DHW. The spread of the resulting annual energy use for DHW in the 78 test data is shown in the boxplots in Figure 10 and Figure 11 for apartments and hotels respectively.

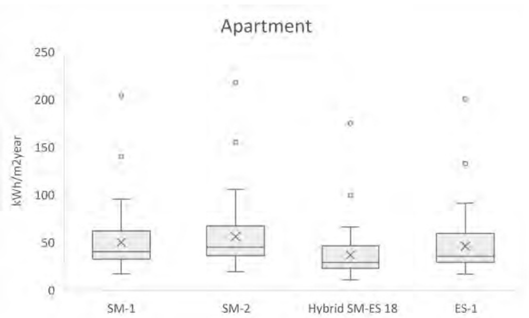

Figure 10 Boxplots of annual specific energy use for DHW decomposed with different methods in 58 apartment blocks.

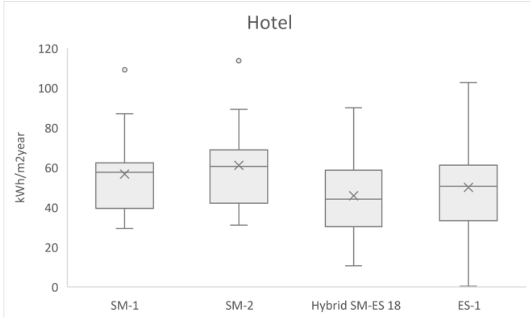

Figure 11 Boxplots of annual specific energy use for DHW decomposed with different methods in 20 hotels.

The mean annual energy consumption is the lowest when the hybrid SM-ES method at 18°C is used, and highest when the SM-2 method is used.

The mean annual specific energy use for DHW created for the test data with the different methods, as well as the mean energy use from the references is listed in Table 3. The results show that all the decomposition methods used on the test data have resulted in higher annual energy use for DHW in both apartments and hotels compared to most of the references. The exception is REF-1 with circulation losses which have higher annual consumption than the resulting mean created with SM-ES-18 for apartments.

Table 3 Mean annual energy use DHW Heating.

	Method	Apartment [kWh/m^{2}year]	Hotel [kWh/m^{2}year]
Test data	SM-1	50.2	56.9
	SM-2	56.3	61.3
	Hybrid SM-ES 16	42.4	50.5
	Hybrid SM-ES 18	37.0	46.0
	Hybrid SM-ES 20	31.8	41.9
	ES-1	45.9	50.0
Reference data	ES-2	48.8	46.9
	NORM	25.1	30.1
	REF-1 w/Losses	40.2	24.5
	REF-1 wo/losses	34.3	-
	REF-2	22.7	-
	REF-3	18.2	-

Discussion

The comparison of decomposition methods is nescessary in order to create realistic energy profiles for achiving energy efficiency in buildings. The proposed Hybrid SM-ES method has showed good results and can be applied in practice.

The simple seasonal method assumes that there is no SH energy use during the summer, however this may not be true for all buildings, especially the buildings with ventilation systems, where the ventilation air is heated before being supplied in the building. By following traditional methods, heating of ventilation air may be faulty interpreted as heating of DHW, resulting in an overestimated total annual demand for heating of DHW, as well as overestimating the hourly energy demand for DHW, especially at night and in the early morning hours when the outdoor temperature is lower, and the heating of ventilation air is higher. An alternative to the simple seasonal method would be to sort the heat load data by outdoor temperature, and look at the warmest days/hours instead of the summer dates. For buildings in colder climates, there may not be enough data points for higher temperatures (above 16°C) at all hours of the day. The hybrid seasonal-signature method offers an alternative approach where the expected value for the heat load is interpolated at higher temperatures. The hybrid summer-signature method shares similarities with (Burzynski et al., 2012), however, it doesn't identify the CPT/break point temperature for each building, and only measurements from the summer season are collected before the linear regression is applied. In some buildings, the interpolated value results in negative values when the SM-ES method is applied, especially when the heat load is interpreted at higher temperatures (20°C). When this occurs, the heat load is set to zero. Negative values suggest that the values should be low – and close to zero, however this is an underestimation as in reality, the circulation losses will be above 0. If the heat load is interpolated at too high temperatures, the resulting DHW value can get too low. Establishing the most suitable temperature for the interpolation must be balanced between reducing the effects of ventilation heating during the night, whilst not underestimating the heat load for DHW energy use during the day.

The energy signature method is a widely used method for extracting the DHW energy use from heat load measurements. The ES-method is based on Piecewise Regression and optimization. If the ES-method is applied to a dataset without a classical shape, where there for instance is little dependence between the heat load and the outdoor temperatures, where there are a significant amount of data points, or where there heat is being turned off at different times (e.g. due to heat storages being used, load controls or other factors), the ES-algorithm will not work normally. Due to this, the ES-method will not be applicable to all datasets, and has not been possible to apply to all files in the test data set.

All typical profiles created from the test data with the different decomposition method show a time-shift compared to the measurements. This could be due to a difference in the registration of data, or different user behaviour in the different data sets.

In all three methods, it is assumed that there is no seasonal variation in the DHW consumption, however (Bagge et al., 2015) has found a seasonal dependence of DHW consumption in apartment blocks, with higher consumption in the winter months. One could also assume that tourist oriented hotels have higher consumption in the summer months, while congress and business oriented hotels have higher consumption outside the summer months. Seasonal variation in DHW is also supported by (Gerin et al., 2014). The methods could be improved by combining the typical DHW-profiles with seasonal coefficients for DHW from (Gerin et al., 2014) or create coefficients based on (Bagge et al., 2015).

The comparison of the DHW energy use in the test data created with the different methods and the measurements indicate that all methods for decomposition likely overestimates the energy use for DHW purposes in apartments and hotels. As the modelled DHW energy use might be used for dimensioning purposes, this is considered to be preferred compared to underestimation of DHW energy use.

Conclusion

Analysis of energy use in existing buildings is a powerful instrument for achieving energy savings in buildings, performing better design and dimensioning of the energy systems, as well as introducing energy planning and demand-side management. Currently, there are no generally accepted recommendations on how to separate the SH and DHW profiles from the total heat use. The aim of the analysis performed in this work has been to compare and verify different methods for estimating typical DHW load profiles by decomposition of heat load measurements into SH and DHW. Three methods have been used for the decomposition of the heat load from 78 apartments and hotels: the seasonal method, the energy signature method and hybrid summer-signature method. All methods have limitations in creating the typical DHW-profile for a building. The hybrid-summer signature method with linear regression at 18°C gave the best results for the decomposition of DHW compared to the measurements for the test data used in this analysis. A similar comparison of the resulting SH energy use profiles with verification against SH measurements should be conducted in further work in order to further evaluate this method.

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Appendix

The hybrid SM-ES method at 18 degrees was applied to 198 buildings from different building categories with measurements of HtTot. This table shows the resulting typical profile for DHW energy use in different building categories. n= the number of buildings in the test data within the building category.

	Apartment n = 58		**Hotel n = 20**		**Nurs. home n = 31**		**Office n = 49**		**School n = 40**	
Hour	WD	WE	WD	WE	WD	WE	WD	WE	WD	WE
0	4.10	3.93	4.85	5.42	2.92	3.09	1.26	1.35	1.49	1.57
1	3.12	3.38	3.40	3.98	2.81	2.92	1.20	1.27	1.42	1.48
2	2.47	2.96	2.58	2.95	2.62	2.78	1.19	1.30	1.31	1.50
3	2.02	2.74	2.19	2.57	2.77	2.79	1.11	1.00	1.23	1.44
4	1.83	2.28	2.33	2.56	3.06	3.01	1.17	1.11	1.13	1.29
5	1.75	2.03	2.70	2.48	3.40	3.19	1.15	1.10	1.22	1.32
6	2.08	2.02	4.17	3.47	3.82	3.55	1.57	1.29	1.39	1.52
7	3.31	2.48	6.76	5.23	4.40	3.88	1.64	1.31	1.41	1.57
8	4.42	3.10	8.58	8.36	5.17	4.63	1.97	1.46	1.84	1.67
9	4.79	4.09	8.81	10.59	6.39	5.32	2.20	1.49	2.52	1.74
10	5.14	5.26	6.79	9.12	6.62	5.30	2.37	1.55	2.83	1.88
11	5.05	5.68	5.99	7.35	6.56	5.33	2.56	1.75	3.01	1.93
12	5.12	5.80	5.48	6.43	6.35	5.38	2.67	1.74	3.22	1.97
13	4.98	5.77	5.07	5.57	6.19	5.35	2.67	1.82	3.30	2.09
14	4.85	5.64	4.76	5.20	6.17	5.36	2.62	1.84	3.28	2.07
15	4.80	5.29	4.63	4.88	5.79	5.13	2.56	1.77	3.34	2.19
16	4.94	5.16	4.64	4.82	5.24	4.87	2.36	1.76	2.94	2.06
17	5.28	5.24	4.70	4.72	5.13	4.83	2.15	1.79	2.63	2.09
18	5.50	5.40	5.19	5.26	4.82	4.73	2.00	1.78	2.44	2.08
19	5.44	5.35	5.62	5.44	4.69	4.62	1.94	1.64	2.25	1.99
20	5.38	5.24	5.64	5.71	4.57	4.51	1.79	1.65	2.07	1.98
21	5.18	4.80	6.07	5.91	4.21	4.00	1.68	1.49	1.89	1.89
22	4.94	4.37	6.68	6.16	3.72	3.63	1.56	1.34	1.68	1.68
23	4.43	4.09	6.78	5.90	3.23	3.10	1.32	1.24	1.53	1.54

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Splitting measurements of the total heat demand in a hotel into domestic hot water and space heating heat use

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A B S T R A C T

To achieve more efficient energy use in buildings, space heating (SH) and domestic hot water (DHW) heat use should be analysed separately. Unfortunately, in many buildings, the heat meters measure the total heat use only, typically not divided into SH and DHW. This article presented a method for splitting the total heat use into the SH and the DHW. The splitting follows the assumption that the outdoor temperature is the main parameter explaining the hourly SH heat use, while the hourly DHW heat use is not influenced by this parameter. In the article, the modelled SH heat use was extracted from the total heat use based on the energy signature curve and the singular spectrum analysis. Thereafter, from the residuals between the modelled SH heat use and the total heat use, the DHW heat use was identified. The application of the method for the hotel in Norway showed that restored values represented the trends of the measured SH and DHW heat use well. The coefficient of determination (R2) for the modelled SH heat use was 0.97, and 0.76 for DHW. The methodology is useful for obtaining valuable information for monitoring and improving the energy performance of SH and DHW systems.

1. Introduction

For the European Union (EU) power system, energy savings in buildings is a vital topic. This topic is important from both an economic and environmental perspective [1]. The amount of energy use in buildings is currently reaching 40% of the total energy use [2]. For this reason, achieving a highly energy-efficient building stock is one of the main targets of the current energy policies in EU [2]. Out of all the technical systems in buildings in the EU, space heating (SH) and domestic hot water (DHW) are often the most significant consumers of energy. According to Ref. [3], SH and DHW heat use together accounts for more than 20% of the total EU energy utilisation. SH consumes approximately 85% of the heat demand in the EU. The remaining 15% is related to DHW use [3]. Thus, increasing energy efficiency in SH and DHW systems is essential for attaining the EU energy targets [4].

The European Directive 2018/844 [5] claims that analysis of the energy performance for buildings should be conducted based on calculated or measured energy use. The estimations shall reflect the typical energy use for SH, DHW, and other technical systems in a building [5]. This approach to analysis is important for the development of energy-saving solutions in all technical components of the building. The proper implementation of this approach requires that energy meters are installed for the main energy-consuming systems in the buildings. As a part of the smart meter promotion strategy, at least 80% of the EU electricity meters should be replaced by smart meters until 2020 [6]. Smart heat meters, on the other hand, are usually not available in buildings [7]. However, a significant share of buildings uses only one heat meter for the total heat use. In such systems, this single meter cannot measure the SH and DHW heat use separately. SH and DHW systems have different regimes of work and influencing factors on their performance. Accordingly, the analysis of heat use in these two systems should be performed independently [8]. Separate statistical data for the DHW and the SH heat use are essential for improving a number of issues, such as SH and DHW systems sizing, designing of energy management and control systems, as well as improving the existing standards, the prediction models and the energy use profiles. Thus, the separation of the total heat demand into the components associated with the SH and DHW heat use is an important task.

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Nomenclature

$f(x)$	piecewise regression model for the ESC
x	independent variable in a piecewise regression, which is the outdoor temperature for the considered case (°C)
β_i	ith coefficient of the piecewise model
ε	residual error
E_{SH}	ESC model of space heating heat use
E_{DHW}	ESC model of domestic hot water heat use
E_{TH}	measured total heat use (kW)
E_{Loss}	heat losses in the DHW system (kW)
E_{TH}	time series of the total hourly heat use in the building
N	number of the elements in the data sample
L	window length
X	Hankel matrix
X_i	i-th elementary matrix of X
σ_i	i-th singular value of the matrix X
U_i	left singular vectors of the matrix X
V_i	right singular vectors of the matrix X
d	intrinsic dimensionality of the time series trajectory space
$\tilde{e}_n$	elementary time series components
$\tilde{e}_i$	ith elementary time series component
$\sum \tilde{e}_k$	sum of the components selected from $\tilde{e}_i$
E'_{SH}	SSA model of space heating heat use
E'_{DHW}	SSA model of domestic hot water heat use

2. Literature review

Several research groups investigate the problem of extracting the SH and the DWH heat use from the total heat use measurements [9,10]. However, since the problem is not trivial, and the researchers set different requirements for the results, there is no unique methodology for performing such data analysis. Some of the existing solutions are discussed in the text below.

A method for separating the total heat demand in the building into SH and DHW heat use is presented in Ref. [9]. In this research, 10-min resolution data from a single-family house in Denmark is used. The method assumes that the DHW heat use generates short-lived spikes in the time series. Opposite, the SH heat use changes slowly during the day due to climate and user behaviour. For this reason, the authors in Ref. [9] propose to estimate the SH heat use by a non-parametric kernel smoother. All the values significantly above the kernel smoother are considered as the DHW heat use spikes. Currently, this method is not yet verified by the SH and the DHW heat use data which are measured separately. Therefore, it is challenging to estimate its accuracy and reliability.

Splitting weekly heat use from 1 m into DHW and SH is considered in Ref. [10]. The authors in Ref. [10] assume that the period when the outdoor temperature is higher than the base temperature [11] is only the DHW heat use period. In this way, they found DHW heat use for several warm weeks during the year. Afterwards, the same authors proposed to use the DHW monthly variation factors to extrapolate the DHW heat use from warm months to other months of the year [10]. For dwellings in the United Kingdom, these factors are given in “The government's standard assessment procedure for energy rating of dwellings” [12]. Further, the research work in Ref. [13] considers the related problem in Belgium. Based on actual measurements in dwellings, the monthly variation factors for DHW heat use are calculated [13]. For other types of buildings, except dwellings, these factors are not presented in the literature. In some buildings, SH heat use can be observed even in the warm months. Therefore, for an individual building, application of monthly variation factors for DHW heat use can lead to inaccurate results.

The research work in Ref. [14] shows a method that estimates the hourly space heating and the daily DHW heat use profile. The mentioned study uses the hourly values of the total heat demand in the building. The method includes the following steps: 1) the daily total heat use profile for an average summer day is calculated; 2) the non-DHW use is calculated as a minimum of total heat use profile for an average summer day or average for hours from 0:00−04:00 o'clock; 3) the DHW profiles are calculated by deducting the non-DHW heat use from the value of the heat use at each hour of the day. This study in Ref. [14] shows that the method gives satisfactory results when the DHW use during summer is at least at the same level as the space heating. The method does not consider the DHW heat use in other periods, except for the warm season.

Some approaches propose the alternative way of the SH and DHW heat use identification. They rely on the application of buildings simulation tools [15]. For example, a methodology which uses occupant focused approach and time-of-use survey (TUS) is considered in Ref. [16]. To develop activity-specific profiles for occupancy and domestic equipment use, the Markov Chain Monte Carlo techniques is applied for TUS activity data. The authors assume that the heat demand is dependent on the household size, type of the day, and the season. The DHW heat use profiles combine the probability distributions for particular TUS activities with average daily DHW heat demand.

Several stochastic multi-energy simulation models are developed for the UK residential building stock [17–19]. Among the models presented in these articles, the CREST Heat and Power (CHAP) model is of particular interest. CHAP model uses a four-state occupancy model and existing activity profiles for DHW modelling. At the same time, the SH model applies a two-node RC approach to determine the required heat input to maintain a specific setpoint temperature. The model shows good results for energy system analyses of UK residential buildings in general. However, it produces less accurate results for a single building with specific configurations.

The DHW heat use profiles are integrated within a set of building performance simulation archetype models. Such simulation also provides the possibility of estimating SH heat use. The research in Ref. [20] describes an approach where volumetric flow rates and water temperatures are measured to characterise the DHW use in 20 buildings of different sizes. The authors execute several stochastic simulations for the measured data to get representative DHW use profiles. They propose to use these profiles as an input to simulation tools [20]. A number of building simulation tools could be also used for estimation of the SH and the DHW heat in the building. Among the popular tools for building simulation are IDA ICE, EnergyPlus, and TRNSYS [21]. However, usually, these tools require the development of a complex model for all the components in a building. Usually, such a model is suitable only for a particular building. In addition, practice shows that such models are less accurate than the analysis based on actual measurements [22].

The application of a test rig for testing heating equipment in the thermo-technical laboratory is discussed in Ref. [23]. In this laboratory, for different heating conditions, the heat demand profiles for SH and DHW heat use is emulated.

Some authors propose to use the models and profiles of the SH and DHW heat use created based on statistical data from the buildings stock databases [24,25]. For instance, the Neural Networks model of the SH and DHW heat use in typical Canadian households is considered in Ref. [24]. The model uses data from the 1993 Survey of Household Energy Use (SHEU) database, which represents information from the Canadian housing stock. Similar models may serve as a basis for the separation of the SH and DHW heat use in typical buildings. However, their development requires the availability of the appropriate database. Moreover, the accuracy of the splitting for individual buildings will be questionable.

Linear regression models may be used to predict heat demand in buildings, e.g. as done in Ref. [26]. Pedersen in Ref. [27] and Sørensen et al. in Ref. [28] use linear regression models to separate DHW from total heat delivery. In Ref. [28], a linear regression model for total heat delivery is developed, taking the outdoor temperature, hour of the day, weekdays and holidays into account. When estimating DHW, the outdoor temperature is set to the approximate break-point temperature of the model, resulting in a DHW daily load profile with hourly mean values [28].

The separated SH and DHW heat use profiles are also modelled in Ref. [25]. The modelling approach is the coupling of the behavioural, stochastic, and energy balance models. The synthetic load profile captures the typical hourly, daily, and annual characteristics of the DHW heat use. The SH model is a combination of a simplified physical method with a behavioural model for standardised buildings. The approach requires knowledge about the activity categories, such as occupant's presence at home, sleeping, hygiene, and cooking activities. Such modelling approach may give good results, but the data required for new studies on a bigger scale (hotels, nursing homes etc.) requires much effort and usually not feasible.

SH and DHW hourly energy loads in buildings are also studied in Ref. [29]. The authors estimate the hourly DHW heat use depending on the water volume use, the building activity, and type of DHW system. Meanwhile, hourly SH loads are modelled, taking into account the outdoor temperatures, the building setpoint temperatures, the night setbacks, and weekends.

The literature review shows that the problem of dividing the total heat use into the parts related to the SH and DHW is not solved yet, especially for larger buildings with limited knowledge about the users. Most of the existing methods are simplified and focused only on restoring average daily profiles for a considered year. Some of the above-mentioned methods allow us to obtain general models of SH and DHW heat use for particular buildings category, but not for an individual building [24]. The other methods solve the considered problem only for several warm months based on the assumption that SH is not working in the summertime [14]. The number of methods requires extensive knowledge about users behaviour, physical properties of the building and parameters of the systems, which limits their application [25]. Moreover, the major part of the existing articles analyses heat use in apartment buildings. For non-residential buildings, including hotels, the problem is less studied.

In this article, we present a method for splitting hourly measurements of the total heat use into the SH and the DHW heat use. The first step of the method was to develop SH heat use model based on the total heat use data. This step relied on the energy signature curve (ESC) and singular spectrum analysis (SSA). The DHW heat use model was extracted from the residuals between the SH heat use model and the total heat use. The methodology was tested on one-year hourly measurements in a hotel, located in Eastern Norway. The investigation was performed in such a way that the results of the total heat use splitting could be compared with the measured SH and DHW heat use, which were measured separately at the hotel. The methodology is useful for obtaining valuable information about DHW and SH heat use in the building where only one heat meter is available. The models obtained by the total heat use splitting for DHW and SH heat use can be used for improving the energy performance in the building and energy efficiency.

The paper has six sections. Section 3 introduces the methodology for splitting the total heat use into the SH and the DHW heat use. Section 4 represents the description of the hotel, where the methodology was tested. In Section 5, the main results of the methodology application are discussed. The values resulting from the splitting are compared with the measured SH and DHW use. Finally, the most important conclusions of the investigation are presented in Section 6.

3. Method

The methodology consists of two subsections. Section 3.1 dedicated to the application of the ESC to extract the models of the SH and the DHW heat use from the total heat use in the building. Section 3.2 proposes the method which is based on the SSA for the decomposition of the SH and the DHW heat use in Section 3.1.

3.1. Energy signature curve for the SH and the DHW heat use analysis

The method proposed in this article uses the assumption that the SH and the DHW have different factors affecting them. It is well known that the main influencing factor on the SH heat use is the outdoor temperature [30,31]. In addition, for the DHW use, a seasonal variation is found related to the outdoor temperature [13]. However, on an hourly basis, the research in Ref. [32] has shown that the correlation between the DHW use and the outdoor temperature is insignificant. Thus, the regression model between the total heat use in buildings and the outdoor temperature is caused by the SH only. Meanwhile, the DHW heat use can be found in the residuals of this model.

The ESC shows the relationship between the heat use in an observed building and the outdoor temperature [27,33]. The ESC is a powerful instrument for the heat use analysis in buildings [34]. Fig. 1 shows an example of the ESC.

For a building with a heating season and no cooling taking into consideration, the ESC often consists of two parts. These parts are divided by the change point temperature (CPT), see Fig. 1. The CPT is a critical outdoor temperature that sets the boundary between the start and the end of the heating season. After the CPT, the SH use in

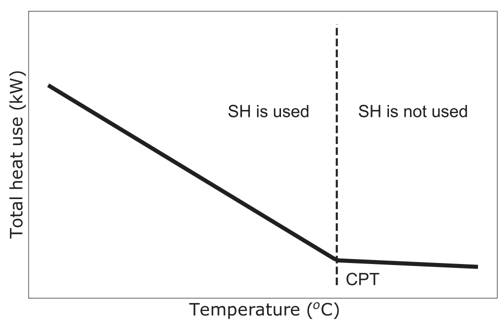

Fig. 1. An example of the energy signature curve.

the building is limited. The part of the curve before the CPT shows the SH season. Usually, in this period, the SH heat use is significantly higher than the DHW heat use. The function after the CPT shows the warm season when SH is not required. During this time, the main share of heat use is related to the DHW system. Nevertheless, depending on the system type, a small amount of heat use associated with the operation of the SH system may occur.

For some buildings, the last day of the heating season or the CPT are known. If the CPT is known, the ESC can be built by using the least square method for two parts of the model, See Fig. 1. Otherwise, the CPT can be identified by using the piecewise regression method. This method allowed us to find the CPT and construct separate models for the two parts of the ESC as shown in Equation (1):

$$f(x) = \begin{cases} \beta_0 + \beta_1(x - CPT) + \varepsilon & \text{If } x < CPT \\ \beta_0 + \beta_2(x - CPT) + \varepsilon & \text{If } x > CPT \end{cases} \quad (1)$$

where $f(x)$ is a model for the ESC, x is the outdoor temperature, β_0, β_1, β_2 are the coefficients of the piecewise model, and ε is the residual error.

Our investigation showed that the ESC model explains well the behaviour of the SH heat use. However, since the total heat use also includes DHW, the model was shifted relative to SH heat use by a certain constant value. In this article, we call this value the shifting coefficient. The shifting coefficient can be revealed from the behaviour of the SH system in the warm season, when the outdoor temperature is above the CPT. During the warm season, there were hours when the SH heat use in the building was equal to zero. The research [11] showed that the minimum value of the ESC coincides with these hours. The study in two other buildings except for the hotel also shows a similar result [32]. Thus, in this study, the coefficient of shifting was accepted to be equal to the minimum value of the total heat use ESC. Extracting this coefficient from the ESC allows us to obtain the SH heat use model. Finally, the following equation was suggested for the SH heat use model:

$$E_{SH} = f(x) - \min(f(x)) \quad (2)$$

The values of the total heat use, which lies above the modelled SH heat use give information about the trend of DHW heat use [9]. Therefore, initially, it was assumed that the positive residuals, obtained as the difference between the total heat use and the modelled SH heat use, represented the DHW heat use. When the negative values appeared in the residuals, the DHW heat use was supposed to be equal to zero. In a DHW system with continuous circulation, the DHW system operates continuously to deliver hot water. Accordingly, the system losses should be added to the DHW heat use obtained from the residuals. These losses can be found as an average value of the heat use at the night time, as proposed in Ref. [14]. Then the model of the DHW heat use can be identified by the following:

$$E_{DHW} = \begin{cases} E_{TH} - E_{SH} + E_{Loss} & \text{If } E_{TH} > E_{SH} \\ E_{Loss} & \text{If } E_{TH} \leq E_{SH} \end{cases} \quad (3)$$

where $E_{TH}$is the measured total heat use and E_{Loss} presents the heat losses in the DHW system.

Finally, the SH heat use was balanced according to the DHW heat use model. SH heat use model was recalculated as a difference between the measured total heat use and DHW heat use obtained by Equation (3). In addition, it was introduced a condition that both DHW and SH heat use should be positive. In a case, if one of the parameters (DHW or SH heat use) becomes negative, the negative value was compensated from the remaining parameter. For example, if for a certain point, the modelled DHW heat use was negative, it was compensated from SH heat use, and vice versa. In such a way, all values of restored DHW and SH heat use were positive, and their sum was balanced to be equal to the total heat use.

The flowchart of the above-introduced algorithm for splitting SH and DHW heat use based on the ESC is shown in Fig. 2.

The proposed method might give a reasonable estimation for the trend of SH heat use. However, ESC is based on linear functions. For this reason, it cannot capture particular spikes and rapid fluctuations of the SH heat use. The residuals of the ESC model also contained some noise from the SH. This noise reduced the accuracy of the DHW model. To capture the spikes in the SH heat use in a better way and to improve both the SH and the DHW heat use models, we suggested performing additional analysis. Particularly, after the application of Equation (2), a time series decomposition was applied. For this purpose, the SSA was used. This step is further explained in Section 3.2.

3.2. Application of singular spectrum analysis for identifying the SH and DHW heat use

SSA is a useful method for time series analysis and data mining [35]. This method allowed us to decompose the time series of the total heat use into a sum of components, $\tilde{e}_i$. The components may give an interpretation of the time series structure. There are several software tools in Python [36] and R [37] for the SSA. The two groups of the components, related to the SH and the DHW heat use, could be found. Summation of the components within each group made it possible to restore the SH and the DHW heat use from the total heat use.

In this article, the time series $E_{TH} = (E_1, E_2, \ldots, E_N)$ of the total hourly heat use in the building was analysed. Where E_i is the hourly heat use, and N is the number of the elements in the data sample. For one-year hourly data sample, N was equal to 8760.

The algorithm of SSA is well developed and presented in many articles and books [38,39]. For example, the book [38] gives detailed explanations of the SSA technique, as well as examples of its application. The main steps of the SSA algorithm were shown in Appendix A.

In order to separate the SH and the DHW heat use by the SSA

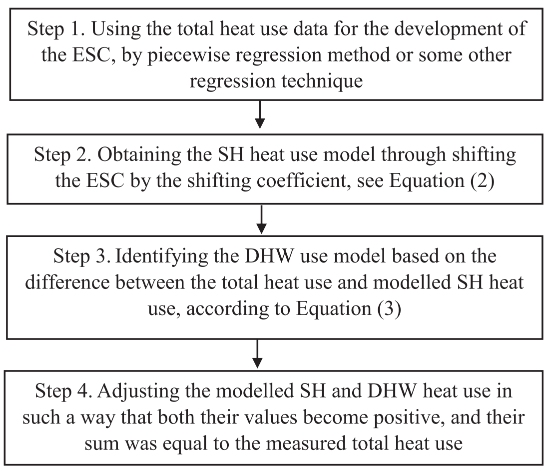

Fig. 2. Flowchart of the algorithm for splitting the total heat use into the SH and the DHW heat use by using the ESC.

method, two main problems were solved. The first problem was the selection of an appropriate window length L for the SSA decomposition, see Appendix A. The SSA does not have strict recommendations for the selection of the optimal window length. Therefore, quite often, the trial and error method is applied. The second problem was identifying the groups of the components related to the SH and DHW. These two problems were attempted to be solved based on the SH heat use model obtained by the ESC method, as described in Section 3.1, see Equation (2). The SSA was iteratively applied for different windows length L (2, 3, …N/ 2). On each iteration for L_i the SSA components were calculated. Of all the components, only the components associated with the SH heat use were identified. These components were selected in such a way that their additive sum has a maximum correlation with the SH heat use model, see Equation (2):

$$corr\left(E_{SH}, \sum \tilde{e}_k\right) \rightarrow max \tag{4}$$

where $\sum \tilde{e}_k$ is the sum of the components selected from $\tilde{e}_i$.

From the considered window lengths, the one that gives the maximum value for Equation (3) was selected. For the best window length, the new SH heat use model as a sum of the components was identified. This SSA model was also shifted in a similar way as in Equation (2):

$$E'_{SH} = \sum \tilde{e}_k - \min\left(\sum \tilde{e}_k\right) \tag{5}$$

Using the E'_{SH} and E_{TH}, the new model for the DHW heat use (E'_{DHW}) was identified by Equation (3). Finally, the values for both the restored SH heat use and the DHW heat use were balanced in such a way that both of them became positive, and their sum was equal to the total heat use. The balancing was performed in a similar way to Chapter 3.1. First, the SH heat use model was adjusted as a difference between the measured total heat use and the DHW heat use, E'_{DHW}. After, all negative values of the DHW heat use and the SH heat use were compensated. Hence, if DHW heat use had negative values, they were compensated from the SH heat use, and vice versa.

The flowchart of the algorithm for splitting the SH and DHW heat use based on SSA is shown in Fig. 3.

The investigation in this article showed that the application of the SSA allowed us to capture the spikes of SH heat use better than when using the ESC alone and to improve both the SH and DHW heat models. In more detail, the application and comparison of both methods are shown in Section 5.

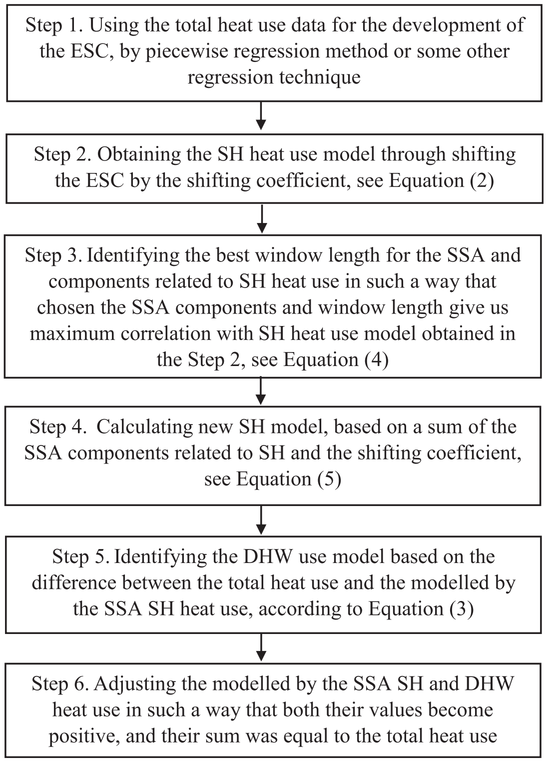

Fig. 3. Flowchart of the algorithm for splitting the total heat use into the SH and the DHW heat use by using the SSA.

4. Building description

The one-year hourly SH and DHW heat use data were measured at a hotel located in Oslo, Norway. The hotel was built in 2000, with a total heated area of 10 571 m^2. It has 260 guest rooms, lobby, gym, and a conference room. The guest rooms are designed for families and solo travellers. The sizes of the rooms start from 23 m^2. All the private rooms have individual bathrooms with toilet facilities and a shower. Breakfast and supper are served in the hotel. According to hotel management, employees use hot water for cleaning, and guests use hot water for personal hygiene. In general, the considered hotel well represents the characteristics and regimes of typical hotels in Scandinavia.

The hotel uses district heating for both SH and DHW heat use. In the DHW system, the hot water circulates permanently to ensure fast delivery of hot water at the tapping points. Two energy meters measure the actual SH and DHW heat use separately. The sum of their readings characterises the measured total heat use in the building. The SH meter is less accurate than the DHW meter. DHW meter is collecting data with 1 kWh-steps, while the steps of SH metering is 10 kWh. The measured SH and DHW heat use include system heat losses. The measurements were carried out from April 1, 2018 to April 1, 2019. However, in January 2019 some data about SH and DHW heat use were missed in the data storage system.

The investigation was performed in such a way that the results

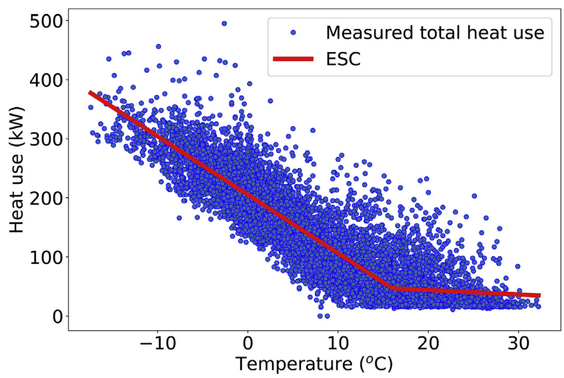

Fig. 4. ESC of the hourly total heat use in the hotel.

of the total heat use splitting could be compared and verified based on the actual measurements from two separate meters for DHW and SH. For this reason, the total heat use in the article represented the sum of the DHW and the SH heat use obtained from two heat meters installed at the hotel. To analyse the influence of the outdoor temperature on the heat use in the hotel, weather data from the closest weather station, Blindern in Oslo, were used [40].

5. Results

The section is separated into subsections that consider the steps of the methodology, see Section 3. Section 5.1 shows the analysis of the heat use by the ESC method. The results of the total heat use splitting into the SH and the DHW heat use based on the SSA method is discussed in Section 5.2. The profiles and validation of the modelled SH and DHW heat use are shown in Section 5.3.

5.1. Analysis of the SH and the DHW heat use based on the energy signature curve

One-year measured hourly data of the total heat use in the hotel and the outdoor temperature were used as input for the modelling and splitting of DHW and SH heat use. Based on this information, the ESC was developed, as shown in Fig. 4. ESC of the hourly total heat use in the hotel Fig. 4. The piecewise regression method was used to find the CPT.

From Fig. 4, we can see that the CPT was approximately 16 °C. Theoretically, there is no need for SH above the CPT. Therefore, above this outdoor temperature, heat use in the building was assumed to be fully dedicated to DHW. This condition makes CPT easily recognised by visual analysis and the regression methods. In the considered hotel, the SH heat use was different from the typical theoretical assumption. In order to explain this fact, the measured SH and DHW heat use after the CPT are presented in Fig. 5.

Fig. 5 shows the daily profiles of SH and DHW heat use in the warmest month of the year. As we can see from Fig. 5 that all the time in the warm months, even after the CPT, a certain amount of heat was consumed by SH. The SH heat use in the warm season might be explained by the fact that the control valve of the heat exchanger connecting the SH system to the district heating was wrongly sized or had faults. This meant that even this control valve was completely closed, it passed some amount of the water flow and gave SH use even above the outdoor temperature of 16 °C. This heat amount was not usefully used in the building, yet it was just heat loss circulating in the system [41].

The actual measurements showed that during the observed year, the SH contributed to 75% of the total heat use and 25% was related to DHW. Above the CPT, SH is responsible only for 7% of the heat use, while 93% was associated with DHW. For most buildings, the CPT is an approximate value. The value of the CPT indicated when SH was significantly reduced due to the warm weather, but not completely diminished. Since, to some extent, the CPT was an uncertain parameter, the only approximate value of the CPT could be found.

In general, the ESC might explain the trend of the measured SH heat use in the hotel as shown in Fig. 6. However, since the total heat use also included DHW heat use, the ESC of the total heat use was shifted according to the coefficient in Equation (2) to obtain the model of the SH heat use. This shifting coefficient corresponded to the minimum value in the ESC model. In our case, the ESC was shifted by 35 kW. Accordingly, the model of the SH heat use was obtained.

The DHW heat use was investigated within the residuals of the SH heat model. The circulation heat losses in the DHW system were estimated to 15 kW, based on the minimum heat use at the night

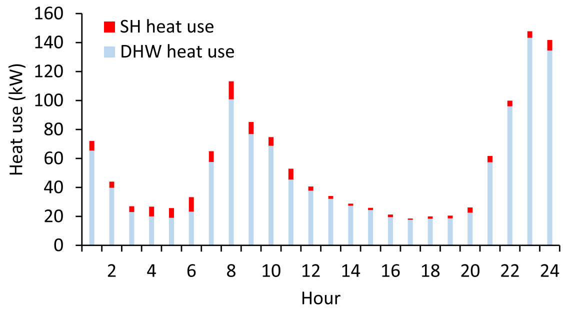

Fig. 5. Daily profiles of the measured SH and DHW heat use in July (heat use after the CPT).

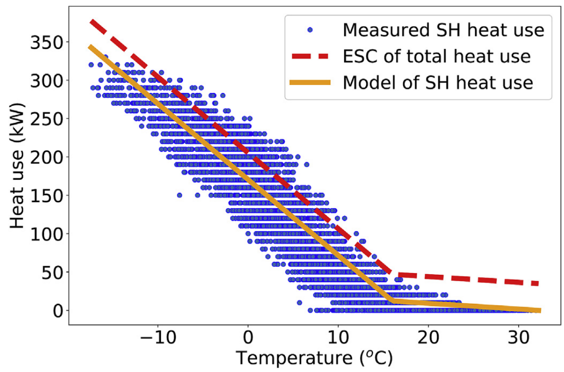

Fig. 6. Model of the SH heat use based on the ESC of the total heat use.

time during the summer, according to Ref. [14]. After, by using Equation (3), the model of the DHW heat use was obtained. Finally, all the values of the modelled SH and DHW use were adjusted in such a way that their sum was equal to the total heat use in the hotel.

Figs. 7 and 8 show the results of splitting total heat use into SH and DHW for February, one of the coldest month in Norway. Fig. 7 shows that the ESC model well explained the trend of the SH heat use in the hotel. For the yearly data sample, the coefficient of determination (R2) between the model and the measured SH heat use was 0.93, and Root Mean Square Error (RMSE) equals to 23. At the same time, the DHW heat use model (see Fig. 8) was affected by

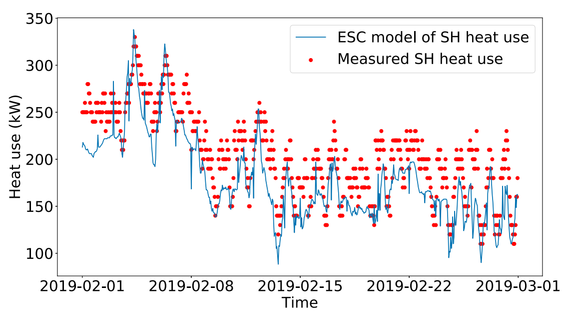

Fig. 7. Restored SH heat use based on the ESC.

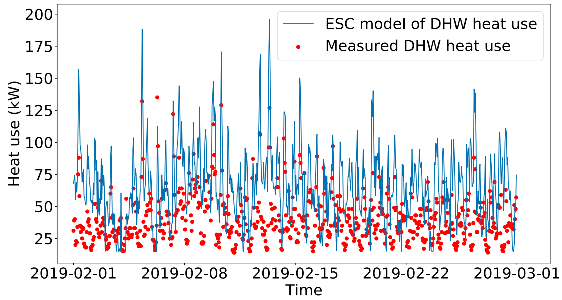

Fig. 8. Restored DHW heat use based on the ESC.

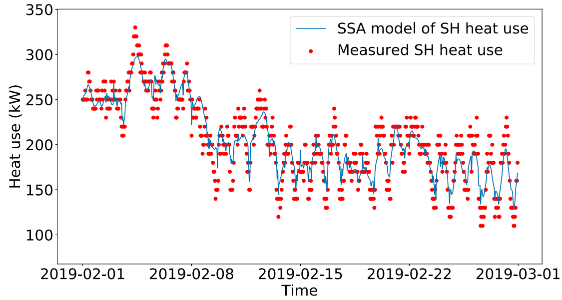

Fig. 9. Restored SH heat use based on the SSA.

the SH noise in the residuals. For this reason, the R2 for the DHW heat use model was less accurate and equal to 0.57, and RMSE was 20.3. Therefore, the SSA method was used to further improve these models.

5.2. *Using the singular spectrum analysis for the decomposition of the SH and DHW heat use in the hotel*

The SSA decomposition for the time series of the total hourly heat use was carried out in order to split the SH and DHW heat use. The Python implementation of the SSA from Ref. [36] was used to perform the SSA decomposition. The SSA was iteratively applied for different windows length. For each step of the iteration, the components which corresponded to the SH were selected in such a way that their additive sum had the maximum correlation with the SH heat use modelled by the ESC (according to Equation (4)). The investigation showed that the same criterion could be applied to select the best window length for SSA modelling. Namely, the SSA models for windows lengths with a higher correlation between the SH heat use modelled by the ESC and the SSA demonstrated the higher accuracy of the SSA DHW heat use model. For this reason, the window length that allows us to receive the highest correlation between SH heat use obtained by the ESC and SSA can be considered as the best for the SSA modelling.

The SSA calculations for large window lengths require high computational power. Therefore, it was impossible to check all the windows lengths from 2 to $N/2$. Although some models were not considered due to computational limitations, the different windows lengths were examined. Based on the proposed criteria in Equation (4), the window length was chosen to 600 and the components related to SH were obtained. From all these components, the first component represented the trend for the SH heat use in the hotel. The other components explained the spikes and fluctuations of the SH heat use. The sum of the SSA components related to SH was shifted according to Equation (5).

The residuals of the SSA SH heat use model were used to develop the new DHW use model. The calculations were done according to Equation (3). Finally, the values for both the SH heat use and the DHW heat use were balanced in such a way that both of them become positive and their sum was equal to the total heat use. Figs. 9 and 10 show the results of splitting total heat use into SH and DHW based on SSA for February.

As we can see from Figs. 9 and 10, the models for both the SH and the DHW were improved compared to ESC model. For the yearly data sample, the R2 for the SSA SH heat use model was 0.97, and RMSE was 15.1. While for the DHW heat use R2 was 0.76, and RMSE 14.7. To recap, see the comment related to RMSE and R2 values for the ESC approach. The RMSE and R2 criteria, as well as

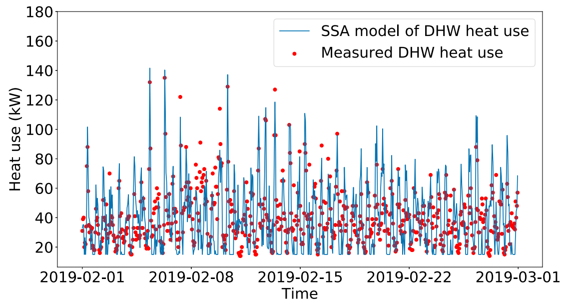

Fig. 10. Restored DHW heat use based on the SSA.

Figs. 9 and 10 show that the SSA allowed us to better capture the spikes of the SH and DHW heat use.

5.3. *Identifying profiles and validation of the modelled SH and DHW heat use*

The restored DHW and SH heat use can be used for identifying the heat use profiles. Heat use profiles are a powerful instrument for estimating the DHW and SH heat use in the buildings. The profiles allow us to determine the hours of peak energy loads and other energy load characteristics of the building. In this article, the restored by SSA profiles for DHW and SH were compared and verified with profiles obtained from measured DHW and SH heat use.

Using the restored data from the model values for the SH and DHW heat use, the average monthly and daily load profiles were constructed. Figs. 11 and 12 compare the hourly and monthly profiles, respectively, with the measured heat use in the hotel.

Fig. 11 shows that the proposed method allows restoring well the average daily load profiles for the SH and the DHW heat use. The profiles obtained from the SSA model well captured the timing of the peak heat use during an average day. The profiles showed that the morning peak of the DHW use in the hotel occurs from 7:00 to 9:00 o'clock and the evening peak from 21:00 to 23:00 o'clock. Comparing to the DHW, the profile of the SH heat use was more uniform. However, it also showed a small increase in heat use in the morning and night-time.

The average monthly profile for the restored SH heat use was representative, compared to the measured SH heat use, see Fig. 12. a. This profile captured well the seasonal variation of the SH heat use. According to Fig. 12. a, the months with the coldest outdoor temperature (November, December, January, February and March)

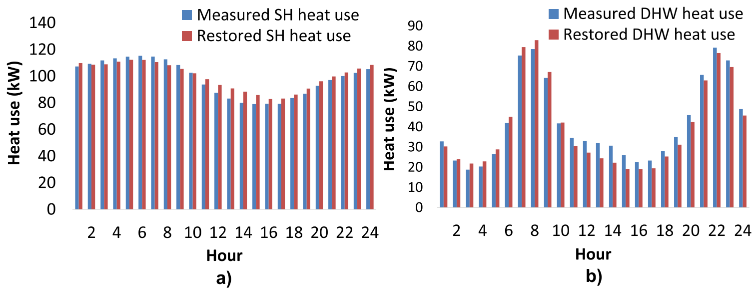

Fig. 11. Restored hourly SH and DHW heat use profiles: a) SH heat use and b) DHW heat use.

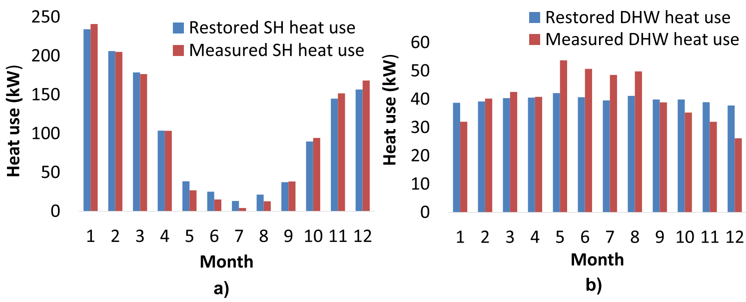

Fig. 12. Restored average monthly SH and DHW heat use profiles: a) SH heat use and b) DHW heat use.

has the highest SH use. At the same time, in the warm season (May, June, July, August and September) the SH heat use was small. The DHW heat use profile, see Fig. 12. b had particular inaccuracy for the months in the warm season. In these months, significant spikes of DHW heat use occurred, most likely related to an increased number of guests in the hotel in the warm season [32]. In addition, due to the SH heat use that occurred after the CPT in the hotel, it was difficult to capture precisely the DHW heat use from the ESC model for certain months. To recap, please see Fig. 5 and the comments related to the possible faults causing SH heat use in the warm period.

The proposed method allowed us to split the SH and DHW heat use from the total heat use. Despite the fact that the obtained values of the SH and DHW heat use have particular inaccuracy, their application may be still useful. Both models for the SH and the DHW well represented the general trends of SH and DHW use. This is essential information for solving many energy saving issues in the hotels heating systems.

6. Conclusions

Statistical analysis and modelling are reliable tools for improving the energy performance of buildings and releasing the energy savings potential. In order to reach better results in this area, it is necessary to carry out data-driven analysis of energy use of the main technical systems in buildings, where SH and DHW systems often are the largest energy consumers. Despite this fact, quite often energy meters in buildings measure the total heat use only, not divided into the SH and the DHW heat use. However, the SH and the DHW have different regimes of work and influencing factors, and it is important to analyse the heat use in these two systems separately. Thus, the separation of the total heat use data into components associated with the SH and the DHW heat use become an essential task. The literature review shows that the problem of dividing the total heat use into the parts related to the SH and DHW for individual buildings is not solved yet.

In this article, the method for splitting the total heat use into the SH and the DHW heat use was proposed. For splitting, we used the assumption that hourly SH heat use is highly correlated with the outdoor temperature. At the same time, the DHW is not affected by this parameter on hourly basis. Using this assumption, the model of the SH heat use was extracted from the total heat use in the building. For this purpose, the method based on the ESC and the SSA was applied. Finally, the DHW use was found within the residuals of the SH heat use model.

The method was tested on the data for the heat use in the hotel in Norway. The hotel has two separate heat meters for the SH and DHW. Thus, it was possible to perform the comparison of the measured SH and DHW heat use with the results of the splitting. The analysis showed that the SH heat use model had the coefficient of determination R2 equal to 0.97, while for the DHW heat use R2 was equal to 0.76. In addition, the proposed method allowed us to restore well the daily load profiles for the SH and the DHW heat use. However, the monthly profiles for the DHW were less accurate than for the monthly SH profiles. The results of the analysis in the hotel showed that the obtained models for the SH and the DHW represented well the general trends of the heat use. The proposed method allows us to gain valuable information about the DHW and the SH heat use in buildings where only one heat meter is available. The models and profiles for DHW and SH heat use, obtained from total heat use splitting, may be used as an instrument for improving energy efficiency in buildings.

The investigation in this study has several limitations. First of all, the proposed approach was dedicated to the case when 1 m measured the total SH and DHW heat use. However, in some buildings, 1 m could be used not only for SH and DHW heat use, but also may include other heat needs. The further consideration for these conditions should be done. The restored DHW heat use was obtained based on the SH heat use model. This means that the DHW heat use model included also particular inaccuracy of the SH heat use model. Therefore, the restored DHW heat use might be less accurate than for the SH heat use, especially for several warm months. For this reason, the ways to modify the approach and improve the model for DHW heat use should be investigated in our future work. Furthermore, the research was done for the regular hotel located in Eastern Norway. SH and DHW heat use in other types of buildings (schools, apartments, offices etc) have their own specific features that may be used to improve the results of splitting. In addition, passive houses were out of the scope of this research. Passive houses consume less heat for SH compering to the regular one, which will influence the shape of the energy signature curve. Therefore, the study for other locations and types of buildings should be performed.

Author statement

Dmytro Ivanko: Conceptualization, Methodology, Formal analysis, Software, Investigation, Writing – original draft, Visualization, Writing – review & editing, Sørensen Åse Lekang: Data curation, Writing – review & editing, Natasa Nord: Conceptualization, Formal analysis, Writing – original draft, Supervision, Writing – review & editing

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

The main steps of the SSA algorithm are as following [38]:

1) Calculating the trajectory matrix for the time series

According to the SSA method, the one-dimensional time series E_{TH} should be transformed into a sequence of multi-dimensional vectors lagged with the window length L. The window length is a value that should be selected from 2 to $N/2$. In such a way, the series $X_1, X_2, \ldots, X_K$ with vectors $(E_i, E_{i+1}, \ldots, E_{i+L-1})$ will be obtained. Where $K = N - L + 1$, for $i = 1, \ldots, N - L$. These vectors will form the following trajectory matrix:

$$X = \begin{matrix} E_1 & E_2 & E_3 & \cdots & E_K \\ E_2 & E_3 & E_4 & \cdots & E_{K+1} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ E_L & E_{L+1} & E_{L+2} & \ddots & E_N \end{matrix} \tag{A1}$$

The matrix X is called a Hankel matrix. The anti-diagonal elements of this matrix are equal.

2) Decomposition of the trajectory matrix

The singular-value decomposition (SVD) of the trajectory matrix can be written as:

$$X = \sum_{i=1}^{d} X_i = \sum_{i=1}^{d} \sigma_i U_i V_i^T \tag{A2}$$

where X_i is the i-th elementary matrix of X, σ_i is the i-th singular value of the matrix X, the vectors U_i are the left singular vectors of the matrix X, vectors V_i are the right singular vectors of the matrix X, d is the intrinsic dimensionality of the time series trajectory space (typically $d = L$)

3) Selection of eigen-vectors

At this step of the SSA, the splitting the elementary matrices X_i into separate groups and summing the matrices within these groups was performed. The grouping procedure partitions the set of indices$\{1 \ldots d\}$ into m disjoint subsets $\{I_1, I_2, \ldots, I_m\}$. These calculations led us to the following decomposition:

$$X = X_{I1} + \ldots + X_{Im} \tag{A3}$$

Selecting the subsets $\{I_1, I_2, \ldots, I_m\}$ is called eigentriple grouping. The choice of several leading eigentriples corresponds to the approximation of the time series in optimality property of the SVD. In this article, the simplified conditions when $m = d$, $I_j = \{\text{j}\}$, $j = 1, \ldots, d$, and $X_{Ij} = \sigma_i U_i V_i^T$ were used. In this case, the corresponding grouping is called elementary.

4) Reconstruction of the one-dimensional series

Based on X_{Ij}, a diagonal averaging was performed to form the elementary time series components $\tilde{e}_i$. In this way, the initial time series $E_{TH} = (E_1, E_2, \ldots, E_N)$ was decomposed into a sum of reconstructed components:

$$\tilde{e}_n = \sum_{1}^{d} \tilde{e}_i \tag{A4}$$

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Prediction of DHW energy use in a hotel in Norway

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Abstract. Domestic hot water (DHW) systems are significant consumers of energy in buildings. This article is dedicated to hourly and daily DHW energy use modeling, with the aim of achieving energy savings in buildings. The methods investigated in the article were tested using statistical data obtained from a hotel located in Oslo, Norway. For better modeling, the influence of various factors on DHW energy use in the hotel was studied. For this purpose, the wrapper approach was used. The analysis indicates that the most important variable that should be used in the model is number of guests. There are also other factors that can be taken in account, even though they do not have such strong influence. Traditionally, only daily data about number of guests are available in the hotels. These data do not allow us to develop accurate hourly model of DHW energy. The article therefore proposes a method which, based on introduction of artificial variables, improve accuracy of the hourly DHW model. Eight models are compered, based on criteria of their adequacy. The Support vector machine model shows the best results for daily modeling and the Partial least squares (PLS) regression for hourly modeling.

1. Introduction

Buildings are responsible for approximately one third of the energy use in the world [1]. Thus, efficient use of energy in buildings is a topical issue from both an environmental and economic point of view. A domestic hot water (DHW) system is an essential part of most buildings, and contribute to 25-35% of the total energy use [2]. Many studies claim that a large potential for future energy savings in buildings lies in improving operation and design of DHW systems [3]. Mathematical modeling of energy use is a powerful tool for achieving energy saving in buildings. Prediction, data recovery, monitoring of energy use and other important tasks could be solved via accurate and physically valid mathematical modeling.

Recently, much attention was paid to the modeling of energy needs required for heating [4]. Meanwhile, the issue of DHW energy use modeling and prediction has not been studied well enough [3]. The majority of publications in this area are dedicated to the modeling of DHW volumetric consumption in building rather than energy use. These two parameters are strongly positively correlated. The knowledge obtained from the studies about DHW volumetric consumption modeling is valuable for development of advanced models of DHW energy use. Therefore, articles considered in this introduction are dedicated to both prediction of DHW volumetric consumption and energy use in buildings.

For instance, according to [5], DHW energy loads are modeled as a function of draw-off temperatures. For three different systems, the models based on application of neural networks (NNs) are calculated. The results show that the models trained on their associated systems produce errors less than 11%. However, when obtained models were used with new systems, they had significant errors.

A bottom-up approach for DHW energy use prediction is proposed in [6]. The developed prediction model calculates the quantity of hot water and timing of each end-use for the next day from historical data and summarizes these as prediction data.

The necessity of development of daily DHW use models, which do not require strong computation time and information about the residents in the buildings, is stressed in [7]. The authors proposed application of Auto Regressive Moving Average method for solving this issue. The developed model takes into account the periodicity of one week, the water use of the previous days and random fluctuations. The results are tested on one-year data of DHW use in eight residential homes in France.

DHW use in flats based on the number of rooms and area of the flat are described in [8]. This study is conducted in 626 apartments in Wroclaw, Poland. To build a model, the bootstrap technique is used. Based on the obtained statistical data, a database is created, consisting of randomly simulated buildings with randomly selected flats in different configurations. After this, the regression model is developed, explaining the relationship between DHW use, number of rooms and floor area.

In [9] proposed to consider the DHW use as stochastic variables. The statistical data for the research has been collected from 65 apartments in Budapest, Hungary. The model presents the relationship between DHW use and number of apartments, sorted duration curve of DHW consumption, as well as minimum, average and maximum daily values of DHW consumption in the buildings.

The necessity of accurate hot water use forecasting for future development of demand-side management in residential dwellings is stressed in [10]. Various forecasting models, such as exponential smoothing, seasonal autoregressive integrated moving average, seasonal decomposition by Loess model and a combination of them, were tested on data obtained from 120 houses in UK.

16 equations for prediction of average hot water use in different times of the day are proposed in [11]. The authors consider weekdays and weekends separately. Each day is divided into periods by combining hours with similar DHW use by time of day, type of day and season. It is also proposed to take additional variables into account in the model, to adjust the predicted hot water use: if the household has a dishwasher, clothes washer, only seniors as occupants, or if the residents pay for hot water or not.

Most of the above mentioned studies are focused on residential buildings, because this type of building is taking a big share in national building stocks. The characteristics, regimes of work, and available data in the hotels are significantly different from residential buildings [3]. Therefore, considered methods cannot be directly applied for DHW energy use prediction in hotels. A better methods of DHW energy use prediction in hotels should be developed.

The aim of this article was to model hourly and daily DHW energy use that may be used for achieving energy savings in hotels. The analysis in this article is based on two years hourly data of DHW energy use collected in a hotel located in Oslo, Norway. The focus was on the statement that obtained model of DHW energy use should be accurate, reliable and take into account particular characteristic of the buildings. In order to meet these requirements, the factors that have significant influence on DHW energy use in the hotel were investigated. To improve the accuracy of an hourly model, the procedure of preprocessing daily data for number of guests and extracting information of their influence on DHW energy use on hourly basis was proposed. After that, various methods for daily and hourly DHW energy use modeling were compared. The comparison was carried out according to the following criteria: the coefficient of determination (R2), the average absolute error (MAE) and the mean square error (MSE). The most accurate models of DHW energy use were identified.

2. Description of the hotel and available statistical data

The characteristics of the analyzed hotel are typical for Scandinavian conditions, and it well reflect the trends of DHW energy use in similar types of buildings. The hotel, located in Oslo, Norway, was built in 1938, and reconstructed in 2007. The total area of the building is 4 939 m^2. The building consists of eight floors with 164 guest rooms. All the guest rooms have bathrooms with toilet facilities and shower. Guests usually arrive between 3 p.m. and midnight and check out before noon. According to the hotel management, employees use hot water for cleaning, and guests use hot water for personal hygiene.

In the DHW system, the hot water is circulated to ensure fast delivery at each tap. The hotel uses electric water heaters for DHW production. Data on energy use for DHW production was collected during several years from a energy meter mouted by the hotel owner. The meters measure electricity delivered to the DHW tanks, which mean that both DHW needs and heat losses in the DHW system are included in the presented DHW energy use. The data about energy for other needs are also known. The daily data about arriving guests and booked rooms in the hotel are available from the hotel reservation system. In addition, in order to investigate the influence of weather conditions on DHW energy use in the hotel, data from the meteorological station in Oslo (Blindern) were used.

3. Methods

We started with the task of choosing the variables which should be taken into the DHW energy model. To determine the proper subset of variables, and taking into consideration characteristics of each modeling method, a wrapper approach of optimal variables selection was used [12]. According to this approach, an iteration algorithm was applied. First, all the variables were sorted by the absolute value of the correlation criteria between a variable and DHW energy use. Then, in each iteration step, one additional variable from the sorted list of variables was added to the model. For each step, parameters and accuracy criteria of the model were recalculated. Thus, parameters that do not improve the accuracy of the model significantly can be determined and eliminated. Despite the higher computational time comparing to correlation matrix analysis, the application of wrapper algorithms is a powerful instrument for assessing the impact of different combinations of variables on DHW energy use and development of accurate prediction models.

3.1 Preprocessing daily data for guest presence

It is known from previous studies that the main factor affecting DHW energy use in a hotel is the number of guests presence [3]. Most hotels have a reservation system, which register number of visitors that check in at the set time, usually after 12 a.m. Thus, the hotel reservation system tells us the number of guests booked into the hotel. However, whether the visitors are actually in the hotel at any given time or not remains unknown.

The peak of DHW energy use in the hotel occurs before 12 a.m. The actual time when visitors are arriving and leaving can vary. Some people can arrive before the set time of check in, and some of them can stay a bit longer in the building after the check-out time. Therefore, the model should take into account both number of guests registered in the reservation system on a given day (***Gst***) and one day before ($\boldsymbol{Gst_{Lag1}}$).

The use of daily data of the number of guests in the hotel cannot significantly improve the accuracy of the hourly model of DHW energy use. Therefore, we propose to introduce an additional artificial variable $\boldsymbol{Gst_{art}}$. We introduce this variable to increase accuracy of hourly DHW model. Eq. (1) was used to identify the numerical value of $\boldsymbol{Gst_{art}}$ for each separate hour:

$$Gst_{art} = Gst \cdot Cgp_i + Gst_{Lag1} \cdot Cgp_{Lag1.i} \tag{1}$$

where Cgp_i and $Cgp_{Lag1.i}$ were the coefficients of guests DHW use intensity for *i*-hour based on the number of people booked into the hotel on the given day and one day before.

It was suggested to calculate the coefficients of guests DHW use intensity for *i*-hour by solving the following optimization problem:

$$\max(corr(\begin{Bmatrix} Cgp_{i=1} \cdot (\overrightarrow{Gst}) + Cgp_{Lag1.i=1} \cdot (\overrightarrow{Gst_{Lag1}}), \dots, Cgp_{i=24} \cdot (\overrightarrow{Gst}) \\ +Cgp_{Lag1.i=24} \cdot (\overrightarrow{Gst_{Lag1}}) \end{Bmatrix}, \{\vec{E}_{i=1}, \dots, \vec{E}_{i=24}\}) \tag{2}$$

where Cgp_i, $Cgp_{Lag1.i}$ were the target variables, $\vec{E}_i$ was the vector of the DHW energy use data in the hotel in *i*-hour, $\overrightarrow{Gst}$, $\overrightarrow{Gst_{Lag1}}$ were vectors of the daily number of guests booked into the hotel on the given day and one day before.

The optimization problem in Eq. (2) gave the values of the coefficients of guests DHW use intensity for each hour of the day. These coefficients are maximizing the correlation between $\boldsymbol{Gst_{art}}$ and DHW energy use, which makes $\boldsymbol{Gst_{art}}$-based predictions more accurate. The obtained coefficients for 2015 and 2016 years are shown in Figure 1. Variation of the coefficients values, Figure 1, in different years was not significant. Thus, the values of coefficients from previous years can be used for identification of variable $\boldsymbol{Gst_{art}}$ in the prediction model. In this article, the values of coefficients were calculated based on the year of 2015, and they were used for predicting the year of 2016.

3.2 DHW energy use modeling

The selection of the DHW energy use model and modeling techniques should be done individually for each building, taking into consideration its characteristics. In this article, the number of models shown in Table 1 was investigated. The detailed explanation of these models can be found in [13, 14]. The best model can be selected by comparing different modeling techniques obtained on the same set of data. In order to compare models, cross validation was used. 70 % of yearly data in 2015 were used in a training set and 30% in testing of the model. Besides, the models were tested on one-year data from the year 2016. The comparison of the models is performed based on R2, MAE and MSE criteria of the model adequacy. The modeling is performed in Python using the Scikit-learn tool [14].

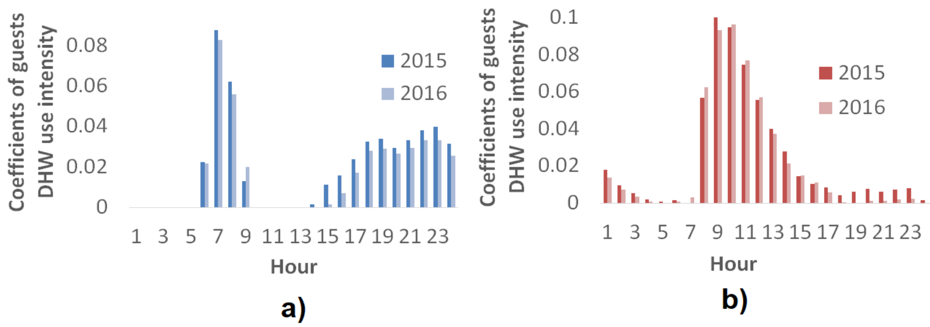

Figure 1. Coefficients of guests DHW use intensity based on the reservation in the given day (a) and one day before (b) in the hotel in 2015-2016

4. Results

The variables ***Gst*** and $\boldsymbol{Gst_{Lag1}}$, which represent number of guests on a given day, and the day before were investigated. The data of energy use for other needs (***Eon***) and number of booked rooms (***Rm***) were also examined. In addition, the influence of the following meteorological parameters were analised: outdoor air temperature (***T***), relative humidity (**Rh**), mean wind speed (***Ff***), atmospheric pressure (***Pa***). The influence of day of the week (***DoW***) and month (***Mth***) was also considered. In addition, the artificial variable $\boldsymbol{Gst_{art}}$ was introduced in the hourly model.

Application of the wrapper algorithm for all the considered models, shown in Table 1, showed approximately the same results. The main parameters for daily DHW energy use modeling in the hotel were ***Gst*** and $\boldsymbol{Gst_{Lag1}}$, and for the hourly model it was $\boldsymbol{Gst_{art}}$. Application of these parameters allowed us to get quite reliable models of the DHW energy use in the hotel. ***Rm*** is highly correlated with number of guests and was taken out of the model, because it does not give additional information and quality to the model. Generally, ***Pa***, ***Ff*** *and* ***Mth*** (in hourly model model) did not increase the accuracy of any model and were therefore eliminated.

DoW, ***T***, ***Rh***, ***Eon*** and ***Mth*** (in daily model) improved the models, but not much. For example, when adding all these parameters to the model, depending on the modeling approach, R2 coefficient increased by 5-15%. Thus, if the target of modeling is to build more accurate model, then these parameters can be taken into account, as we have done in this article. However, if the simple model is more preferable, then only data about number of guests in the hotel can be used.

When choosing our parameters we also must take into consideration that some data, such as weather data, will not be readily available when we are running prediction models. For analysis of historical data, knowledge about all the data is available, but for forecasting, meteorological and energy data must be forecasted as well, which brings additional uncertainty into the prediction. In this work we had accurate values of these data, since the models were tested on previous years.

To choose the most appropriate prediction model for DHW energy use in the hotel, eight different models were used, see Table 1. We tested the models using both the cross validation approach and one year ahead prediction. Based on Table 1 for these data sets, the best model for daily modeling was the Support vector machine method. The result of the daily modeling based on the cross validation testing of the data set is shown in Figure 2. For daily model, R2 equals 0.881 for the Support vector machine model based on the cross validation of the data set, and 0.777 for one year ahead data set. For hourly model, Ridge regression gave the best results based on the cross validation of the data. However, for one year ahead prediction Partial least squares (PLS) regression was more accurate. Since PLS regression was more stable, the preference was given to this model. The hourly DHW energy use modeling based on PLS regression is shown in Figure 3.

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Table 1. Comparison of different hourly and daily models of DHW energy use

Period	Daily model						Hourly model					
Testing data	Cross validation			Testing based on the next year data			Cross validation			Testing based on the next year data		
Type of regression model	R2	MAE	MSE	R2	MAE	MSE	R2	MAE	MSE	R2	MAE	MSE
Support vector machine	0.881	30	2485	0.777	39	3919	0.781	4	66	0.725	5	79
Partial least squares	0.855	32	3030	0.776	34	3928	0.780	4	66	0.731	5	77
Ridge	0.855	34	3029	0.777	34	3922	0.794	5	62	0.685	7	90
Lasso	0.855	33	3030	0.777	34	3923	0.794	5	62	0.704	6	85
Linear Discriminant Analysis	0.776	40	4683	0.664	48	5903	0.768	4	70	0.670	4	95
Stochastic Gradient Descent	0.855	32	3030	0.777	34	3923	0.794	5	62	0.686	6	90
Bayesian Ridge	0.855	33	3030	0.777	34	3919	0.794	5	62	0.685	7	90
Passive Aggressive	0.840	36	3342	0.735	38	4662	0.720	4	84	0.712	5	83

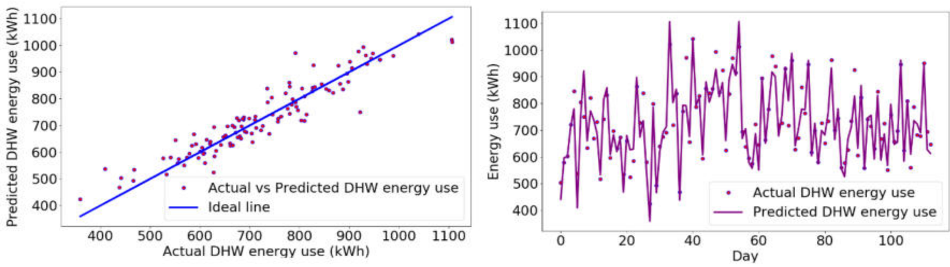

Figure 2. Daily modeling of DHW energy based on Support vector machine method

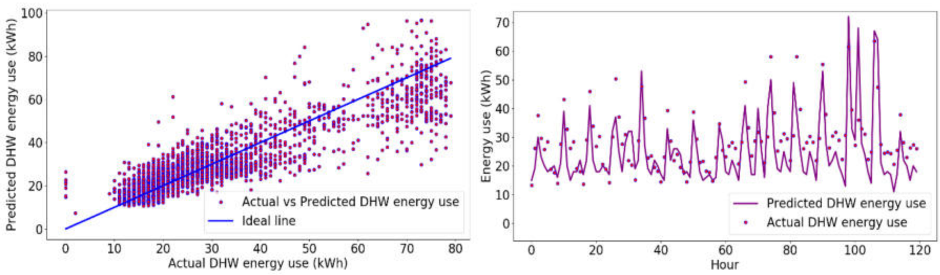

Figure 3. Hourly modeling of DHW energy based on PLS method

The investigated methods of the hourly and daily models could find application for the prediction of DHW energy in similar types of buildings. In addition, these models are useful for DHW energy use modelling in hotels in Norway under the similar conditions.

5. Conclusion

Prediction of the DHW energy use in buildings is a complex task, due to previously lower focus on the DHW energy use and high requirement for relevant, but not easily available data. This article focused on modelling DHW for a typical hotel located in Norway. The wrapper approach shows its high efficiency for determining variables affecting DHW energy use in the hotel. The analysis indicated that the main variables that influence the DHW energy use were numbers of guests registered in the reservation system during the given day and the day before. However, the daily values of the guest numbers did not allow us to develop an accurate hourly model for the DHW energy use. Therefore, introduction of the additional artificial variables, which explain the hourly intensity of the guests DHW

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use was proposed. The method of identifying these variables based on solving optimization problem was shown in the article. Selection of the best DHW energy use model requires comparison of different models based on the criteria of models adequacy. Appropriate comparison of the models for the hotel showed that the best daily model was based on the support vector machine method, and the hourly model obtained by using the PLS regression.

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Selecting the model and influencing variables for DHW heat use prediction in hotels in Norway

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ABSTRACT

Domestic hot water heat use prediction modelling is an important instrument for increasing energy efficiency in many buildings. This article addressed hourly domestic hot water heat use prediction, using a Norwegian hotel as a case study. Since the information available for buildings may vary, two widespread situations with different input variables were studied. For the first situation, the prediction is based only on data obtained from historical measured domestic hot water heat use. For the second situation, additional variables that affect domestic hot water heat use were applied. These variables were determined using the Wrapper approach. The Wrapper approach showed that factors related to the guests presence have the most significant influence on the domestic hot water heat use in the hotel. Nevertheless, daily data about the number of guests booked at the hotel did not appear to be informative enough for precise hourly modelling. Therefore, to improve the accuracy of the prediction, it was proposed to use an artificial variable. This artificial variable explained the hourly intensity of the guests domestic hot water use. In order to select the best model for the domestic hot water heat use prediction, ten advanced time series and machine learning techniques were tested based on the criteria of models adequacy. For both considered situations, the Prophet model showed the best results with R2 equal to 0.76 for the first situation, and 0.83 the second situation.

1. Introduction

Buildings are one of the largest categories of energy consumers in the European Union (EU) [1]. Buildings are currently responsible for approximately 36% of global energy use [2]. Therefore, increasing energy efficiency in buildings is an essential step for reducing fossil fuel use and improving the environmental situation.

Nowadays, most building constructions have complex technical systems, to realize a comfortable living condition for people. Among these systems, the domestic hot water (DHW) system is an integrated component of every building. DHW systems are significant consumers of energy. According to [3], 15% of the total heat demand in the EU is associated with DHW use. In regular buildings, DHW systems typically consume 25–35% of the total energy use [4]. However, in highly insulated constructions, the share of DHW heat use is increasing and may exceed the space heating [5]. Therefore, substantial opportunities for energy savings in buildings can be achieved by improving the performance of DHW systems [6]. The investigation [7] shows that DHW account for almost 26% of total energy use in the hotel, and therefore it should be prioritized in energy-saving measures.

Data-driven analysis and predictive modelling are powerful instruments for increasing the efficiency of heat use in DHW systems. Improving the design and operation of DHW systems requires both validated forecasting models, heat use profiles, effective utilization of monitoring and control systems. In order to solve all these issues, accurate predictive models of DHW heat use should be developed.

The introduction of modern technical energy solutions in DHW systems is essential for energy efficiency in buildings [8]. The proper implementation of these solutions requires the application of data analysis for DHW heat use. For example, the conceptual designs for DHW heating systems in a hotel with the application of wastewater technologies are considered in [9]. The research shows that the DHW system control is prioritized to operate with the wastewater technologies and heat pumps. This control can be performed based on DHW predictive models. Using a solar-assisted DHW water heating systems in hotels becomes popular all over the world [10]. The prediction of DHW heat use is necessary for the optimal operation of these systems [11]. Different types of DHW heating systems are investigated in [12]. This study

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summarises that DHW energy use can be reduced through using combined systems based on traditional and renewable energy solutions. However, due to unstable behaviour of renewable energy sources, development of accurate profile and prediction of DHW heat use becoming crucial for successful operation of combined DHW heating systems.

In recent years, increasing attention is paid to the investigation for the modelling of space heating heat use and the development of Energy Signature Diagrams [13]. On the contrary, the DHW heat use predictive modelling has not been studied sufficiently [6]. It is important to stress that the majority of existing publications are focused mainly on the modelling of DHW volumetric use rather than heat use. These two parameters have a strong positive correlation. Besides, the factors that affect the DHW volumetric use have a similar effect on the DHW heat use. Since not so many publications are dedicated to DHW heat use prediction, both previous experience of the predictive modelling for DHW volumetric and heat use are considered in this introduction.

Traditionally, predictive modelling includes the following main steps: identifying influencing variables, selecting the method for prediction, and determining the parameters of the model.

1.1. Identifying influencing variables

Identifying influencing variables with significant impact on the DHW heat use in the building is an initial step for prediction. There is a number of scientific papers analyzing the influence of different factors on DHW volumetric and heat use, as shown in Table 1.

Most of the articles represented in Table 1 assume that the number of occupants, seasons, day of the week and time of the day have a significant influence on the DHW heat use. The information about activities, such as occupant's presence, sleeping, hygiene and cooking, as well as a time when appliances are in use (sinks, showers, baths, clothes washer, and dishwasher) gives a better understanding of the DHW heat use [19]. It should be noticed that the factors influencing DHW heat use can vary from one building type to another, and also depending on the location of the building. For example, in the investigation [15], it is concluded that the influence of seasons, outdoor temperature, and rainy days on DHW in the dwellings is negligible. However, in the articles [23], the seasons and outdoor temperature are considered as essential variables and taken into account. Therefore, it is necessary to evaluate the influence of variables on the DHW heat use for each building type in Norway based on reliable statistical methods.

1.2. Selecting the method for prediction and determining parameters

In accordance with selected influencing factors, the model of DHW energy use should be built. Machine learning and deep learning techniques show high accuracy for solving prediction and data analysis problems in DHW systems [27]. The review of prediction techniques that different researchers use for solving this issue is represented below.

The application of artificial neural networks (ANNs) for DHW modelling in Canadian households is considered in [31]. The DHW heat use as ANNs model of draw-off temperatures is presented in [26]. The model is tested in three residential DHW systems. The archived ANNs model accuracy is more than 89% for the trained data. However, the use of the ANN model for new data obtained from other systems shows significant inaccuracy.

Creation of easy to use forecasting model of DHW use is considered in [32]. Autoregressive moving average (ARMA) model as a solution to this problem is proposed. The ARMA model takes into consideration the periodicity of the week, the water use of the days before and random fluctuations of DHW use. The model based on data from eight apartments in France is examined [32].

Table 1
Investigations of variables that have a significant impact on DHW volumetric use and heat use.

Influencing variables	Authors
Number of occupants, day of the week	Ferrantelli, Ahmed, Pylsy and Kurnitski [14]
Day of the week	de Santiago, Rodriguez-Villalón and Sicre [15]
Number of rooms, area	Chmielewska, Szulgowska-Zgrzywa and Danielewicz [16]
The magnitude of the drains, the start times of DHW use, the time between two successive drains	Beeker, Malisani and Petit [17]]
Occupancy in the hotel and regulation of the system	Todorovic, Tomic, Bojanic, Bajatovic and Andelkovic [9]
Hotel star rating, DHW system type, occupancy	Priyadarsini, Xuchao and Eang [18]
Activities, number of DHW tap starts, time of tapping, the duration of tapping	Fischer, Wolf, Scherer and Wille-Haussmann [19]
Flow rates, cold and supply temperatures	Verhaert, Bleys, Binnemans and Janssen [20]
Type of the tap (conventional mixer tap or low flow electronic tap)	Fidar, Memon and Butler [21]
Activities, appliances	Good, Zhang, Navarro-Espinosa and Mancarella [22]
Outdoor temperature, season, number of tenants, type of building (apartment or detached), the location, the household area, month, density of water, specific heat of water, reference temperatures, cold inlet temperature	Gutierrez-Escolar, Castillo-Martinez, Gomez-Pulido, Gutierrez-Martinez and Stapic [23]
Socioeconomic characteristics, activities, appliances, and type of apparatuses that use water	Fan, Liu, Wang, Geissen, Ritsema and Tong [24]
Occupant behaviour, appliances, demographic conditions, and occupancy rate	Swan, Ugursal and Beausoleil-Morrison [25]
Draw-off temperatures	Barteczko-Hibbert, Gillott and Kendall [26]
Activities	Widen, Lundh, Vassileva, Dahlquist, Ellegard and Wackelgard [27]
Appliances, flow rates and times of DHW use	Hendron and Burch [28]
The day of the week, time of the day, season, appliances, age of occupants (seniors or not), pay or does not pay for hot water	Lutz, Liu, McMahon, Dunham, Shown and McCure [29]
Family size, season, day of the week, time of the day	Papakostas, Papageorgiou and Sotiropoulos [30]

The linear regression models were used for DHW energy use identification in apartment blocks in Norway [33].

A bottom-up model that estimates the day ahead DHW use for end-users is investigated in [34]. The type of facilities and timing of DHW use is applied as an input in the model. The prediction for the next day of the total DHW use in the system is calculated as a sum of end-users DHW use.

The survey of DHW use in 626 apartments in Poland is carried out in [16]. The authors create a database of DHW use for residential buildings with different parameters. The configuration of apartments in these buildings is randomly selected by using the bootstrap method. Based on the database, the regression model is constructed. This model considers DHW use as a function of the number of rooms and the floor area.

The stochastic analysis of DHW use for 65 apartments is performed in Hungary [35]. As an input for the stochastic model, the authors use the number of apartments in the building, the duration curve, daily average, minimum and maximum values of DHW use.

The issue of DHW use forecasting for demand-side management in residential buildings in the UK is reviewed in [36]. Various time series forecasting techniques, such as exponential smoothing, seasonal autoregressive integrated moving average, seasonal decomposition by Loess model and a combination of them, were tested on data from 120 dwellings.

A model for DHW use prediction that consists of 16 equations is proposed in [29]. These equations take in account season, day of the week, and hours with similar DHW use. To improve the model, the authors propose to consider additional factors to adjust the predicted hot water use. These factors include the availability of dishwashers, cloth washers, age of occupants, and if the residents should pay for hot water or not.

The Long-Short Term Memory (LSTM) neural networks were used for DHW heat use prediction in [11]. The performance of simple LSTM neural network, Attention-based LSTM neural network (ALSTM) and Attention-based LSTM using decomposed data (ALSTM-D) are compared. The authors claims that the Long-Short Term Memory (LSTM) neural network shows the best results for DHW heat use prediction in the case of solar-assisted DHW systems.

As we can see, the largest part of the above-mentioned studies performed investigations for residential buildings. Practice shows that for residential buildings, information about the DHW heat use is more opened and accessible [6]. Despite this fact, the share of DHW heat use in non-residential buildings is also significant and cannot be neglected [37]. Among non-residential buildings, hotels [38] are those with the most energy-consuming categories [39]. In hotels, the specific DHW heat use, the regimes of work, and available information about factors affecting DHW heat use are substantially different from the residential buildings [6]. Accordingly, the approaches proposed in the above-mentioned studies cannot be directly applied for the DHW heat use modelling in hotels. Therefore, more reliable prediction models of DHW heat use for non-residential buildings, including hotels, should be created.

1.3. Contribution and organization of the paper

The purpose of this article is to develop an accurate and reliable hourly DHW heat use prediction model for hotels, using a hotel in Norway as a case. In order to make the results of the investigations applicable to other buildings, two alternative situations with available inputs for prediction were considered.

Situation 1 assumed that information about influencing variables for the DHW heat use was not available. Only historical data about DHW heat use weres known. For these conditions, the article investigated the various methods to handle the prediction based on the time series of the DHW heat use only. In general, Situation 1 is less common for hotels. Usually, measurement systems in hotels collect data about building energy performance. In addition, useful information about guest presence can be obtained from the hotel booking system. However, for certain non-residential buildings, these variables are unknown. The results of the investigation and developed models for Situation 1 may be useful and applicable to such buildings.

In Situation 2, the research focused on identifying factors affecting DHW heat use and developing a prediction model based on these variables. The influencing variables on DHW heat use is identified based on the wrapped approach. In order to improve the accuracy of the prediction, the article proposes procedure for preprocessing data of daily guests presence and extracting information of their influence on DHW heat use on an hourly basis. Finally, advanced time series and machine learning techniques were tested, to find the best prediction model among them.

The paper is organized as the following. Section 2 describes the main characteristics of the hotel for which the prediction of DHW heat use was made. Section 3 introduces the methodology for DHW heat use prediction in the following situations: for Situation 1, only retrospective Time Series of DHW heat use is known. For Situation 2, also other parameters that could influence DHW heat use were available. In Section 3, the methodology was applied for the DHW heat use prediction in a hotel located in Oslo, Norway. Among considered modelling techniques, the model that gives the most accurate and robust prediction for Situation 1 and Situation 2 was identified.

2. Description of the hotel

The investigations in this article were performed based on data obtained from an urban hotel, located on the west side of Oslo, Norway. The characteristics of the hotel are typical for Scandinavian conditions. The building was built in 1938. There has been several renovation projects, where the most recent was in 2007. The total area of the building is 4 939 m^2. The building has eight floors with 164 guest rooms. All the guest rooms are equipped with bathrooms that have toilet facilities, washbasin, and a shower. The check-in time for the guests is between 15:00o'clock and midnight, and check out before 12:00o'clock.

The considered hotel well represents the general tendency of the DHW heat use in similar building types. According to hotel management, employees use hot water for cleaning and guests use hot water for personal hygiene. In the DHW system, the hot water is circulated to ensure fast delivery at each tap. The hotel uses electric water heaters for DHW production. Data on heat use for DHW production was collected within several years from a stationary energy meter in the hotel. The meter measures electricity delivered to the DHW tanks, which means that both DHW needs and heat losses in the DHW system are included in the presented DHW heat use. The data about electrical use for other needs in the hotel are also measured. The hotel booking system allows us to obtain daily information about the number of arriving guests and booked rooms in the hotel. The influence of weather conditions on hourly DHW heat use was investigated, too. For this purpose, data obtained from the nearest meteorological station located in Oslo were used [40].

3. Methods

This chapter consists of two subsections that are dedicated to modelling in Situation 1 and Situation 2. Subsection 3.1 investigates the hourly prediction based on the historical time series of DHW heat use. Subsection 3.2 considers the issue of identifying variables that affect DHW heat use, followed by making prediction when using these variables. For this purpose, time series and machine learning techniques were used. In addition, in Subsection 3.2, a method which introduced the artificial variable reflecting the hourly intensity of the guests DHW use and improved the accuracy of the hourly DHW models was proposed.

3.1. Prediction based on the historical time series of DHW heat use

For certain types of buildings, information about users presence and other explanatory variables are unknown. In these conditions, only DHW heat use data from previous periods of time can be used for prediction. Practice shows that the DHW heat use may vary at different hours of the day, day of the week, and months. For this reason, the preference was given to methods that allowed us to make a prediction based on the historical time series of DHW heat use and additionally take in account the day, week, and month when the DHW heat use occurred. Among different methods such as classical methods for time series analyses, Exponential Smoothing (ES) and Autoregressive Integrated Moving Average (ARIMA), and modern methods of machine learning, Neural Network (ANN), Prophet and XGBoost, were considered.

The ES method uses recurrence relations between the current and the previous values of the parameter. According to ES, predictions are calculated by applying weighted averages where the weights are exponentially decreasing as observations come further from the past [41]. In detail, the ES method is presented in [41]. According to [41], exponential smoothing uses the following equation for prediction:

$$\hat{E}_{T+1|t} = \alpha \cdot E_T + (1 - \alpha) \cdot \hat{E}_{T|t-1} \quad (1)$$

where $\hat{E}_{T+1|t}$ is the predicted value and $\hat{E}_{T|t-1}$ is the prediction for the previous moment of the time. E_T is the most recent observation. α is the smoothing parameter, accepted from 0 to 1.

The ARIMA method predicts the next step in the sequence as a linear function of the differenced observations and residual errors at previous time steps [42]. This method combines autoregressive (AR), Moving Average (MA) and the integrated (I) parts in one model. An integrated part of the model performs a differentiation pre-processing step of modelling that removes the non-stationarity of the time series. AR and MA are the core of prediction. The algorithm and theoretical bases of ARIMA modelling technique are well explained in [42].

The Prophet is a package for time series prediction developed by Facebook [43]. Prophet uses additive regression model $E(t)$ that includes the following components:

$$E(t) = g(t) + s(t) + h(t) \quad (2)$$

where $g(t)$ is a trend for non-periodic changes that may be obtained by a simple Piecewise Linear Model. $s(t)$ is a seasonal (periodical) component of the model obtained based on Fourier series. $h(t)$ is a component of the model that takes into account the effects of holidays and other untypical days with irregular schedules of DHW heat use.

XGBoost is a machine learning prediction technique based on gradient boosting decision tree method [44]. XGBoost sequentially sums the prediction of multiple weak learners, such as regression trees models, in order to ensemble a robust prediction model [45]. By adding additional regression trees models in such a way, the errors made by the initial model are reduced. The regression trees models are added until further improvements of the initial model can no longer be obtained. The gradient boosting is related to a gradient descent algorithm that is used in XGBoost to minimize the loss when adding new models [46]. Mathematically, gradient boosting can be represented by the following equation [46]:

$$\widehat{E}_i = \sum_{k=1}^{K} f_k(X_i), f_k \in \mathrm{F} \quad (3)$$

where $\widehat{E}_i$ is predicted DHW heat use. X_i are influencing variables. K is the number of functions (regression trees) in the function spaceF.

In XGBoost the parameters of the functions can be found automatically by solving the following optimization function [46]:

$$\boldsymbol{obj}(\theta) = \sum_{i}^{n} l(\widehat{E}_i, E_i) + \sum_{k=1}^{K} \Omega(f_k) \quad (4)$$

where l is a differentiable loss function. Ω is the regularizing function that introduces penalties for the complexity of the model. A more extensive introduction to XGBoost modelling technique and its mathematical apparatus are given in [47].

Artificial Neural Network (ANN) is a powerful modelling technique that mimics the behaviour of the brain with its homogeneous elements - neurons. For prediction, classification and solving of other tasks, ANN uses the number of simple nonlinear functional blocks that are called neurons. Multiple neurons are organized into layers [48], where the actual processing of data is performed via a system of weighted connections [47]. The ANN represents the group of mathematical models of high complexity. This method demonstrates good results for nonlinear relationships among between variables. In this article, the ANN model with the two-layer feed-forward network [49] was used for DHW heat use prediction.

In order to estimate the accuracy of DHW heat use models, cross-validation was used. Hourly data of DHW heat use in 2015 were used in a training set, and data from 2016 were applied to test the models. The prediction for all the above-mentioned methods, except ANN, was performed in Python, using Statsmodels, XGBoost, and Prophet packages [50]. For Neural Networks modelling, the Neural Network Toolbox in Matlab software was utilized [49]. The comparison of the models was performed based on the Coefficient of Determination (R2), Mean Absolute Error (MAE), and Mean Squared Error (MSE) criteria of the model adequacy [50].

3.2. Prediction based on the variables that have a significant influence on the DHW heat use

Compared to Subsection 3.1, Subsection 3.2 considers more favourable conditions for DHW heat use prediction. In these conditions, in addition to DHW heat use data from previous periods of time, information about the guest's presence and other explanatory variables are known. The procedure for DHW heat use prediction in this subsection includes three main steps: data preprocessing, identifying variables that affect DHW heat use, and selection of the best model for hourly prediction of DHW use. The preprocessing step included removing outliers and unrealistic data. Finally, as a part of preprocessing, a method for introducing an artificial variable, which reflects the influence of hourly guest presence on DHW heat use, was proposed. This method, in detail, is explained in Section 3.2.1. The set of variables that affect the DHW heat use was selected according to the Wrapper approach. This approach is explained in Section 3.2.2. After, the selected set of influencing variables was used as an input for modelling. The accuracy of various machine learning methods for the DHW heat use prediction was carried out. The general information about the considered methods is presented in Section 3.2.3.

3.2.1. Preprocessing the daily data of the guest presence

It is well known that occupancy has a significant effect on the DHW heat use in buildings [6]. Among all influencing factors, the number of guests being present in a hotel is typically the key factor that affects DHW heat use the most.

Traditionally, a hotel booking system stores information about the number of guests who were booked into the hotel for each particular day. For a given date, both the number of guests booked in one day before (Gst_{Lag1}) as well as on the date itself (Gst) are influencing the DHW heat use. In general, Gst shows the number of guests who are staying in the hotel after 15.00o'clock, and Gst_{Lag1} reflects information about people who are leaving before 12:00o'clock. Nevertheless, despite the official check-in/out time, in practice, the actual time when guests are arriving and leaving can vary. Sometimes guests arrive before the set time of check-in, and it happens that some guests can stay longer in the building after the check-out time.

The daily profiles in the hotel showed that the highest DHW heat use occurs before 12:00o'clock. Consequently, the influence of Gst_{Lag1} on daily DHW heat use can be more significant than Gst. For this reason, it is crucial to take both factors Gst and Gst_{Lag1} into account in the model.

The investigation showed that using Gst and Gst_{Lag1} allows us to perform a quite accurate daily prediction of DHW heat use. However, if we consider hourly analysis of the DHW heat use, *Gst* and Gst_{Lag1} do not give sufficient information about hourly occupancy in the hotel. These parameters do not show whether the guests are present in the hotel at certain hours or not. For this reason, the considered factors cannot substantially enhance the accuracy of the hourly model of the DHW heat use. To increase the accuracy of the hourly model, we propose to introduce an additional artificial variable (Gst_{art}) that reflects the hourly influence of the guests presence on DHW heat use. The following equation proposed to use to determine the numerical value of the Gst_{art} for each separate hour:

$$Gst_{art} = Gst \cdot Cgp_i + Gst_{Lag1} \cdot Cgp_{Lag1.i} \tag{5}$$

where Cgp_i and $Cgp_{Lag1.i}$ are the coefficients for the guest DHW use intensity for *ith*-hour, which were identified based on the number of people booked into the hotel on the given day *Gst* and one day before Gst_{Lag1}.

In order to identify the coefficients of the guest DHW use intensity for *ith*-hour the following optimization problem was solved:

$$\max(corr(\left\{\begin{array}{c} Cgp_{i=1}\cdot\left(\overrightarrow{Gst}\right)+Cgp_{Lag1.i=1}\cdot\left(\overrightarrow{Gst_{Lag1}}\right),\cdots,Cgp_{i=24}\cdot\left(\overrightarrow{Gst}\right) \\ +Cgp_{Lag1.i=24}\cdot\left(\overrightarrow{Gst_{Lag1}}\right)\end{array}\right\},$$

$$\left\{\overrightarrow{E}_{i=1},\cdots,\overrightarrow{E}_{i=24}\right\}) \tag{6}$$

where Cgp_i and $Cgp_{Lag1.i}$ are the target variables. $\overrightarrow{E}_i$ is the vector of the DHW energy use data in the hotel in *ith*-hour, $\overrightarrow{Gst}$, $\overrightarrow{Gst_{Lag1}}$ are vectors of the daily number of guests booked into the hotel on the given day and one day before.

By solving the optimization problem in Equation (6), the values of the coefficients of the guest DHW use intensity for each hour of the day can be obtained. These Cgp_i and $Cgp_{Lag1.i}$ coefficients are maximizing the correlation between Gst_{art} and the DHW heat use. Application of the coefficients makes Gst_{art} based predictions more accurate. For the considered hotel, the values of Cgp_i and $Cgp_{Lag1.i}$ were calculated for several years. The obtained coefficients for 2015 and 2016 years are shown in Fig. 6. and Fig. 7. in Section 4.2. The investigation indicated that the changes in the values of the Cgp_i and $Cgp_{Lag1.i}$, see Fig. 6. and Fig. 7., in different years, were not substantial. Thus, their values from previous years may be used for the identification of the variable Gst_{art} and prediction for the next year. In this article, the numerical values of the coefficients were calculated based on the year of 2015, and they were used for predicting the DHW heat use in 2016. Besides, to conduct a thorough investigation, both cases for modelling with application of the artificial variable Gst_{art}, and without it, were considered.

3.2.2. Wrapper approach for selecting the influencing variables on the DHW heat use

Choosing the proper set of influencing variables is a crucial step for the DHW heat use prediction. The use of irrelevant and redundant input variables in the model leads to an increase in computational demand, an inadequate interpretation of the model, and generally makes prediction more complicated and less accurate. Traditionally, three different approaches may be used for feature selection: Filtering, Wrapper, and Embedded method [51].

In this article, the Wrapper method was used for optimal variables selection. This method is one of the most precise methods, because it detects possible interactions between variables and takes into account the specific characteristics of the prediction algorithm [51]. According to the Wrapper method, first, all the variables were sorted by the absolute value of the correlation criteria between a variable and the DHW energy use. Afterwards, an iteration algorithm was applied. In each iteration step, one additional variable from the sorted list of variables was added to the model. For each step, parameters and accuracy criteria of the model were recalculated. The obtained criteria of model accuracy on a current step were compared with criteria on a previous step. Thus, parameters that do not improve the accuracy of the model were determined and eliminated from the model, and a set of variables that makes predictions more precise was selected. Despite the higher computational time compared to commonly used analysis based on the correlation matrix (Filtering method), the application of the Wrapper method is a more potent instrument for assessing the impact of different combinations of variables on the DHW heat use and selecting their proper set for accurate prediction [51].

3.2.3. Prediction techniques for modelling DHW heat use based on influencing factors

The prediction techniques for the considered case are presented in Table 3, see Section 4.2. The advanced time series techniques have the ability to take into account explanatory variables. For this reason, some models in Subsection 3.1 were also used for prediction in current conditions. In addition to the models in Subsection 3.1, the availability of data on influencing factors allowed us to apply more diverse prediction techniques.

Group Method of Data Handling (GMDH) is a computer-based method for calculating complex multivariable models. GMDH stands on self-organization theory of mathematical models. The method recursively combines selective submodels (base function) to obtain a more accurate predictive model. On each step of the modelling, the number of submodels included in the main model is gradually growing. In this way, the accuracy and complexity of the model are increasing. The GMDH allows us to find a model structure with optimal complexity based on the minimum value of an external criterion [52]. As base functions in GMDH can be used various models: linear, polynomials, exponential, etc.

Partial Least Squares Regression (PLSR) is a powerful instrument for prediction in conditions when a large number of independent variables is used in the model. PLSR works well with highly collinear variables, too. This method performs the decomposition of the initial data into a subspace of latent variables (scores and loadings). Latent variables are representing the main features of covariance among the dependent and the independent variables [53]. PLSR calculates the linear regression model via the projection of the predicted variables and the observable variables to a subspace of the latent variables [53].

Support Vector Regression (SVR) is based on the computation of a linear regression function in high dimensional feature space [54], where the input data are mapped via a nonlinear function. SVR is minimizing the generalized error bound [55]. The generalization error bound includes the training error and a regularization term that controls the complexity of the hypothesis space [55]. The comprehensive overview of this method is given in [56].

Ridge and LASSO methods are used to deal with overfitting and variables that may be affected by multicollinearity [57]. Both these methods are based on principals of regularization, i.e. introduction penalties to the coefficients of features. Ridge Regression is penalizing the square of the magnitude of coefficients [58]. LASSO introduces penalties to the absolute value of the magnitude of the coefficients [58].

In Subsection 3.2, the general principles for the DHW heat use modelling were applied in the same way as in Subsection 3.1. The data about DHW heat use and influencing variables from 2015 were used in a training set and data from 2016 were used for testing. The best model was selected based on R2, MAE, and MSE criteria of the model adequacy. The prediction for the methods mentioned above, was performed in Python, using Statsmodels and GmdhPy packages.

4. Results

This section is divided into two subsections, which examines two situations for modelling with different input data. The hourly prediction based on information from the historical DHW heat use is investigated in Section 4.1. A more favourable situation with using additional influencing variables is shown in Section 4.2.

4.1. Results on hourly DHW heat use based on the historical time series

DHW heat use measurements are widely used for paying utility bills in non-residential buildings in Norway. As a consequence, historical data about hourly DHW heat use are available for building owners for many types of non-residential buildings in Norway, including hotels. Historical data about hourly DHW use provide us with a valuable basis for DHW heat use modelling.

For more precise prediction, the variation of DHW heat use in different periods of time should be taken into account. Certain factors, which explain appropriate variation, can be identified based on the descriptive statistical analysis of the retrospective time series. Box plot is a statistical method, that graphically depicts the median, first quartile and third quartiles, minimum and maximum, and outliers for the data. A visual study of the box plots showed that hourly DHW heat use in the hotel varies depending on the hour of the day, day of the week, and the month, as shown in Fig. 1.-Fig. 3. Fig. 1. and Fig. 3 shows hourly heat use in kW, while Fig. 2. shows average hourly DHW heat use for each day in kW.

It is generally known that changes in the DHW heat use during the day normally is associated with personal hygiene activities. The box plot of the hourly DHW heat use in Fig. 1. indicates that the significant peak of the DHW use could be observed in the morning from 7:00o'clock to 10:00o'clock. The heat use for DHW in the evening looks pretty even, with the small spikes from 22:00o'clock to 23:00o'clock. The minimum of the DHW heat use occurred at night time from 1:00o'clock to 5:00o'clock in the morning.

Weekly variation of the DHW heat use, See Fig. 2., is usually related to the preferences of visitors to make trips on different days of the week. The days of the week in Fig. 2. are displayed from Monday to Sunday. Fig. 2. shows that heat use for the DHW may vary depending on the day of the week. For this specific hotel, the highest average daily DHW heat use in 2015 was observed on Saturdays and the smallest on Mondays.

The box plot of DHW heat use from January till December 2015 is shown Fig. 3. From Fig. 3. the seasonal changes in DHW heat use

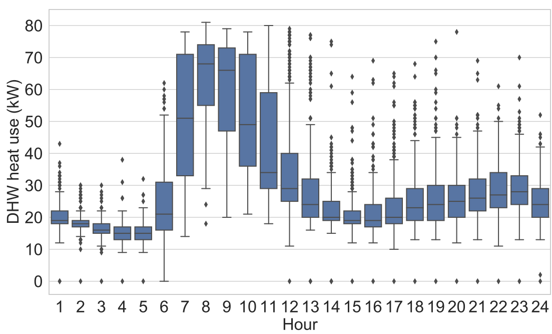

Fig. 1. Box plot of hourly DHW heat use in 2015.

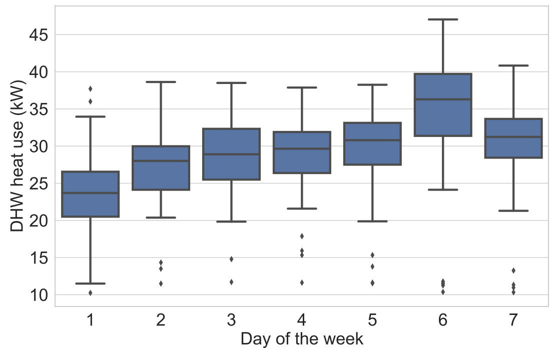

Fig. 2. Box plot of the average hourly DHW heat use for different days of the week in 2015.

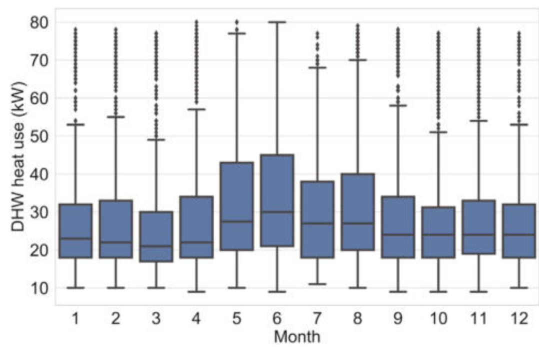

Fig. 3. Box plot of hourly DHW heat use for the different month of the year in 2015.

can be noted. The highest monthly heat use took place from May to September. Such a pattern may arise due to an increase in the number of tourists in the warm season. Another parameter that affecting the monthly heat use is the variation in cold freshwater inlet temperature in the DHW system.

The box plots gave us only rough information about the variation of heat use in different periods of time. However, this method clearly shows that parameters such as hour, day of the week and month should be included in the model. Accordingly, in Situation 1, the retrospective time series of DHW heat use and the hour, day and month were used as inputs for different prediction techniques.

The classical time series modelling techniques, ES and ARIMA showed high values of MAE and MSE, and R2 less than 0.6. Due to the low accuracy of ES and ARIMA models, they were not considered for DHW heat use modelling in further analysis. The NN, Prophet, and XGBoost techniques showed better outcomes. The MAE, MSE, and R2 criteria for these models are presented in Table. 2.

Among the models considered for Situation 1, see Table 2, the Prophet had the best accuracy for hourly DHW heat use modelling. In addition, this model stays robust. The R2 remained equals to 0.76 for both the training and the testing set. The results of hourly prediction based on the Prophet model are shown in Fig. 4. The analysis indicates that most of the actual values of DHW heat use lie within the confidence intervals [59] of the model, as shown in Fig. 4. The predicted versus actual values are distributed around the ideal line, as shown in Fig. 5. This means that the Prophet model developed for Situation 1, can be used for forecasting

Table 2
Prediction modelling based on historical time series of DHW heat use.

Prediction technique	Training set			Testing set		
	R2	MAE	MSE	R2	MAE	MSE
Prophet	0.76	3.8	67.7	0.76	4.46	73.27
NN	0.73	4.4	78.6	0.73	4.7	79.13
XGBoost	0.73	3.56	59.67	0.68	4.11	71.14

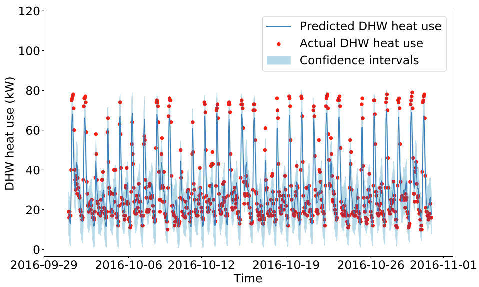

Fig. 4. Hourly modelling of DHW heat use based on the Prophet method in Situation 1.

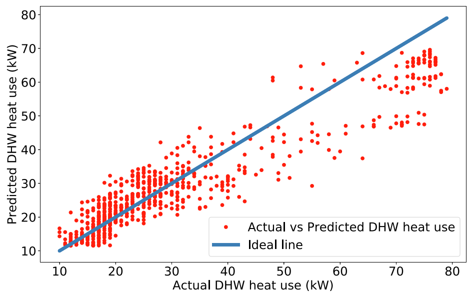

Fig. 5. Predicted by the Prophet method vs. actual values of DHW heat use in Situation 1.

DHW heat use in the hotel. However, despite this fact, the model can be improved. For this purpose, additional variables that affect the DHW heat use should be taken into account. The results of the prediction for corresponding conditions (Situation 2) are presented in Section 4.2.

4.2. Results of hourly DHW heat use based on influencing variables

As a part of the investigation for Situation 2, the feasibility of using different variables for DHW heat use modelling was tested. In order to identify the variables that may affect the DHW heat use, data from the hotel's measurement and booking systems were collected, as well as climate data from a weather station located nearby the building. The following variables were considered as potential inputs for the DHW heat use prediction modelling: *Gst* and Gst_{Lag1} – the number of guests on a given day and the day before, *Rm* – number of booked rooms in the hotel. *Eon* – energy use for other needs in the building, *T* – outdoor air temperature, *Rh* – relative humidity, *Ff* – mean wind speed, *Pa* – atmospheric pressure, *H* – hour of the week, *DoW* – day of the week, *Mth* – month of the year.

The *Gst* and Gst_{Lag1} are representing only the daily values of the guests presence. To take into account the daily variation of the guests presence and improve the prediction, the artificial variable Gst_{art} was used. Gst_{art} was identified based on Equation (1). The coefficients of the guests DHW use intensity in Equation (5) were calculated by solving the optimization problem in Equation (6). These coefficients for a given day and the day before are shown in Fig. 6. and Fig. 7. The patterns in Fig. 6. and Fig. 7. coincided with a shape of the box plot of hourly DHW heat use in Fig. 1, which represents the hourly habits of DHW use in the hotel. The coefficients calculated on the basis of the data for 2015 were used to determine Gst_{art} in 2016. Models with and without application of artificial variable Gst_{art} were tested to determine the most accurate.

The Wrapper algorithm was applied to categorise the best set of influencing variables. It was found that the most influencing parameters for all models are related to the guest presence in the building. *Gst* and Gst_{Lag1} showed the best result for the models created only based on measured data, and Gst_{art} for models where this artificial variable was applied. These three parameters allowed us to receive quite reliable models of DHW heat use in the hotel.

Rm, number of booked rooms, is highly correlated with a number of guests. It does not give additional information and quality to the models. For this reason, *Rm* was taken out of consideration. Application of mean wind speed, *Ff*, and atmospheric pressure, *Pa* in the models, did not increase their accuracy. In this regard, these parameters also should be excluded from modelling. When relative humidity, *Rh*, was used, only a few models showed insignificant improvement. Thus, application of *Rh* is usually not reasonable.*T*, outdoor air temperature *and Eon*, energy use for other needs improved the models, but not much. For example, when adding these parameters to certain models, *R2* coefficient was increased by several percents. In some instances, the application of *T* and *Eon* may be useful for modelling. However, it should be mentioned that when choosing these parameters, we also must take into consideration that some data, such as weather data, will not be readily available when we are running the prediction. For analysis of the historical data, knowledge about all the data is available, but for forecasting, meteorological and energy data must be forecasted as well, which brings additional uncertainty into the prediction.

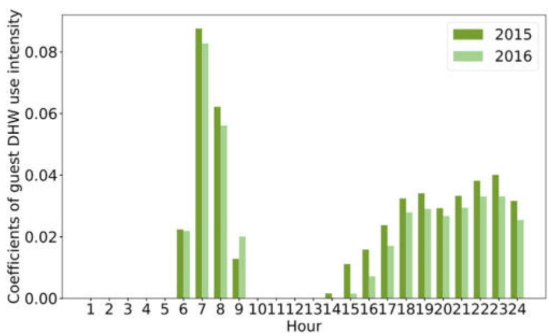

Fig. 6. Coefficients of the guest DHW use intensity based on the booking in the given day in the hotel in 2015–2016.

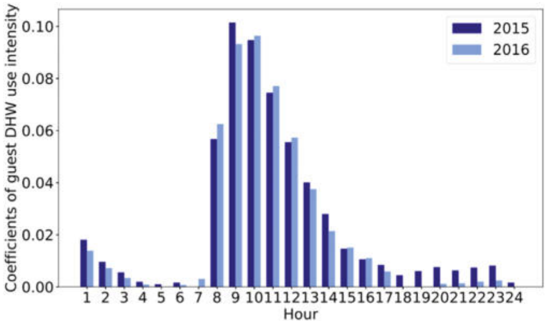

Fig. 7. Coefficients of the guest DHW use intensity based on the booking one day before in the hotel in 2015–2016.

The parameters hour (*H*), day of the week (*DoW*), and month (*Mth*) represented changes in the DHW heat use in different periods of time. In complex and accurate models such as Prophet, NN and XGBoost, applying these parameters gave us good effects. However, some models were unable to extract useful information from *H*, *DoW*, and *Mth* for DHW heat use prediction.

Since the main target of modelling was to build a more accurate model, all parameters that may improve the accuracy of modelling were taken into account. Generally, two sets of influencing variables showed the best outcomes:

a) the set of variables without using the artificial variable Gst_{art}: *Gst*, Gst_{Lag1}, *T*, *Eon*, *H*, *DoW*, and *Mth;*

b) the set of variables with using the artificial variable Gst_{art}: Gst_{art}, *T*, *Eon*, *H*, *DoW*, and *Mth.*

In order to select the most accurate DHW heat use prediction model, nine different prediction techniques, see Table 4, were tested. For the set of variables that do not include Gst_{art}, the MAE, MSE and R2 criteria of models adequacy were specified in Table 3. On the other hand, Table 3 contains the same criteria for prediction based on Gst_{art}.

It should be noted that unacceptably inaccurate models were removed from consideration. Therefore, such models are not included in Table 3. When the set of the variables without Gst_{art} was used, only Prophet, NN, XGBoost, and GMDH models showed satisfactory results of prediction. On the contrary, the application of artificial variable Gst_{art} allowed us to improve the accuracy of prediction. Therefore, more models met the minimum acceptable criteria with R2 greater than 0.65. In general, the models in Table 4 showed better outcomes compared to the models in Table 3. However, for advanced and complex prediction techniques, the effect of application of Gst_{art} was less visible. These consequences can be explained by the fact that Prophet, NN, XGBoost, and GMDH models can better reflect hidden relationships in explanatory variables than the other models in Table 4. Accordingly, these models may give us a quite reliable forecast based on both sets of variables, both with and without the application of Gst_{art}.

Table 3 and Table 4 indicate that Prophet and NN are the best models for hourly prediction DHW heat use in the hotel. The NN model showed better performance on the training set, while Prophet on a testing set. For the NN model, R2 calculated on a training set was 0.89. Nevertheless, for the testing set, this criterion was reduced to 0.8. Such changes of R2 may indicate a tendency of the given model to overfitting.

Compering to the NN model, the Prophet model allowed us to obtain more robust results with minor changes in R2, MAE, and MSE. For this reason, the Prophet method was selected as the best model for the DHW heat use prediction in the considered hotel. The result of the hourly modelling based on the testing data set is shown in Fig. 8. Fig. 8. and Fig. 9. confirm the adequate performance of the model. As shown in Fig. 8., the actual values of DHW heat use were within the confidence intervals of the Prophet model. The predicted versus actual values lies close to the ideal line, as shown in Fig. 9.

The study confirmed that by means of easily accessible data, it is possible to obtain a fairly accurate model for the DHW heat use prediction for a hotel. Comparing the results in Situation 2 with a model that uses only historical DHW heat use data (Situation 1), the application of additional variables (Situation 2) allowed us to improve the accuracy of prediction. For example, R2 was increased from 0.76 to 0.83 in the testing set, if using an artificial variable. For all considered cases, the Prophet model proved to be an accurate and reliable model that can reflect periodical changes in DHW heat use. The developed models are useful for the DHW heat use modelling for other hotels under similar conditions.

5. Conclusions

Predictive modelling is a powerful instrument for increasing the efficiency of the DHW heat use in buildings. The modelling involves the following tasks: selecting input variables for prediction, determining the prediction technique, and parameters for the model. This article highlightes the issue of the DHW heat use prediction for a hotel located in Norway.

For accurate prediction, it is crucial to select a proper set of input variables. These variables should include the main factors that affect the DHW heat use in the building. Yet, the data availability may vary from one building to another. Therefore, two common situations with data availability were considered. Situation 1 assumed that only information from the historical DHW heat use might be used for prediction. Situation 2 demonstrated more favourable conditions, where also additional variables that affect DHW heat use were included in the model.

The Wrapper approach showed high efficiency in determining the variables that should be included in the prediction model. This approach indicated that the main factor that affected the DHW heat use in the hotel were number of guests booked in the hotel on the given day and the day before. Nevertheless, the number of guests are collected on a daily basis, which makes them less efficient for hourly modelling. Therefore, to improve the accuracy of the hourly model, the introduction of an additional artificial variable was proposed. This artificial variable reflects the hourly inten-

Table 3
Prediction modelling without using the artificial variable $Gst_{art.}$

Prediction technique	Training set			Testing set		
	R2	MAE	MSE	R2	MAE	MSE
Prophet	0.8	3.7	56	0.79	4.6	63
NN	0.88	3.18	33.65	0.8	4	59
XGBoost	0.89	2.5	25	0.78	3.8	51
GMDH	0.81	4.35	58.9	0.64	4.7	116.3

Table 4
Prediction modelling with using the artificial variable $Gst_{art.}$

Prediction technique	Training set			Testing set		
	R2	MAE	MSE	R2	MAE	MSE
Prophet	0.82	3.26	52.4	0.83	3.67	52.46
NN	0.89	2.85	31.04	0.8	3.48	59
XGBoost	0.88	2.64	28.7	0.81	3.12	45.04
GMDH	0.82	3.57	56	0.8	3.67	62
SVR	0.77	3.88	69.52	0.72	4.90	79.03
ARMAX	0.85	3.8	43.3	0.66	5.33	83.2
PLSR	0.77	4.13	69.25	0.73	4.91	77.21
Ridge	0.79	4.52	64.39	0.68	6.52	90.50
Lasso	0.79	4.47	64.64	0.70	6.19	84.97

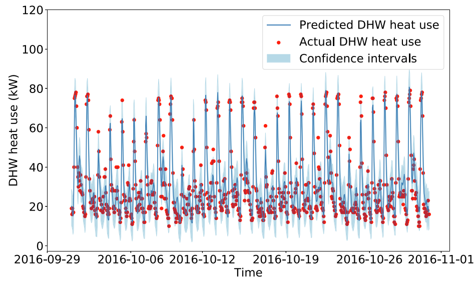

Fig. 8. Hourly DHW heat use model based on the Prophet method in Situation 2.

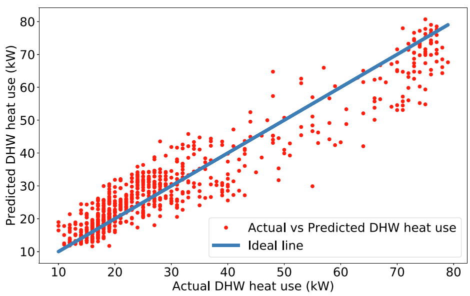

Fig. 9. Predicted by the Prophet method vs. actual values of DHW heat use in Situation 2.

sity of the guests DHW use with a major peak of the heat use in the morning and a small peak in the evening. The method for identifying this variable was based on an optimization problem, presented in the article. In addition, several other factors were identified, that may increase the accuracy of the prediction to a certain extent.

Identifying the DHW heat use model requires a comparison of various prediction methods. Selection of the best method among those considered should be based on the criteria of model adequacy. In order to obtain an accurate and reliable DHW heat use model for a hotel, ten different time series and machine learning prediction techniques were tested. Among considered methods, the Prophet model showed the best accuracy and robustness for the DHW heat use prediction in the case study. In Situation 1, the R2 criterion for testing set obtained via the Prophet model was 0.76. However, with the introduction of additional explanatory variables in the model (Situation 2), the R2 criterion was increased to 0.83. The outcomes of the hourly DHW heat use predictive modelling for the hotel could also find application in similar building types.

CRediT authorship contribution statement

Dmytro Ivanko: Conceptualization, Methodology, Formal analysis, Software, Investigation, Writing - original draft, Visualization, Writing - review & editing. **Åse Lekang Sørensen:** Formal analysis, Writing - review & editing. **Natasa Nord:** Conceptualization, Formal analysis, Writing - original draft, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

The investigation in this study has several limitations. The research was limited to the hotel located in Eastern Norway. The influence of the location on the DHW heat use requires additional consideration. Using the methods proposed in the article with consideration of additional variables may improve the accuracy of the prediction model. For example, the inlet cold water temperature and hot water temperatures have a significant impact on DHW heat use. However, in regular buildings that do not have advanced measuring systems, these parameters are usually not measured. This information was also not available for the considered hotel. For this reason, in the future work, the additional investigation for buildings with more advanced measuring systems will be conducted. Furthermore, it is planned to perform a similar analysis for those types of buildings that were not covered in the current study (office buildings, shopping centres, schools, etc.).

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Paper VI D. Ivanko, N. Nord, A. Tartaglino, Analysis of DHW energy use profiles for energy simulations in a hotel located in Norway. *REHVA European HVAC Journal*, Volum 56 (4), 2019.

Analysis of DHW energy use profiles for energy simulations in a hotel located in Norway

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Domestic hot water (DHW) system is significant energy consumer in hotels. For this reason, energy modeling and simulations in hotels should provide an accurate and representative assessment of the energy performance of domestic hot water systems. The majority of dynamic simulation tools use DHW energy use profiles as the basic for estimating DHW energy needs. In this article, energy simulations in EnergyPlus software for a large hotel were carried out. All inputs in the EnergyPlus simulation model were adjusted according to Norwegian national regulations. Application of different DHW energy use profiles in the simulation model was explored. The profiles given in the national and international standards were compared with profiles obtained from measurements in the hotel located in Oslo, Norway. Simulations in EnergyPlus showed that application of profiles from measured data have higher accuracy then simulations based on standards. The results of the study may give indication for sizing and planning of DHW systems.

Domestic hot water (DHW) systems make a substantial contribution to the energy balance in hotels in Norway [1]. They are responsible for approximately 20–35% of the total energy use in these buildings [2]. Michopoulos, Ziogou [3] estimate that CO_2 emissions for hot-water use in the hotels remains quite high, 2.87–3.2 kg-CO_2/(person·night). Hot water usage is the second largest energy consumer in hotels after heating [4]. Recent studies emphasise that a large potential for increasing energy efficiency in buildings can be achieved by improving operation and design of DHW systems [4]. One of the aims of the simulation approach of DHW system performance is to estimate and predict the DHW volume and the energy use for hot water production in existing building, or in building at the design phase. This information is essential for sizing and optimising of DHW system and its components [5].

The DHW profiles are the basis for simulation of DHW systems performance in buildings, as well as useful instrument for understanding the process of DHW energy use in the buildings [6]. The profiles of DHW energy use show how the energy for DHW is used most of the time.

Building simulation tools may require diverse input data for DHW energy use simulation. In many simulation tools, average yearly DHW energy use profiles per m² of building area are applied as input for modelling. Other tools require three types of input data: average DHW use in l/(person·day), occupant number, and DHW usage profile. In addition, the default values for DHW supply temperature and cold-water temperature are considered for energy estimation. The so-called bottom-up approach requires a detailed information of occupant presence, profiles of occupant activities, available domestic appliance, corresponding technical details, etc. [7]. The methods based on detailed information about DHW use activities and DHW system, usually require extensive input data, which increases the complexity of obtaining this information and process of energy use estimation.

A comparative analysis of five different software calculation tools based on technical standards for predicting monthly and daily DHW consumption profiles in residential buildings are investigated in [5]. The deviation in results from measured data are −30% to +40%. Better estimations are obtained with methods based on standards specific to the country where measurements were done.

A better understanding of DHW energy use profiles and their application in simulation tools is a crucial factor in achieving energy savings in hotel buildings. Therefore, in this article DHW profiles based on measured energy use in the hotel in Oslo, Norway, were developed. The data comprises five years of hourly measurements of energy use for DHW. The obtained profiles, as well as profiles from national and international standards for heat demand calculation, were applied in simulation model of a representative hotel. The model was developed in EnergyPlus [8]. The possible benefits from using more accurate energy profiles were explained.

Methods

For modelling of the hotel, EnergyPlus model from the Department of Energy (DOE) Large Hotel model [9] was used. The model was adjusted according to Norwegian regulations and requirements.

For the analysis of DHW energy use in the hotel, it was considered few different scenarios:

1) DHW energy use was derived from profiles obtained based on measurements in the real hotel, located in Oslo.
2) DHW energy use was derived from profiles in ISO 18523-1 [10].
3) DHW energy use were derived profiles obtained from the technical specification SN/TS 3031:2016 [11].

The results of simulations based on different DHW energy use profiles were compered.

Description of the real hotel building

The parameters of the hotel are typical for Norway. The hotel reflects well the trends of DHW energy use in similar types of buildings. The building was renovated in 2007. The area of the hotel is 4 939 m². The building has eight floors with 164 guest rooms. All the guest rooms have bathrooms with toilet facilities and shower. According to the hotel management, employees use hot water for cleaning, and guests use hot water for personal hygiene.

In the DHW system, the hot water is circulated all the time to ensure fast delivery at each tap all the time. The hotel uses electric water heaters for DHW preparation. Data on energy use for DHW were collected during several years from an energy meter installed by the hotel owner. The meters measure electricity delivered to the DHW tanks. This means that both DHW needs and heat losses in the DHW system were included in the presented DHW energy use.

Description of the simulation model

It is supposed that a reference building simulation model represents the average building stock in a Norwegian geographical area in terms of building characteristics and functionality [8]. The model for the reference hotel was selected from the U.S. DOE database. The building in EnergyPlus present 7 floors: 6 floors above the ground level and 1 basement, see **Figure 1**. The total building area is 11 348 m². Based on the geometry and shape of the real hotel in Oslo, it was estimated that the model in **Figure 1** would fit well for the analysis. The weather data for Oslo, Norway, were used as input in this study.

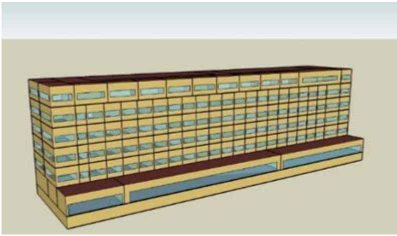

Figure 1. Reference hotel.

The modifications were done to conform the model to Norwegian national limits on building thermal properties, indoor comfort, and annual energy use. To initialise, the building parameters and schedules for human occupancy were used from the following national and international standards: ISO 18532-1, EN 15232, and NS 3031:2007 [10-12].

Results

DHW energy use profile based on measurements

Statistical data of energy use in the hotel show that DHW tap systems have significant impact on energy use in buildings. More specifically, in the observed hotel, DHW energy use constituted more than 20% of total energy use.

Since the simulation model and actual hotel have different area, energy use profiles from measurements were calculated per m² of building area. As discussed above, both DHW needs and self-use in the DHW system were included in the presented measurements. Self-use includes water leakages in the pipes, circulation losses, energy use for maintaining the required temperature of DHW in the system and other consumer-independent losses in the system. Due to these losses, a DHW system is constantly using a certain amount of heat, even if there are no visitors in a hotel. Reducing self-use is an essential task in achieving efficient energy use in the buildings. Statistical data for the hotel showed that information about self-use could be obtained based on profiles of the DHW energy use in public holidays. From **Figure 2**, we can see that hourly average and variation of DHW energy use during the holidays is very small. This phenomenon could be explained by the fact that on holidays, the hotel was closed for visitors. Consequently, the DHW energy use in the hotel in these days mostly caused by self-use in the system.

Accordingly, it was proposed to consider the average profiles of DHW energy use during the public holidays as a way to assess self-use in DHW system of the hotel. Average profiles of energy use on holidays evaluate the share of energy use for self-use of DHW system. The identified percentage of the energy use for self-use in the hotel constituted 39.15% of the average DHW annual energy use.

Comparison of DHW energy use in the standards and measurement data in the real hotel

"ISO 18523-1:2016: Energy performance of buildings" provides reference domestic hot water usage for different types of rooms. Based on ISO 18523 and EnergyPlus model, DHW energy use profiles for the typical hotel were obtained. "SN/TS 3031:2016: Energy performance of buildings. Calculation of energy needs and energy supply" is a national standard in Norway. Calculation of energy needs and energy supply gives recommendation on DHW profiles that should be used as input for energy demand calculation [11].

In this study, the profiles of the actual DHW energy use in the real hotel, see **Figure 2**, and the profile for the same type of building based on the standards ISO 18523, see **Figure 3**, and SN/TS 3031, see **Figure 4**, were compared. The analysis indicates the big difference between these tree types of profiles.

Compered to profiles in real hotel, **Figure 2**, the profile based on ISO 18523, see **Figure 3**, significantly overestimates the DHW energy use in the hotel. ISO 18523 shows morning and evening peaks of the DHW energy use, which occur from 6 a.m. to 10 a.m. and from 6 p.m. to 11 p.m. The peak energy use modelled based on ISO 18523 are about three times higher than those measured in the real hotel. Besides, evening peak of DHW energy use in a real hotel is not expressed as obvious as in the ISO 18523.

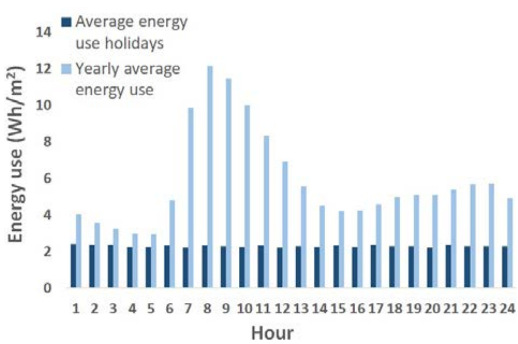

Figure 2. Profiles of hourly DHW energy use on holidays and all days in the year in the hotel.

As shown in **Figure 4**, the DHW energy use from 1 a.m. to 5 a.m. in the standard SN/TS 3031 is equal to zero. This fact means that the standard does not take in account the so-called self-use of the system. On the contrary, the actual data obtained with the help of energy meters usually contain both the system's self-use and DHW energy use by visitors. It should be noticed, that self-use of the system is responsible for the significant share of energy use in DHW tap systems (up to 40% during the year) and therefore cannot be neglected.

From the standard SN/TS 3031 profile (see **Figure 4**), we can assume that morning peak of energy use occurs from 7 a.m. to 8 p.m., and evening peak from 6 p.m. to 7 p.m. The maximum heat demand during the day is approximately 8 W/m². Meantime, from the profiles of energy use obtained from the statistical data, it was possible to notice that morning peak usually occurs from 7 a.m. to 11 a.m., and a small increase in energy use can be observed from 10 p.m. to 11 p.m. The maximum energy use during the day was approximately 12 W/m². The difference in the values of maximum energy use in considered profiles was 6 W/m², which was 30% of the total DHW use. This difference could be explained by self-use of DHW system that the standard SN/TS 3031 does not take into account. However, it could be noticed from **Figure 4**, the timing of actual peaks of energy use also does not match the information presented in the standards.

Monthly and annual DHW energy use

The simulation results from EnergyPlus with different DHW profiles as inputs were compared with the actual energy use in the hotel. Monthly energy use is given in **Figure 5** and annual energy use is given in **Figure 6**. The simulation results for the DHW energy use revealed the drawbacks of the considered standards.

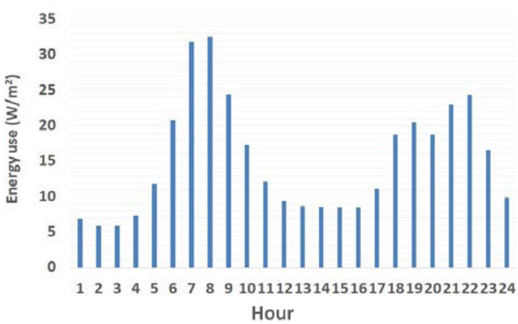

Figure 3. Hourly profile of DHW energy use of the hotel obtained based on "ISO 18523-1:2016: Energy performance of buildings".

For example, the difference between the annual DHW energy use simulated by profiles obtained from the measurements and the real total DHW energy use was approximately 10%. Meantime, the national standard, SN/TS 3031:2016, underestimated annual DHW energy use for 32% and ISO 18523-1:2016 overestimated for 2.3 times.

Simulation results indicated that the DHW energy use was responsible for significant share of the total energy use of the hotel see **Figure 7**.

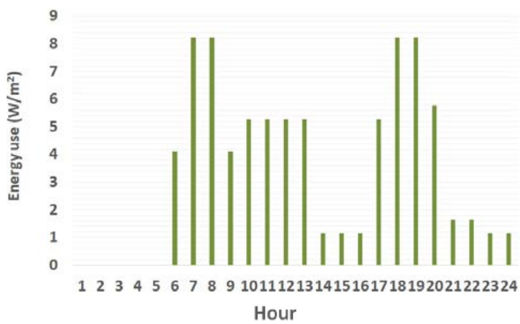

Figure 4. Hourly profile of DHW energy use according to the standard "SN/TS 3031:2016: Energy performance of buildings. Calculation of energy needs and energy supply".

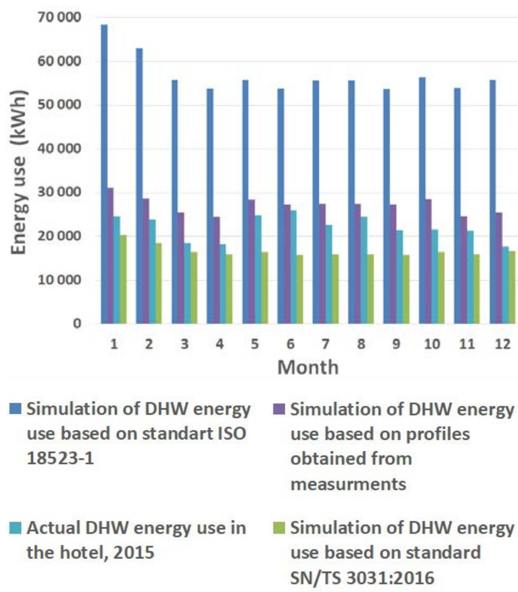

Figure 5. Simulated and actual monthly DHW energy use in the hotel.

Comparison with the DHW energy use in the real hotel revealed that simulations based on profiles obtained by measurements gave better explanation of the DHW energy use than the standards. The standard ISO 18523-1:2016 significantly overestimated the DHW energy use in the hotel in Norway. Meantime, for annual and monthly simulations of the DHW energy use, the technical specification SN/TS 3031:2016 demonstrated quite reasonable result. However, in addition to using the technical specification SN/TS 3031:2016, the assumption about self-use in DHW system should be included in calculations. Making this assumption for a real building can be problematic.

The factors that introduce uncertainty to simulations are number and types of DHW use facilities in the hotels. The presence of a restaurant, swimming pool, sauna, and gym increase DHW energy use at the hotel. The profiles given in the standards are usually too simplified. These profiles were created for certain categories of buildings such as hotel, offices, school, etc. However, even within one type of buildings, DHW energy use can behave differently. For example, studies showed that specific DHW use in large and luxury hotels is much higher than in a regular one [4]. Therefore, there is a need to develop more aggregated profiles, which will take into account the main factors that influence DHW energy use. It should be emphasized that these profiles should be based on accurate and up-date statistical data from real buildings and reliable methods of processing available information.

Conclusion

DHW systems play essential role in achieving efficient energy use in buildings. For this reason, evaluation of DHW energy during simulations should be representative and corresponds to real energy use in buildings. The DHW profiles are the basis for simulation of DHW systems performance. Moreover, analysis of DHW energy use profiles is a powerful instrument for gaining knowledge about DHW system operation.

In this article, the EnergyPlus model from the DOE Large Hotel model was adjusted according to Norwegian regulations and requirements. For analysis of the DHW energy use in the hotel, it was considered few different scenarios with various profiles used as input. Profiles obtained based on measured DHW energy use in the real hotel, profiles derived from international standard ISO 18523-1, and the national standard SN/TS 3031:2016 were used in this study. The comparison of the standards revealed the significant difference between hourly DHW energy use obtained by measurement and standards. Besides, the timing of actual peaks of energy use does not match the information presented in the standards. Implementation of the EnergyPlus model indicated that simulations based on profiles obtained by measurements gave better explanation of the DHW energy use than using the standards. Simulations based on ISO 18523-1:2016 overestimated the annual DHW energy use approximately two time and peak energy use three times. Meantime, the national standard SN/TS 3031:2016 showed better result. However, the standard SN/TS 3031:2016 does

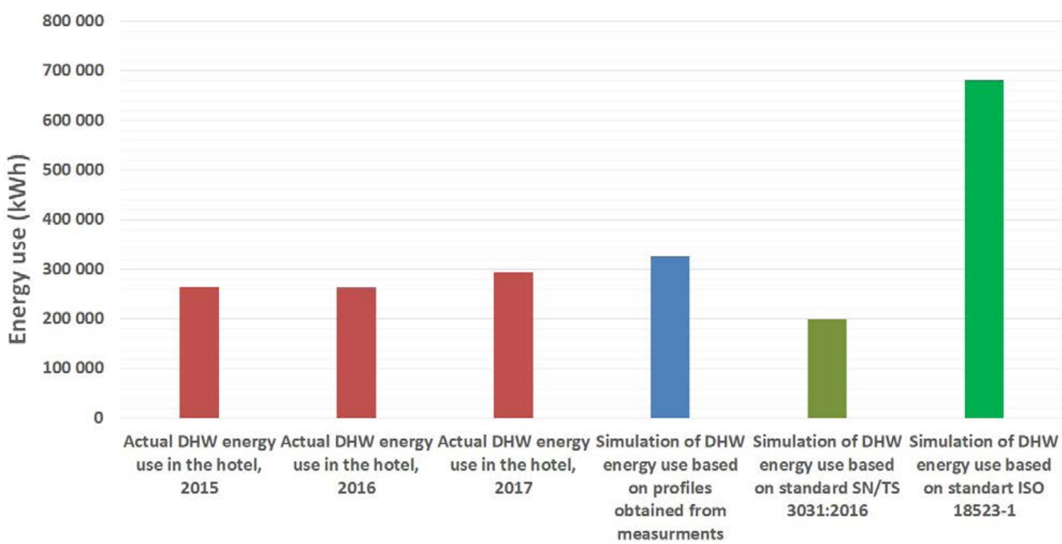

Figure 6. Simulated and real yearly DHW energy use in the hotel.

not take in account self-use of DHW system. Therefore, information given in this standard should be supplemented by estimation of self-use of DHW system in the building. At the same time, profiles which are based on actual measurements, allowed us to obtain the most reliable results. The difference between yearly DHW energy use simulated by profiles obtained from measurements was approximately 10%. ■

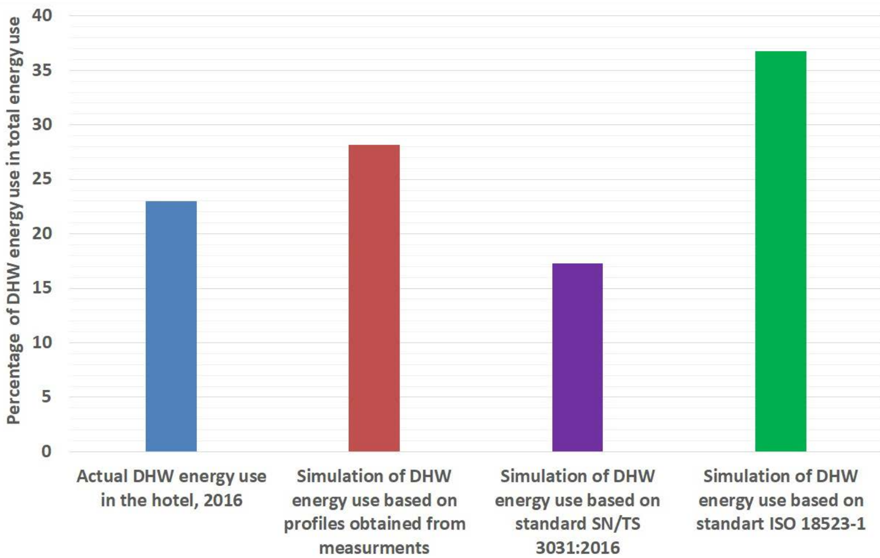

Figure 7. Percentage of DHW energy use in total energy use of the hotel.

Acknowledgement

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Paper VII H.T. Walnum, A.L. Sorensen, B. Ludvigsen, D. Ivanko, Energy consumption for domestic hot water use in Norwegian hotels and nursing homes. *10-th International Conference on Indoor Air Quality, Ventilation and Energy Conservation in Buildings IAQVEC 2019. IOP Conference Series: Materials Science and Engineering.* Volume 609, 2019, 052020

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Energy consumption for domestic hot water use in Norwegian hotels and nursing homes

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Abstract. Domestic Hot Water (DHW) production constitutes a significant proportion of the energy demand of modern buildings, and as the building envelope is improved the share increases. This article discusses the results from a measurement campaign in Norwegian hotels and nursing homes. The energy demand for DHW and distribution heat losses for 3 hotels and 3 nursing homes are shown. The results show that number of bedrooms is a better parameter for describing DHW consumption than sqm of heated floor area. There are large variations in the measured distribution losses, mainly due to malfunctioning of the hot water circulation system. For nursing homes, the measured energy consumption is significantly lower than the normative profiles, which can have large impact on the requirements for the design of the building heating system. For hotels, the measured energy consumption is in the range of the normative profiles.

Nomenclature

$\dot{Q}_{prod}$	Delivered energy to the DHW production unit (kWh)	T_{HTHW}	High temperature hot water outlet temperature. Before mixing valve (°C)
$\dot{Q}_{HW}$	Energy in consumed hot water (kWh)	$\dot{V}_{CW}$	Total cold water flow rate (l/s)
$\dot{Q}_{HWC}$	Energy loss in circulation (kWh)	$\dot{V}_{CWT}$	Cold water flow rate into the DHW production unit (l/s)
$\dot{Q}_{distr}$	Total distributed energy (kWh)	$\dot{V}_{HW}$	Hot water flow rate (incl. hot water circulation flow) (l/s)
T_{CW}	Cold water inlet temperature	$\dot{V}_{HWC}$	Hot water circulation flow (l/s)
T_{HW}	Hot water outlet temperature. After mixing valve (°C)	cp	Heat capacity of water (kJ/kgK)
T_{HWC}	Hot water circulation return temperature (°C)	ρ	Density of water (kg/m^3)

1. Introduction

In the last decades, there has been an increasing focus on the energy demand in buildings, and the building regulations are moving towards zero energy buildings. The main measures have been on improving the building envelope. As the space heating demand in buildings is reduced, the relative importance of the energy for domestic hot water (DHW) increases. The energy needed for DHW in the developed world constitutes of between 10 and 20% of the total energy demand in residential buildings and between 5 and 10% of the total energy demand in commercial buildings [1]. With the current Norwegian building regulations, over 50% of the total calculated thermal energy demand is used for DHW for several building categories [2]. However, the assumption on DHW demands and heat losses are based on old and uncertain values. Previous studies have shown heat losses in the DHW circulation lines up to 70% of the total energy demand for DHW in residential buildings and even higher in offices and institutions [3]. In modern buildings with highly efficient building envelopes, uncontrolled heat losses contribute less to useful heating, and might even increase the energy demand for cooling.

To improve the knowledge on energy consumption for DHW, a measurement campaign has been initialised. The campaign comprises twelve buildings, focusing on nursing homes (4), hotels (4) and apartment blocks (4), as these building categories have high DHW consumption according to the Norwegian standard normative numbers [4]. Measurements are performed to investigate both maximum flow rates and energy flows in the system and are set up to measure energy demand for both hot water use and heat losses in the system.

2. Description of buildings

6 buildings, 3 hotels (HO) and 3 nursing homes (NH) are included in this study. The main parameters describing the buildings are shown in Table 1.

HO1 and HO2 are built according to similar specifications, and are both typical conference hotels, but HO1 does have higher share of non-business guests. HO3 is a more compact hotel, without restaurant and conference halls.

The main difference between the nursing homes, is the room density (# rooms per total area). NH3 has a much lower room density than the other two buildings. In addition, NH3 has bypassed a large part of the circulation system

Table 1. Main building parameters

Hotels	Area [m^2]	# Rooms	Heat source	Distribution heating	Storage	Measurement period
HO1	21 278	434	District Heating	Circulation	None	April-May 2018
HO2	24 500	355	District Heating	Circulation	6 x 1000 liter	Aug.-Sept 2018
HO3	4 934	165	Electric water heaters	Circulation	8 x 1000 liter	Aug.- Sept.2018
Nursing Homes						
NH1	11 618	148	Electric water heaters	Circulation	6 x 400 liter	Jan-Feb 2018
NH2	3 327	52	Electric water heaters	Electric heat tracing	3 x 600 liter	May-Jun 2018
NH3	6 774	50	Local area heating + electric water heaters	Circulation	3 x 400 liter	May-Jun 2018

3. Measurements

Flow, temperature and energy measurements were performed on DHW production system in each building. At each location, the measurement equipment was installed for a period of approx. 6 weeks. Flow rates and temperatures were measured with an interval of 1s, and then averaged to 2 seconds before analysis. In the energy analysis in this article, the data are resampled to 1 hour time steps, to analyze typical profiles.

3.1. Measurement equipment

An important feature for the measurement equipment was that it had to be non-intrusive to the DHW system. Therefore, clamp-on ultrasonic flow meters were used for flow measurement and Type-T thermocouples where mounted on the pipe wall.

The flow meters have a specified accuracy of 1.6% of reading ±0.01 m/s [5], and the Type-T thermocouples have an error specified as maximum of 1.0 °C or 0.75% above 0 °C [6].

3.2. Installation of measurement equipment

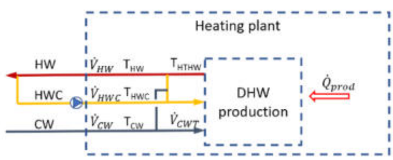

Figure 1. Principle drawing of DHW heating plants with typical measuring points.

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There are variations in how DHW systems in Norway are designed, both in regard to energy sources, but also with respect to system layout. Figure 1 shows a principle drawing of how most heating plants are built, with typical measuring points used in the DHW measurements. When possible, all measuring points shown, are logged. However, in many cases, the pipe sections between junctions are too short or there are other branches that influence the measurements. As a minimum, T_{HW}, T_{HWC}, T_{CW}, $\dot{V}_{HW}$ and $\dot{V}_{HWC}$ are measured.

3.3. *Energy calculations*

Equation (1), (2) and (3) shows the formulas for calculating the energy flows. If $\dot{V}_{CW}$ is not available, it is calculated with equation (4).

$$\dot{Q}_{HW} = \frac{\dot{V}_{CW}}{\rho} * cp * (T_{HW} - T_{CW}) \tag{1}$$

$$\dot{Q}_{HWC} = \frac{\dot{V}_{HWC}}{\rho} * cp * (T_{HW} - T_{HWC}) \tag{2}$$

$$\dot{Q}_{distr} = \dot{Q}_{HW} + \dot{Q}_{HWC} \tag{3}$$

$$\dot{V}_{CW} = \dot{V}_{HW} - V_{HWC} \tag{4}$$

4. Results and discussion

For comparison of the daily energy consumption profiles, the energy in consumed hot water ($\dot{Q}_{HW}$) is used. For comparison of the distribution efficiencies between the buildings, the average daily energy consumption is calculated, assuming that the measurement period is representative for the whole year.

In the following, the hotels and nursing homes are studied separately, and they are then both compared to the normative consumption profile in the Norwegian technical standard SN/TS 3031 [4].

4.1. *Hotels*

Figure 2 shows the daily mean energy profile for hotels per heated floor area, per room, and per overnight guest. All the three hotels have a similar DHW profile, with a large energy peak in the morning. The results indicate that number of rooms or number of guests are better parameters for describing the consumption than the floor area, which is commonly used in normative numbers, as the curves are better aligned and the relative difference is smaller. HO2 deviates somewhat from HO1 and HO3 in energy consumption per guest. A possible explanation can be that, since HO2 is a conference hotel situated in the suburbs of Oslo, there are daytime visitors that are not counted as overnight guests. These guest do not shower, but they do increase the activity at the kitchen. However, it is difficult to see that this should explain the whole difference.

Table 2. Average daily energy consumption and distribution energy losses for hotels

	HO1				HO2				HO3			
	kWh /day	Share of total	Wh /m2	Wh /room	kWh /day	Share of total	Wh /m2	Wh /room	kWh /day	Share of total	Wh /m2	Wh /room
$\dot{Q}_{HW}$	1581	75 %	74	3642	1142	85 %	47	3216	432	81 %	88	2617
$\dot{Q}_{HWC}$	527	25 %	25	1215	194	15 %	8	547	102	19 %	21	618
$\dot{Q}_{distr}$	2108	100 %	99	4856	1336	100 %	55	3763	534	100 %	108	3235

Table 2 shows the daily average energy consumption for consumed DHW and the distribution losses (in the circulation system). When comparing the circulation losses, it is important to note that in HO1 it was discovered that the circulation system was highly unbalanced. A large part of the circulation system did not have sufficient flow to maintain the temperature. This will result in lower distribution losses, but parts of the hotel will have long waiting time for hot water. Based on the knowledge from HO1 one can question if the circulation system at the other hotels are working properly. This especially applies to HO2, which has very low specific losses (Wh/m^2)

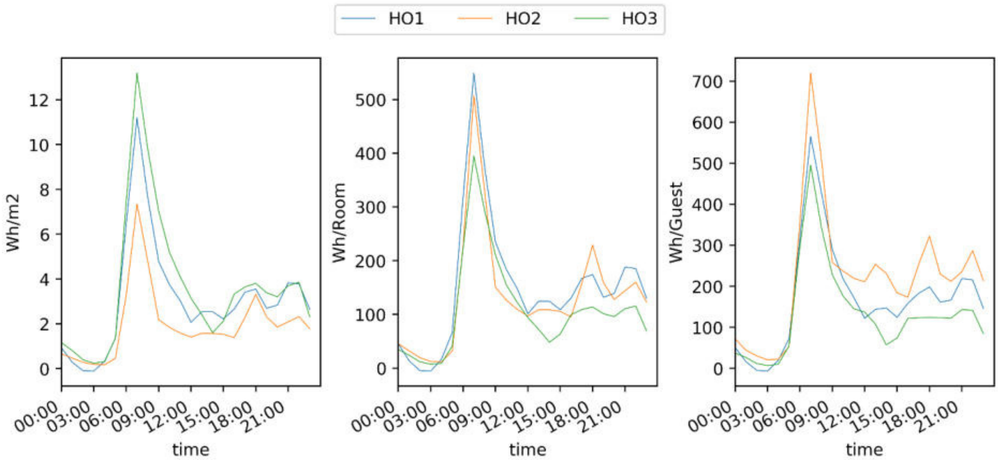

Figure 2. Daily mean energy consumption with hourly resolution for hotels per area, number of rooms and guests

4.2. *Nursing Homes*

Figure 3 shows the daily mean energy profile for nursing homes per heated floor area and per guest room. The shape of profiles show that the nursing homes have similar routines when it comes to DHW use, linked to morning routines and scheduled meals.

Again, one can see that the profiles per room deviates less than per square meter. For the energy consumption per room, NH1 stands out with a higher consumption. However, the measurements at NH1 were performed during winter, and the measurements at NH2 and NH3 during summer. Gerin et al. [7] showed how the consumption of hot water varies with season, mainly driven by the variation in cold water inlet temperature. During winter extra energy is needed to heat the cold water with lower inlet temperature. We measured an average difference in cold water inlet temperature of about 6 °C between NH1, and NH2 and NH3. This can explain 70% of the difference in daily energy consumption between NH1 and NH2.

Table 3. Average daily energy consumption and distribution energy losses for nursing homes

	NH1				NH2				NH3			
	kWh /day	Share of total	Wh /m2	Wh /room	kWh /day	Share of total	Wh /m2	Wh /room	kWh /day	Share of total	Wh /m2	Wh /room
$\dot{Q}_{HW}$	420	61 %	36	2836	111	63 %	33	2087	91	89 %	13	1823
$\dot{Q}_{HWC}$	272	39 %	23	1838	65*	37 %*	20*	1235*	12	11 %	2	234
$\dot{Q}_{distr}$	692	100 %	60	4674	176	100 %	53	3322	103	100 %	15	2057

* Energy consumed by electric heat tracing.

Table 3 shows the daily average energy consumption for consumed DHW and the distribution losses (in the circulation system or electric heat tracing). NH3 stands out with very low circulation losses. This turned out to be due to a large part of the circulation system being bypassed and that most of the circulation water returnes back to the hot water production unit. The measured temperature drop in the circulation loop was 0.5-1.0 °C. What is interesting, is the relatively high energy consumption of the heat tracing system in NH2. With reduced piping length (no circulation pipe), it would be expected that the energy consumption would be lower. In addition, local temperature measurements in the distribution show that the heat tracers are not able to sustain the hot water temperature above 45 °C during periods with low consumption. This indicates that the heat tracing system is very dependent on correct installation, to make sure that the energy is transferred into the DHW and not the surroundings.

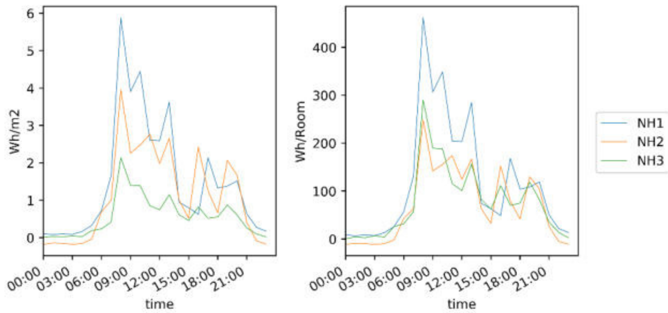

Figure 3. Daily mean energy consumption with hourly resolution for nursing homes per area and per bedrooms

4.3. Comparison with national normative profiles

Figure 4 shows a comparison between the measurement data and the Norwegian normative profiles. The normative profiles are used for verification of the building energy performance against the national regulation on technical requirements for construction works [8]. The normative profiles are defined by kWh per sqm of heated floor area. For the hotels, the daily energy consumption is similar, but the daily profile deviates significantly. The normative profile includes an afternoon peak, that is not seen in the measurements, but the measured morning peak is higher. For the nursing homes, the normative profiles are the same as for the hotels, while the measurements in the three buildings show significantly lower consumption. The normative profiles are not meant for dimensioning of hot water systems in buildings, but for calculation according to the building regulations. However, the building regulations have requirements to the design of the energy supply system (no fossil fuels and central distribution system). These requirements do only apply for 60% of the yearly heating energy demand (space heating, ventilation heating and DHW). Therefore, the applied values for DHW can have a large influence on the requirements to both the DHW production system and the heating system.

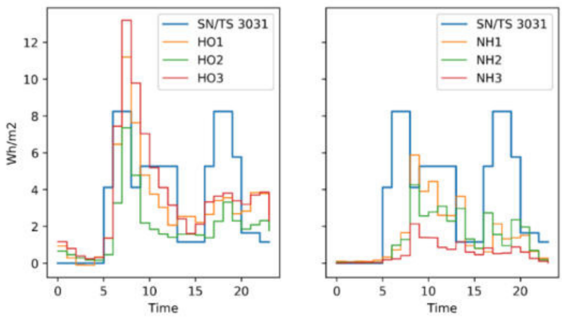

Figure 4. Comparison between the measurements and the Norwegian normative profiles *[4]*.

4.4. Measures for reduced energy losses

In general, the measured relative distribution losses are smaller than expected based on previous studies [3,9]. However, there are several indications that this is at least partly due to malfunctions in the circulation system. The most obvious measure for reduced energy losses is to increase the insulation of the system. When designing new buildings and DHW systems it is important to consider the location of tapping points and the optimal path for distribution lines. Electric heat tracing can also be an efficient option [3], especially in Norway where DHW is often produced with direct electric heating, but it requires high quality installation to operate efficiently.

5. Conclusion

Measurements on energy consumption for DHW production have been performed in three hotels and three nursing homes. The results show that sqm of heated floor area, which is often used, is a poor parameter for describing specific energy consumption. The measurements show large differences in the distribution energy losses, and in several cases, these are lower than expected. The measurements indicate that more than 50% of the measured circulation systems are not working as intended. Compared to the normative values used for calculations against the technical building regulations, the measurements from nursing homes deviated significantly on both daily and hourly basis, and this can have significant impact on the design of the building energy system. The conformity of the measured profiles and consumption may indicate that they are representative for the building categories. All the three have significantly lower consumption than the norm. However, three buildings in each category are not enough to give a statistically valid basis for defining new standard values, so more measurements are necessary.

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Development and analysis of hourly DHW heat use profiles in nursing homes in Norway

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ABSTRACT

Representative profiles for domestic hot water (DHW) heat use are the main instruments for improvement in operation and design of DHW systems in buildings. To improve the existing method for DHW heat use profiles development and analysis, investigations in the three nursing homes in Norway were conducted. Statistical methods to assess the similarities of the profiles by days of the week and seasons were proposed. The analysis allowed us to identify two seasons of DHW heat use: the warm season from June to October, and the cold season including the rest of the year. In addition, it was investigated that the DHW heat use in the working days was significantly different from the weekends. According to these results, unified profiles for the months and days of the week with similar characteristics of the DHW heat use were developed. After, the method for statistical grouping of the DHW hourly heat use was applied to recognize the timing of the peak, average, and low heat use. Finally, the profiles for the DHW heat use obtained for the nursing homes were compared with profiles in the national and international standards. The drawbacks of the standards were identified.

1. Introduction

Nowadays, energy efficiency and decarbonisation are the key driving forces in the development of European Union (EU) energy industry. Among all sectors, buildings sector is one of the most energy-intensive. The Energy Performance of Buildings Directive (EPBD) estimates the share of energy use in building as 40% from the total energy use in the EU [1]. Considering the huge potential of energy saving in buildings, European Commission (EC) develop a set of long-term and short-term goals for increasing energy efficiency in buildings [2]. For example, by 2020 all new buildings should be constructed in accordance with zero emission standards, and at least 3% of the total floor area of governmental buildings should be renovated [1]. The energy infrastructure in buildings that were built 30–40 years ago needs to be replaced by more energy efficient [3]. According to Energy roadmap 2050 [3], the goal to reduce CO_2 emission to 80–95%, when compared to 1990 level, by 2050 scenarios is set [3]. To achieve this goal, all technical systems in buildings must be designed and operated in such a way as to ensure efficient energy use.

Until recently, in many European countries, including Norway, a lot of effort has been put on the investigation of the performance of the space heating systems [4]. Meanwhile, the DHW heat use was considered as a small part of the energy needs required for heating. Therefore, DHW heat use has obtained little focus, especially in countries with cold climate [5]. However, with introduction of passive house technologies and improvement of building envelope, the space heating heat use in buildings is constantly decreasing. At the same time, reduction of DHW heat use remains insignificant [6]. For example, the experience from design of low energy buildings in Denmark is shared in [7]. In this study, to achieve low heat use, passive building strategies with highly insulated, resource efficient, and airtight solution are used, without focusing on DHW use. The authors in [7] conclude that detailed design values for the passive building show that energy demand for the DHW use is almost twice bigger than space heating. The analysis of energy use in four apartment buildings in Finland with various construction years is performed in [8]. In this study, to assess DHW heat use, the profiles obtained from measured DHW demand in apartment buildings are used as input in IDA-ICE simulation software. Simulation shows that in the modern buildings, the domestic hot water is the most significant component in heat use. In two buildings constructed before 2002, the DHW heat use contributes 24% and 30% to the total energy use in the buildings. However, in

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two well-insulated buildings, the DHW systems is responsible for 52% and 63% of the total energy use. As we can see, the share of the DHW energy use tends to increase from approximately 20% in regular buildings [5] to above 50% in passive houses and well insulated buildings [9]. Consequently, heat use for DHW systems is becoming the critical component for energy saving, especially in passive houses and nearly zero energy buildings (NZEB) [10].

Nowadays, heat losses from the hot water tanks and the circulation systems in houses, schools, and other institutions remain high [11]. As a result, further energy saving measures in buildings should shift the focus from improving space heating to improve DHW systems. To realize potential of energy savings in DHW systems, the research and innovations in the field of DHW energy performance becoming increasingly relevant and valuable [9].

It should be noted that the operation of the DHW systems is associated with sanitary and health safety issues. These issues for different types of buildings is discussed in [12]. Appearance of Legionella bacterium in DHW systems is a serious problem. Legionella bacterium can lead to different forms of pneumonia and even death. The conditions for Legionella spreading are water temperatures from 25°C to 42°C, nutrients, and stagnating water. Therefore, many countries, including Norway, develop regulations to minimize the risk of Legionella disease appearance. For example, despite of energy ineffectiveness, to prevent risks of the bacteria growth, the DHW systems in Norway store and distribute hot water at temperatures above 60°C. Among all buildings, special attention is paid to the nursing homes, because the elderly, who usually have respiratory problems and weakened immune system, are heavily affected by this bacterium. The safety of energy effective solutions is the key factor in DHW systems.

The share of DHW heat use is varying from country to country and one type of building to another [5]. For example, specific DHW heat use in households in different EU countries are significantly varying as shown in [13]. Comprehensive comparison of DHW energy use in residential buildings in Denmark, Norway, and Sweden is performed in nineties [14]. Even though that study is somewhat outdated, it describes well the general trends in the DHW use in these countries. Sweden, Norway, and Denmark share a similar living standard, comparable patterns of household formation, and a similar climate. Nevertheless, the DHW heat use in Denmark is significantly below those in Sweden and Norway. In addition, the authors conclude that national average, electricity use per capita for the DHW heating in Norway has almost not changed for 15 year, and remains high when compared with other countries within The Organization for Economic Cooperation and Development (OECD). The authors explain this phenomenon by difference in occupants' behaviour and the insulation of DHW systems in different countries. More resent research confirms this statement [15] and it shows that the average individual DHW use reaches 40 L/person/day in Norway, while in Denmark, the average value is at 20 L/person/day [15].

For the sake of simplification, many methods propose to consider the DHW use as a constant value for calculations [16]. Practical experience shows that the commonly used standards are based on assumptions for the DHW heat use in the buildings, but these standards do not correspond to the real use [17]. For example, simplified, but meantime common way of DHW system performance simulations is shown in [18]. Further, DHW system performance are simulated based on daily water need as a constant value of 90 l/day per bedroom and with 25 K temperature difference between supply and return in [18]. Such simplifications could lead to oversizing of the components for DHW systems and additional financial and energy losses [19].

DHW heat use profiles are the primary instrument for estimating the DHW heat use in the buildings [5]. Analysis of DHW heat use profiles shows the changes in heat use in different time intervals [20]. The profiles of DHW heat use allow us to determine the hours of peak energy loads and other energy load characteristics of the building.

Performance of DHW systems is a complex and multidisciplinary issue. It includes economic, sanitary, behavioral, and technical areas. DHW heat use profiles is a useful for identifying energy efficient solutions within all these areas. For example, the economic analysis of DHW pricing is performed in [21]. The study shows that the DHW use positively correlated with income and reacts to the changes in water prices. Introduction of new energy or heat tariffs is a way of reducing the DHW use is buildings. However, in order to implement advanced and flexible energy or heat tariffs, the in-depth knowledge about profiles of DHW use is required. Technical solutions dealing with sanitary problems are considered in [22]. Some of these solutions require knowledge of the profiles and timing when DHW water is used. Different types of DHW heating systems are investigated in [23]. This study summarises that DHW energy use can be reduced through using combined systems based on traditional and renewable energy solutions. However, due to unstable behaviour of renewable energy sources, development of accurate profile and prediction of DHW heat use becoming crucial for successful operation of combined DHW heating systems. Most of building simulation software tools such as IDA ICE, EnergyPlus, TRNSYS, TRANSOL, etc. require DHW profiles as the basis for simulation of DHW systems performance in buildings [5]. For example, it is noted that the variations between the simulated and the real heat use for DHW are caused by inappropriate profiles [24]. Consequently, the authors in [24] claim that input data for DHW volume flow rates used in the standards represent perhaps one of the more critical points in simulation models. Therefore, actual knowledge of DHW usage profiles can capture the real heat use in buildings, making it possible to size systems properly. Effective demand-side management, energy conservation measures, improvement of legislation and standards require accurate DHW profiles for different types of buildings [25]. As we can see, scientific and practical work confirms the need to use profiles of the DHW heat use to solve important issues in the DHW systems.

The issue of DHW heat use analyses in buildings based on profiles is investigated by researchers in Norway and abroad [5]. However, due to differences in particular characteristic of each buildings, quality of available data, and calculation requirements, there is no unique method of performing appropriate analysis. The number of scientific works is dedicated to the issue of DHW energy profiles development and analysis. For example, hourly DHW profiles for five groups of buildings with 1, 3, 10, 31, and 50 residents are developed based on data from Finnish apartments in [26]. Further, the profiles for each group with the closest to mean profile and have a similar shape, are selected among measured candidates as representative. The volumetric flow rates, cold and supply temperatures are measured to characterise the DHW use in 20 buildings of different sizes in [27]. Based on the obtained data, the authors executed several stochastic simulations to get a representative DHW use profiles for end users [27]. Number of methods for DHW profiles development are based on operating schedules for the primary DHW energy users (showers, baths, sinks, dishwasher, and clothes washer) and occupant activities. As an illustration, the Building America House Simulation Protocols document provides guidance for such analysis in new and existing apartment buildings [28]. Lombardi in [29] shows that domestic water use can be presented as the result of probabilistic use of domestic appliances, each one with its particular characteristics. The research of Good and Zhang in [30] share the experience of calculation for DHW heat use profiles based on occupant activities. The DHW modelling approach by the coupling of behavioural activities, energy balance models, and stochastic modelling is presented in [31]. Time-use data of activities in households in Sweden are used for generating DHW profiles in [32]. For DHW energy analysis, the occupant behaviour, appliance ownership, demographic conditions, and occupancy rate are considered in neural network model in [33]. Most of the reviewed research work are dedicated to the apartments and households, meaning that required parameters were easier to obtain. However, in non-residential buildings obtaining in-depth knowledge about occupant activities and equipment operation become time consuming and expensive task [5]. The available input data limits the practical application of these methods.

The problem of validation of DHW simulated profiles in non-residential buildings is proposed in [34]. For simulation, the authors use SIMDEUM in [35], which is based on the design rules for appliance performance and dominant variables in buildings. It is assumed that the dominant variable for hotels is the number of rooms, for offices is the number of employees, and for nursing homes is the number of beds [36]. The validation procedure consists of two steps. In the first step, the outcome of simulation is compared with measured demand values. In the next step, it is proposed to check if the assumptions on the standardized building based on the design rules are validated with measurements and surveys [34]. This study shows that it is challenging to find information of users and appliances in each functional room to equip the standardised buildings. However, regular demand pattern for dominant functional room can be obtained.

The problems of comparing the actual DHW energy use profiles with the standards, and their verification, are also not going unnoticed. For example, the comparison of the actual DHW profiles in apartments with profile proposed by American Society of Heating, Refrigeration and Air Conditioning Engineers (ASHRAE) is conducted in [37]. The research shows that the primary difference between the actual and the ASHRAE derived data is that the water use is less evenly distributed in the actual data, and there are higher peaks and lower troughs and much less use in the early morning hours in the actual data. Differences in shapes and parameters of the actual DHW heat use profiles for particular types of buildings and profiles represented in publications and standards are considered in [38]. As a conclusion, in this work, the authors recommend to rely on actual profiles obtained from measurement systems for the analysis of DHW use in the existing buildings.

The aim of our paper was to improve the existing approaches for the DHW heat use analysis and gain in-depth knowledge about it in nursing homes in Norway. Non-residential buildings such as nursing home, hospitals, hostels, schools, etc. in Norway and other European countries are less studied then residential [5]. The knowledge about actual DHW heat use profiles in nursing homes in Norwegian is currently incomplete and contain many gaps. The study in [39] shows that the specific heat use in the hospitals and nursing homes in Norway is approximately 270 kWh/m^2 per year, and one of the highest comparing to other types of buildings. Quite often, profiles presented in standards for nursing homes cannot represent the actual DHW heat use [39]. For this reason, the investigation on the DHW heat use in nursing homes in Norway is required. Such a study is the basis for the further introduction of energy saving in nursing homes in Norway.

In this article, we presented the methods for developing and analysing profiles for DHW heat use. The proposed methods allow us to assess the similarities of the profiles by days of the week and seasons, and identify the timing of the peak heat use of the DHW system. The methods were tested based on one-year hourly measurements from three nursing homes, located in Eastern Norway. The unified profiles for the months and days of the week with similar characteristics of the DHW heat use were identified. For these profiles the timing of the peak, average, and low heat use was estimated. The profiles obtained from measurements were compared with profiles from the national standard SN/TS 3031:2016 [41] and

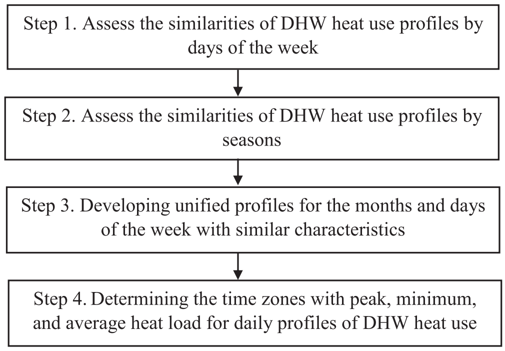

Fig. 1. Method for the analysis of DHW heat use profiles.

international standard NS-EN 12831-3:2017 [42]. The possible benefits from using more accurate energy profiles, obtained by measurements and statistical analysis, are explained in this study.

The paper was organised as the following. Section 2 introduced the method for developing profiles, divided by days of the week and seasons with similar characteristics of the DHW heat use. In this section, the method for determining the peak, average, and low zones of the DHW heat use from the profiles was also presented. Section 3 explained the main characteristics of DHW system for the case study - three nursing homes located in eastern Norway. In Section 4, the method was implemented on the real data. The obtained profiles for the nursing homes were analysed and compared with the profiles of DHW heat use given in the standards. The main results of this investigation were presented. Finally, the main conclusions of the study were emphasized in Section 5.

2. Method

The method for the analysis of DHW profiles included the four main steps shown in Fig. 1.

The three following subsections covers the methods that were used to solve issues in shown Fig. 1. Section 2.1 described the method for comparison of the DHW heat use profiles from different days of the week and assessing their similarities. In this study, we did not assume, beforehand that the profiles can be divided in a certain way. Student's t-test and Fisher's exact test were used for solving this issue. By using this method, the data tests may be used for samples with standard normal distribution and t-distribution. This allowed to us to determine the statistically justified days of the week with similar DHW heat use profiles. In Section 2.2, a method for determining the duration and boundaries of time zones with peak, minimum, and average heat use during the day was showed. In Section 2.3, a statistical method for identifying the number of seasons, as well as the months included in each season was described. By using this method, the impact of seasonality on DHW heat use was taken into account.

2.1. Comparing similarity of DHW heat use profiles in different days of the week

To determine the days of the week with similar characteristics of DHW heat use, a method based on test statistics was proposed. The similarity of two DHW heat use profiles is checked based on the Student's t-test and Fisher's exact test. Appropriate tests can be used for samples with standard normal distribution and t-distribution.

By applying the Student's t-test, it was possible to check if the mean values of DHW heat use from two days of the week were equal or not. To achieve this, the DHW heat use within each day was considered as a statistical sample with 24 elements, which represented the number of hours in the day. The t-test statistical value was calculated as follows:

$$T_{cal} = \frac{\bar{E}_{prof1} - \bar{E}_{prof2}}{\sqrt{\frac{S^2_{prof1}}{n_{prof1}} + \frac{S^2_{prof2}}{n_{prof2}}}} \quad (1)$$

where $\bar{E}_{prof1}$, $\bar{E}_{prof2}$ were the mean values of the DHW heat use in the first and second samples. S_{prof1}, S_{prof2} were the standard deviations of the DHW heat use profiles in the first and second samples. n_{prof1}, n_{prof2} were the number of elements in the first and second samples. Finally, the equation for the standard deviation for i-th day was written as:

$$S_{profi} = \sqrt{\frac{\sum \left(E_{profi.j} - \bar{E}_{profi}\right)^2}{n_{profi} - 1}} \quad (2)$$

where i was the number of the sample, j was the number of element in the sample, $E_{profi.j}$ was the DHW heat use in j-th element in i-th sample.

The obtained value for t-criteria, T_{cal}, was compared with the critical value, T_{cr}. T_{cr} may be found in literature for different degrees of freedom and significance level k. The comparison may lead to three possible situations as the following:

- If $T_{cal} \le T_{cr}(n_{prof1} + n_{prof2} - 2, k = 0.05)$, then the mean values of the first and the second samples are similar;
- If $T_{cal} \ge T_{cr}(n_{prof1} + n_{prof2} - 2, k = 0.01)$, then the mean values of the first and the second samples have a significant difference;
- If $T_{cal} \le T_{cr}(n_{prof1} + n_{prof2} - 2, k = 0.01)$ and $T_{cal} \ge T_{cr}(n_{prof1} + n_{prof2} - 2, k = 0.05)$, then the mean values of the first and the second samples may be considered as similar. However, the final decision should be done based on the knowledge of researchers.

Meanwhile, Fisher's criterion allowed us to estimate the similarity of two samples by variances:

$$\mathrm{f_{cal}} = \frac{\max\left(\mathrm{S^2_{prof1}}, \mathrm{S^2_{prof2}}\right)}{\min\left(\mathrm{S^2_{prof1}}, \mathrm{S^2_{prof2}}\right)} \quad (3)$$

The comparison obtained by calculations of the Fisher criterion, f_{cal} with its critical value, f_{cr} led to the following results:

- If $f_{cal} \le f_{cr}(n_{prof1} + n_{prof2} - 2, k = 0.05)$, then the variances of the first and the second samples are similar;
- If $f_{cal} > f_{cr}(n_{prof1} + n_{prof2} - 2, k = 0.05)$,then the variances of the first and the second samples have significant difference.

The two profiles are considered to be similar if both Student's t-test and Fisher's exact test show the same results. If at least one of two tests shows that the mean values or variances of profiles in the first and the second samples are not similar, it is possible to conclude that the profiles are dissimilar and should be analysed separately.

Splitting the DHW profiles by the days of the week should be made based on a large dataset, which represents DHW heat use during the year. Therefore, in this study, it was proposed to divide initial statistical data into separate weeks. Within each week, all combinations of the daily DHW profiles should be compared among themselves by Student's t-test and Fisher exact test. For instance, profiles for Monday and Thursday, Monday and Wednesday, Saturday and Sunday and so on should be compared. Afterwards, for all the combinations of days, the number of the weeks can be identified, when statistical tests show that profiles in considered pairs of days are similar. For further analysis, for each combinations of days of the week, the number of matches of the DHW profiles in percentage can be found as:

$$\mathrm{n_{i.j} = N_{i.j} \cdot 100/N_{total}} \quad (4)$$

The elements in Equation (4) are the following, $\mathrm{n_{i.j}}$ is number of matches in percentage, when the DHW profiles of i-th and j-th days were similar. $N_{i.j}$ was the number of the weeks, when statistical tests showed that the i-th and j-th days were similar. N_{total} was the total number of the weeks in the statistical data sample of DHW heat use. i was the day of the week of the first comparable profile (from 1 to 7). j was the day of the week of the second comparable profile (from 1 to 7). For better clarity, the results could be presented in the form of matrix of the matches as in Table 1.

Table 1
The form of the matrix of matches.

	Mo.	Tu.	We.	Thu.	Fr.	Sa.	Su.
Mo.	$n_{1.1}$	–	–	–	–	–	–
Tu.	$n_{2.1}$	$n_{2.2}$	–		–	–	–
We.	$n_{3.1}$	$n_{3.2}$	$n_{3.3}$	–	–	–	–
Th.	$n_{4.1}$	$n_{4.2}$	$n_{4.3}$	$n_{4.4}$	–	–	–
Fr.	$n_{5.1}$	$n_{5.2}$	$n_{5.3}$	$n_{5.4}$	$n_{5.5}$	–	–
Sa.	$n_{6.1}$	$n_{6.2}$	$n_{6.3}$	$n_{6.4}$	$n_{6.5}$	$n_{6.6}$	–
Su.	$n_{7.1}$	$n_{7.2}$	$n_{7.3}$	$n_{7.7}$	$n_{7.5}$	$n_{7.6}$	$n_{7.7}$

Based on the matrix of matches, the groups of the days of the week with similar profiles of DHW heat use could be identified. Namely, the days of the week, which have $n_{i.j} \ge 100 - error$, have similar characteristics of DHW heat use and should be placed in one group and analysed together. The value of the error included the accuracy of Student's t-test, Fisher's exact test, and the percentage of days in the year when the building is not in operation in typical regimes such as holidays.

2.2. Determining the time zones with peak, minimum, and average heat load for daily profiles of DHW heat use

To implement energy management in buildings, it is essential to identify the typical duration and boundaries of time zones with peak load, minimum, and average heat load during the day. To solve this issue, we proposed to perform statistical grouping of the hourly heat use of the DHW system based on the method presented by Nakhodov in [40]. Initially, this method is used for identification of the tariff zones of electricity energy use in the power system. In this article, we adapted the method for analysis of DHW heat use in buildings. The method allowed us to divide the hours of DHW heat use into several groups with statistically different mean values within each group. It is based on an iteration procedure and analysis of the mean values of DHW heat use by applying Student's t-test. In this case, DHW heat use profile was considered as a statistical sample e. The sample contained N=24 elements (hours) with DHW heat use in these hours equal e_j (where e_j was DHW heat use in the j-th hour. j was the number of the element in the sample). The flowchart for the algorithm for determining the time zones with peak, minimum, and average heat load for daily profiles of DHW heat use is shown in Fig. 2.

The detailed algorithm of the method for determining the time zones was as the following:

Step 1. Sorting the elements of the sample in the order of their increase

The elements e_j in the sample e were sorted in the order of their increase. Such an arrangement of elements from smaller values of hourly DHW heat use to bigger values allowed us to obtain

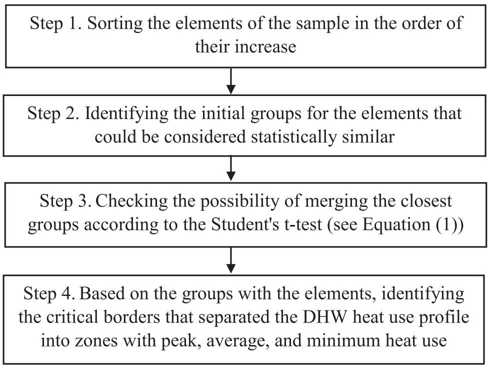

Fig. 2. Flowchart for the algorithm for determining the time zones with peak, minimum, and average heat load for daily profiles of DHW heat use.

the sorted sample E with N elements E_i (where $E_{i+1} > E_i$, i is the number of element in sample E).

Step 2. Identifying the initial groups for the elements that could be considered statistically similar

Based on the sample E, an iterative procedure of generating of two statistical subsamples R_1 and R_2 with variable number of elements was applied. For each step of iteration, sample R_1 contained M elements, while R_2 should have M+1 elements. The elements in samples R_1 and R_2 were taken consistently from the initial sample E. With each iteration, the number of elements M in these subsamples increased by one. The value of M varied from 1 to 23.

For each step of these iterations the value of Student's t-test for two subsamples R_1 and R_2 were calculated by using Equation (1).

For instance: iteration 1) $R_1 = [E_1]$, $R_2 = [E_1, E_2]$, M=1, and T_{cal1}; iteration 2) $R_1 = [E_1, E_2]$, $R_1 = [E_1, E_2, E_3]$, M=2, and T_{cal2};… iteration 23) $R_1 = [E_1, E_2 \ldots E_{23}]$, $R_1 = [E_1, E_2 \ldots E_{24}]$, M=23, and T_{cal23};

Step 3. Checking the possibility of merging the closest groups according to Student's t-test

Based on the iteration procedure of Step 2, the series of t-criteria for all the combinations of the subsamples R_1 and R_2, T_{cal} =[T_{cal1}, $T_{cal2} \ldots T_M$] were found.

If an ordered sample of hourly DHW heat use was monotonous, then the numerical values of elements in this sample increase evenly. In that case, the series of t-criteria obtained by iteration procedure would also be monotonous. This means that the values of t-criteria obtained by Equation (1) would decrease monotonically with each next iteration ($T_{cal1} > T_{cal2} \ldots > T_M$). If the ordered sample of hourly DHW heat use was uneven, then a monotonic decrease of the calculated values of the t-criteria would be violated by periodic abrupt growth ($T_{cali} < T_{cali+1}$). Thus, the identification of points of growth of the calculated values of the t-criteria allowed us to determine between which hours there is a noticeable statistical difference of DHW heat use. This assumption allowed us initially to divide hours in the profile of DHW heat use into several groups. Each of these groups was the sample of data, where DHW heat use data varied monotonously. Created in this way, neighbouring groups of hourly DHW heat use could be checked in terms of the possibility for their further merge. For this purpose, the data samples of two neighbouring groups were assessed by Student's t-test (see Equation (1)). As a result, the calculated value of the t-criteria, T_{cal}, could be compared with critical value, T_{cr}. This comparison could lead to the three possible situations:

- If $T_{cal} \le T_{cr}(n_{group1} + n_{group2} - 2, k = 0.05)$, then the mean values of the two groups were similar and should be merged;
- If $T_{cal} \ge T_{cr}(n_{group1} + n_{group2} - 2, k = 0.01)$, then the mean values of the two groups were different and they should be considered separately;
- If $T_{cal} \le T_{cr}(n_{group1} + n_{group2} - 2, k = 0.01)$ and $T_{cal} \ge T_{cr}(n_{group1} + n_{group2} - 2, k = 0.05)$, then the mean values of the two groups could be considered as similar. However, the final decision should be done based on the knowledge of researcher.

After we merged the groups based on explained above conditions, the new set of groups was created. The calculations of Step 3 should be repeated from the beginning with the new set of groups in the sample. Iterative calculations of Step 3 was continued until the t-test showed that no groups can be merged together and that the total number of groups could not be reduced.

Step 1. Based on the groups with the elements, identifying the critical borders that separated the DHW heat use profile into zones with peak, average, and minimum heat use

Critical borders that separated the DHW heat use profile into zones with peak, average, and minimum heat use can be identified by the following:

$$\mathrm{E_{min}} = \bar{\mathrm{E}}_{\mathrm{group.1}} + \mathrm{T_{cr.1}}\left(\mathrm{M_{group.1}} + 1 - 2, k = 0.01\right)\sqrt{\frac{\mathrm{S^2_{group.1}}}{\mathrm{M_{group.1}}}} \quad (5)$$

$$\mathrm{E_{max}} = \bar{\mathrm{E}}_{\mathrm{group.K-1}} + \mathrm{T_{cr.K-1}}\left(\mathrm{M_{group.K-1}} + 1 - 2, k = 0.01\right)\sqrt{\frac{\mathrm{S^2_{group.K-1}}}{\mathrm{M_{group.K-1}}}} \quad (6)$$

where $\bar{E}_{group.1}$, $\bar{E}_{group.K-1}$ were the mean values of the DHW heat use in the first group and the next to the last group. $M_{group.1}$, $M_{group.K-1}$ were the numbers of the elements in the first group and the next to the last group. $S^2_{group.1}$, $S^2_{group.K-1}$ were the standard deviations in the first group and the next to the last group. $T_{cr.1}$, $T_{cr.K-1}$ were the critical values of the t-criteria for the first group and the next to the last group. The hours in which the DHW heat use was below E_{min} should be considered as zone with the minimum DHW heat use. If the DHW heat use was between E_{min} and E_{max}, it could be assumed that in these hours the DHW heat use was in a zone of average heat use. The hours with the DHW heat use higher than E_{max} lied within the zone of the maximum heat use.

2.3. Determining the seasons of DHW heat use

The method described in Section 2.2 can be applied in order to identify the groups of months with similar characteristics of the DHW heat use. In this case, in contrast to the sample of 24 hours for each daily profile as considered in Section 2.2, the initial sample contains 12 elements for the monthly DHW heat use during the year. The basic principles and procedure of calculations in both hourly and monthly analysis was the same. As a result, the number of seasons of the DHW heat use in the year and the months included in each season could be identified.

3. Description of buildings

One year of hourly measured data for the DHW heat use were collected from three nursing homes located in the Eastern Norway. The characteristics and work regimes of the nursing homes were typical for Norwegian conditions and was expected to be representative for DHW heat use in the similar types of buildings.

Table 2
Main properties of measured nursing homes.

ID	Area [m^2]	Number of rooms	Heat source	Distribution heating	Storage	Measurement
NH1	3 327	52	Electric water heaters 3 × 25 kW	Electric heat tracing	3 × 600 liter	Electricity energy to water heaters
NH2	2 609	25	Electric water heaters 2 × 25 kW	Electric heat tracing	2 × 900 liter	Electric energy to water heaters
NH3	6 774	50	Local area heating + electric water heaters 3 × 15 kW	Circulation (short-circuited)	3 × 400 liter	Electric energy to water heater and thermal energy from district heating

Table 2 shows the main properties of the observed buildings, and Fig. 3 shows the principle layout of the DHW plants, including the measurement points. The energy meters are marked with EM in Fig. 3.

For all the buildings, the measured heat use was the total heat delivered into the system, i.e. including the heat losses. The two buildings, NH1 and NH2 did not have hot water circulation systems, but electric heat traces. The power use of the heat tracers were not included in the measurements, which means that the distribution losses were not accounted. The third building, NH3, had a circulation system, but the system was short-circuited close to the heating plant, which means that the thermal losses in the circulation were minimal. Based on this, it was assumed that the measured heat use for the DHW in all the buildings were without distribution losses, and thereby compared on equal ground.

The main differences between the nursing homes was the room density (the total area per room), with a range from 64 to 136 m^2/room. All nursing homes have private rooms only, all with the individual bathrooms, and the nursing homes are normally fully occupied. Therefore, the number of rooms was also representative for the amount of people living in the buildings. For investigation, the weather data obtained from the closest weather station were used.

4. Results and Analysis

The section is divided in several subsections that consider specific steps of the method explained in Section 2. The analysis of the variation of DHW heat use in the nursing homes, as well as the indicators that explains its variability, was shown in Section 4.1. Section 4.2 investigates the nursing homes DHW heat use profiles aggregated by similar days of the weeks and seasons. The hours of peak, average and minimum heat use for these profiles were studied. In Section 4.3, the standards were compared with the profiles obtained from the measurements. The drawbacks of the standards were highlighted.

4.1. Initial analysis of DHW heat use in the nursing homes

Even within the same building type, the characteristics of heat use may vary. To compare buildings with different characteristics, specific heat use may be used. Specific heat use is actual heat use of the building divided by certain physical indicator. This indicator explains variability of the DHW heat use in different buildings, and makes them comparable with each other. For this purpose in buildings, the specific heat use per number of rooms or area is commonly used. To choose which of these indicators to use in further analysis, the box plots of daily heat use were analysed as shown in Fig. 4.

The results in Fig. 4 show that the relative difference in the average daily use is 67 % per area and 41% per room. Since the main reason for DHW use at nursing homes are related to hygienic purposes and nourishment of the residents, it is reasonable to think that the number of rooms is better parameter for describing the DHW heat use. Accordingly, in the further analysis, attention will be paid mainly to the specific energy use per room. Only in the parts of the article dedicated to the standards, where it is relevant, the heat use per m^2 also will be considered. The DHW heat use per room is quite high (see Fig. 4 b)) since rooms in the nursing homes have large area from 64 to 136 m^2/room.

The nursing homes considered in the article had similar trends and regimes of the DHW heat use. The difference in variance in their DHW heat use was within 30%. The energy distance test [41] showed that distributions of the DHW heat use in nursing homes were identical and it provided a foundation for further statistical analysis. Therefore, in order to simplify analysis and make

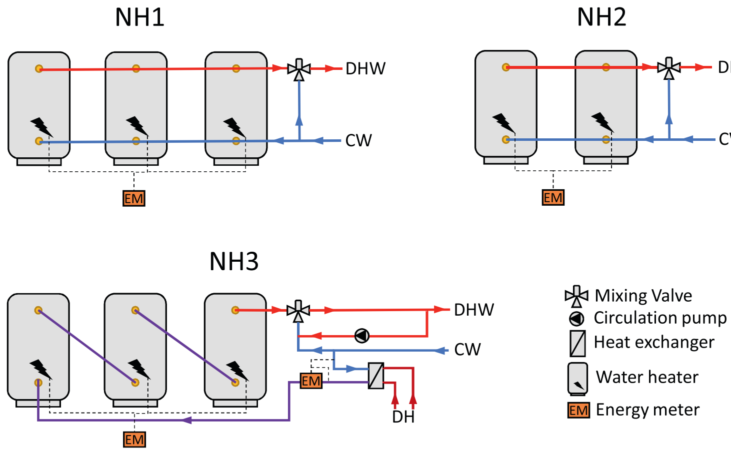

Fig. 3. Principle layout of the three DHW plants.

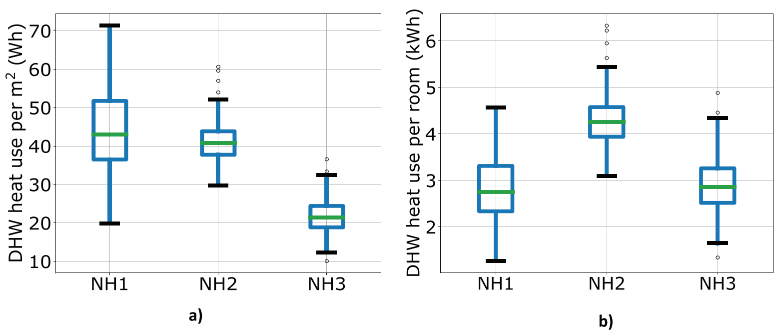

Fig. 4. Box plot of daily DHW heat use in the nursing homes, where: a) DHW heat use per m^2, b) DHW heat use per room.

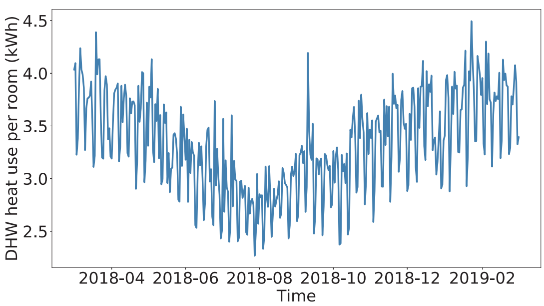

Fig. 5. Average hourly DHW heat use in three nursing homes.

the results more representative, the average DHW heat use of the three nursing homes was investigated. One-year data of the average specific DHW heat use for the three nursing homes are shown in Fig. 5.

From Fig. 5 it can be noted that the DHW heat use during the year were varying, and seasonal influence was clearly present. Seasonality of the DHW heat use will be explained in detail in Section 4.2. In addition, some spikes may be noted in the data, for example on September 9th, 2018 at 24:00 o'clock. These spikes showed untypical behaviour of the DHW heat use. Untypical spikes where taken in account in the analysis of DHW heat use. Another point that was taken into account in the analysis was the difference in behaviour on holidays compared to ordinary days. Fig. 6 shows the DHW heat use in the nursing homes in the week without holidays (from January 1st to January 13th), the week that contained Christmas holidays (from December 24th to December 30th), and days which are official public holidays (from December 25th to 26th December, and January 1st).

As we can see from Fig. 6, the shapes of the DHW heat use patterns during the public holidays on December 25th and 26th were similar to the patterns in the weekends. The DHW heat use during the week that contained Christmas holidays was lower than in a regular week. This can be explained by the fact that some families took their elder relatives home from the nursing homes for Christmas celebrations. Finally, on the last day of holidays elder people were arriving back to the nursing home. Therefore, January 1st, the DHW heat use was becoming similar to a regular day. Thereby, during the holidays, water use was usually reduced.

4.2. DHW heat use profiles aggregated by similar days of the weeks and seasons

Fig. 7 shows average daily DHW heat use per room for each month and corresponding outdoor temperature.

From Fig. 7, strong negative correlation between monthly DHW heat use and outdoor temperature may be noted. In nursing homes, it is expected that the routines for DHW use are simi-

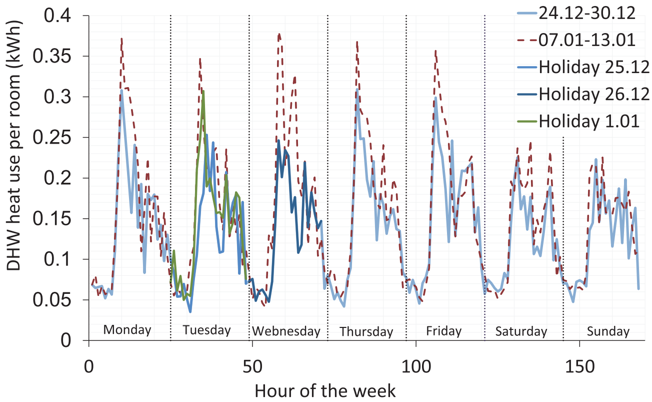

Fig. 6. DHW heat use within the Christmas holidays.

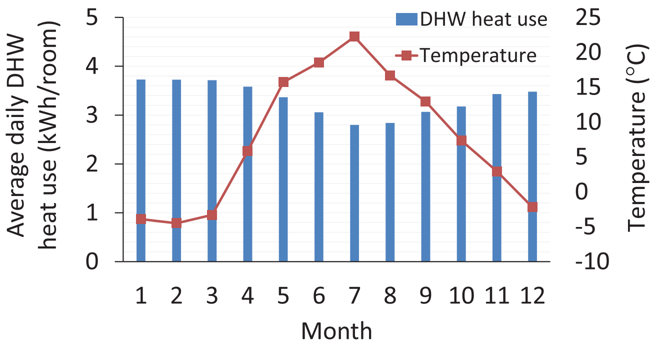

Fig. 7. Daily DHW heat use and outdoor temperature for different months over the year.

lar around the year, and the variation on monthly heat use for DHW can be described by the variation in cold fresh water inlet temperature [42]. Through our investigation of the correlation between the monthly heat use and the lagged monthly average outdoor temperature, the highest coefficient of determination, 0.96, was found between the monthly heat use and the average outdoor temperature of the previous month. This fits well with the fact that the cold inlet water temperature has a slow response to the outdoor temperature. Further, this effect leads to seasonal variation of the DHW heat use in the nursing homes. Therefore, to take into account variation of the DHW heat use in the nursing homes over a year, the seasonality was investigated. The number of seasons during the year and the months associated with each season were identified based on the average daily DHW heat use for nursing homes in different months, applying the method described in Section 2.3. Using Student's t-test, the months of the year were divided into two groups with substantially different mean values of the heat use within each group. The results of the seasonality identification are shown in Fig. 8. The groups represent the cold and warm seasons. The cold season included the following months: January, February, March, April, May, November, and December. Meanwhile, June, July, August, September, and October were assigned to the warm season. Finally, for these seasons were developed separate profiles of DHW use.

As explained in the method, Section 2.1, at the next step of the investigation, the days of the week were assessed for similarity. The DHW heat use data from nursing homes were divided into separate weeks. In total, there were 52 full weeks within the year. According to the method in Section 2.1, within each week, all combinations of daily DHW profiles were systematically compared among themselves by Student's t-test and Fisher exact test. The matrix of matching of daily profiles is shown in Table 3.

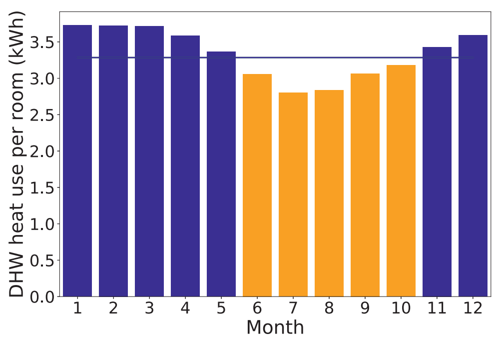

Fig. 8. Cold and warm seasons of DHW heat use in nursing homes.

In order to find the critical value that shows when the profiles in different days of the week could be considered as statistically similar, the three following factors were taken in account: the accuracy of Student's t-test, the accuracy of Fisher's exact test, and percentage of days in the year when the buildings operation was not typical, including holidays. The accuracy of Student's t-test and

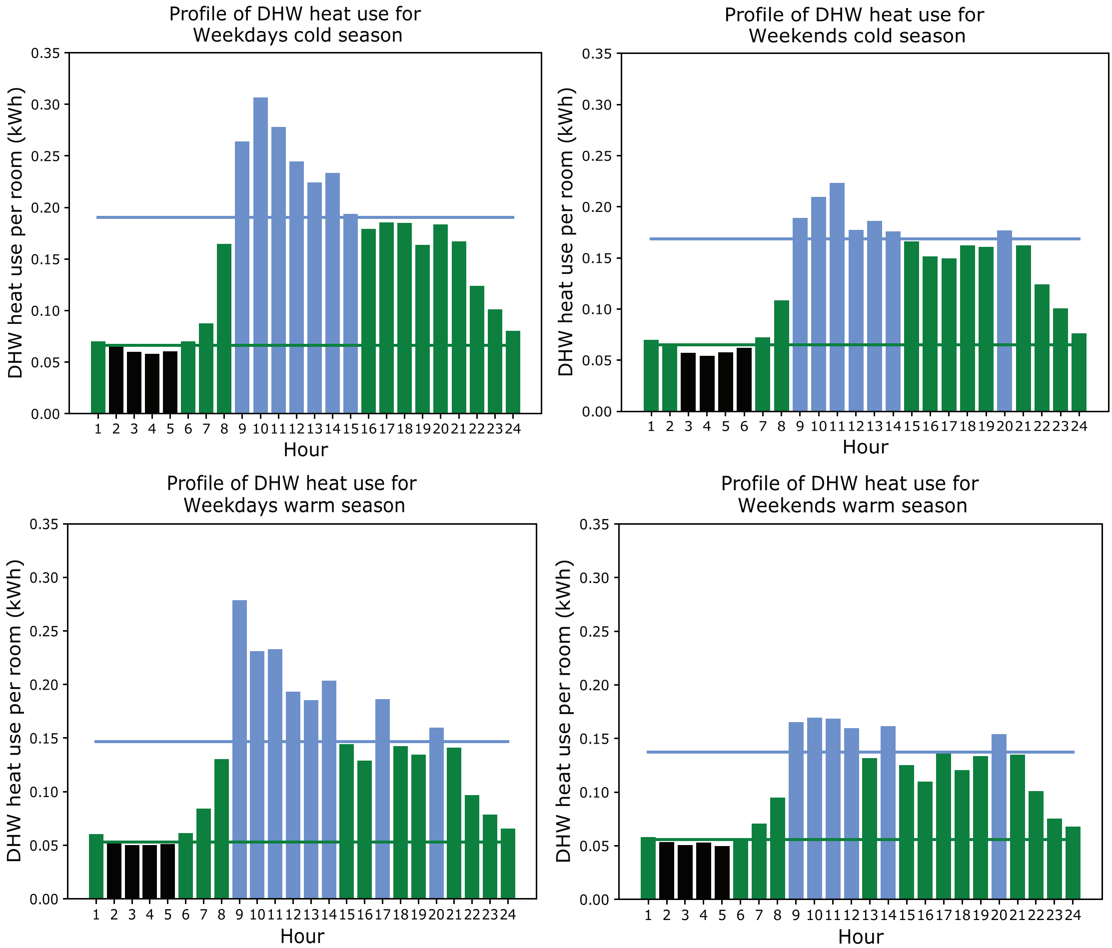

Fig. 9. Profiles of DHW heat use in the nursing homes divided by day of week and seasons.

Table 3
Matrix of matching daily DHW heat use profiles in nursing homes.

	Mo.	Tu.	We.	Thu.	Fr.	Sa.	Su.
Mo.	100	–	–	–	–	–	–
Tu.	93	100	–	–	–	–	–
We.	97	97	100	–	–	–	–
Th.	87	97	93	100	–	–	–
Fr.	95	97	97	97	100	–	–
Sa.	32	59	32	55	51	100	–
Sun.	30	71	48	71	61	97	100

Fisher's exact test were accepted equal to 5%. In addition, taking into account the number of the days with untypical DHW heat use, the values of the acceptable error (see Section 2.1) was estimated as 14%. Therefore, the days of the week in nursing homes that have statistically similar profiles in more than 86% of the considered weeks were identified, see Table 3. Based on this conclusion, the following groups of the days were identified:

- The first group: 1) Monday, Tuesday, Wednesday, Thursday and Friday,
- The second group: 2) Saturday and Sunday.

Detailed DHW heat use profiles organized by similar days of the weeks and seasons are shown in Fig. 9. For these profiles, the time zones were identified based on average daily DHW heat use by the method explained in Section 2.2. Fig. 9 demonstrated the time zones with a peak heat load (heat use above Emax, see Equation 6), minimum (heat use below Emin, see Equation 5) and average (heat use in the range between Emin and Emax) heat load of DHW. The borders between time zones in Fig. 9 are shown in the form of the horizontal lines.

The identification of the time intervals when minimum, average, and peak heat use occurred during the day was one of the key information from the analysis of the DHW heat use profiles. Thereby, the application of the method presented in the Section 2.2 allowed us to determine the following borders of time zones:

1) The peak heat use of the DHW heat use occurred when the heat use was higher than: 0.19 kWh/room for Monday-Friday in the cold season, 0.168 kWh/room for Saturday-Sunday in the cold season, 0.147 kWh/room for Monday-Friday in the hot season, and 0.137 kWh/room for Saturday-Sunday hot season;
2) The minimum heat use of the DHW heat use occurred when the heat use was less than: 0.066 kWh/room for Monday-Friday

in the cold season, 0.065 kWh/room for Saturday-Sunday in the cold season, 0.053 kWh/room for Monday-Friday in the hot season, and 0.052 kWh/room for Saturday-Sunday in the hot season;

3) The average heat use of the DHW heat use occurred when it was between: 0.066 kWh/room and 0.19 kWh/room for Monday-Friday in the cold season, between 0.065 kWh/room and 0.168 kWh/room for Saturday-Sunday in the cold season, between 0.053 kWh/room and 0.147 kWh/room for Monday-Friday in the hot season, and between 0.052 kWh/room and 0.137 kWh/room for Saturday-Sunday in the hot season.

From Fig. 9 it can be observed that the hourly values of the DHW heat use, as well as its peak, were much higher from Monday to Friday compering to Saturday and Sunday. In general, DHW heat use during the cold season was higher than in the warm season. Moreover, in the different seasons, there are some shifts in intensity of the DHW heat use between the hours. From Monday to Friday in the cold season, the peak of the DHW heat use occurred from 9:00 to 15:00 o'clock, with the maximum heat use from 9:00 to 11:00 o'clock. Opposite, the evening peak in the cold season was not clear and cannot be observed easily. Sunday and Saturday in the cold season, the maximum of the DHW heat use was much lower and may be noticed at 11:00 o'clock. Furthermore, the low peak heat use appeared at 20:00 o'clock. Meanwhile, in the working days in the warm season, the peak of DHW heat use occurred from 9:00 to 14:00 o'clock, with the maximum heat use at 10:00 o'clock and the values that are close to the maximum at 9:00 and 11:00 o'clock. In addition, two small peaks could be observed at 17:00 and 20:00 o'clock in the warm season. In the weekends in the warm season, the peak was from 9:00 to 12:00 o'clock, and at 14:00 and 20:00 o'clock. The minimum of the DHW in all the profiles was at night, usually from 2:00 until 5:00 o'clock.

Changes of the DHW heat use intensity and the occurrence of the peak values of the heat use in different profiles in Fig. 9 could be explained by different work regimes in the nursing homes at the weekends and the working days, as well as at different seasons. In general, our study showed that dividing the DHW heat use profiles by seasons and days of the week was reasonable. The profiles obtained in this way were more informative and allow us retrieve additional information about DHW heat use in buildings.

4.3. Comparison of the standard profiles for DHW heat use with the profiles obtained based on measurement data

In this section, two standards were compared with the profiles obtained from the measurements and analysis in Section 4.2 in the nursing homes. The Norwegian standard, "SN/TS 3031:2016: Energy performance of buildings. Calculation of energy needs and energy supply" [43] is a national standard for calculations of buildings energy need and heat losses. Among different information, this standard gives recommendation on DHW heat use profiles per m^2 in nursing homes that should be used as an input for energy demand calculation [43]. The standard "NS-EN 12831-3:2017: Energy performance of buildings" [44] is European standard, which is recommended for application in Norway. NS-EN 12831-3 provides reference profiles of DHW heat use per person in nursing home. As mentioned earlier, in Norway, each room in the nursing homes is occupied by only one person. Thus, heat use per room is approximately equal to heat use per person. The profiles in the both standards show DHW tap heat use without losses in the storage tank and the system. Meanwhile, typically the measurements in the nursing homes include losses in the storage tanks. For this reason, to remove the losses from the profiles obtained by measurements, the method proposed in [45] was used in this study. This method is based on the assumption that the hourly DHW heat use with minimum values represents system losses [43]. Consequently, extracting the minimum DHW heat use during these hours from measured data gives us approximate value of the DHW heat use without system and tank losses. Accordingly, using profiles in Fig. 9, the hour with the minimum DHW heat use was identified. After that, the DHW heat use profiles were recalculated according to the method in [45]. The DHW system losses obtained by this method were approximately 20% of the total DHW heat use. For the comparison, both profiles obtained by the measurements with adjustments according to the losses, and the profiles from the standards SN/TS 3031 and NS-EN 12831-3 are presented in Fig. 10. In addition, for a better understanding of the DHW heat use in the nursing homes, the box plots of hourly DHW heat use per m^2 and per room are presented in the Fig. 11.

Fig. 10 indicates on the big difference between the DHW heat use profiles obtained from the measurements and both standards. The comparison with actual profiles showed the following drawbacks of the standards: 1) standards are not taking into account seasonality and influence of the day of the week on DHW heat use, 2) standards significantly overestimate average daily DHW heat use 2) for certain hours the profiles in the standards overestimate or underestimate DHW heat use, 3) standards can not properly reflect hours with peak and minimum DHW heat use.

The profile in the standard SN/TS 3031, see Fig. 10. a), overestimated the daily DHW heat use in the nursing homes approximately 3.5 times. Even if we compare it with the maximum heat use in the nursing homes, shown in the box plot, see Fig. 11. a), the DHW heat use in the standard SN/TS 3031 was still much higher. Despite this fact, the standard making the assumption that there is no DHW heat use from 1:00 to 5:00 o'clock. The actual profiles, see Fig. 10, showed a small amount of DHW heat use even at night time.

Information about magnitude and timing of the peak heat use in the buildings is crucial for solving a number of issues in energy planning. However, from Fig. 10. a) we can see that SN/TS 3031 is not representing this information in a proper way. From the standard profile, we could assume that the morning peak of heat use occurred from 7:00 to 8:00 o'clock, and the similar peak could be observed from 18:00 to 19:00 o'clock. Meanwhile, in the profile based on actual measurements, the maximum DHW heat use was from 9:00 to 11:00 o'clock, and the evening peak was not clearly visible. The peak value in the standard is 3.7 times higher than in the measured profile. These differences between the profiles were significant and they show the drawbacks of the standard SN/TS 3031. It should be noted that a sample of three nursing homes is probably not enough to be sure that the measurements are representative for the national average. However, this sample represented well the DHW heat use in nursing homes in the central part of Eastern Norway.

The standard, NS-EN 12831-3, overestimated the daily DHW heat use by 1.65 times, see Fig. 10. b). Unlike SN/TS 3031, the standard NS-EN 12831-3 shows DHW heat use at night time, which makes it more realistic. The values in the NS-EN 12831-3 standard are closer to the maximum than the average hourly values of the DHW heat use in the nursing homes presented in Fig. 11. b). From Fig. 10. b) it may be noted that the timing of the actual peaks of the DHW heat use did not match perfectly the information in the standard NS-EN 12831-3. The morning peak of heat use in the standard is shown from 7:00 to 8:00 o'clock. It is shifted by two hours compared with the actual one, see Fig. 10. b). The value of the maximum DHW heat use in the standard is 2.7 times higher than in the profile based on measurement. The behaviour of DHW in the evening time was similar to the measured profile. Despite the fact that NS-EN 12831-3 is the international standard, it explains the DHW nursing home heat use much better than the Norwegian national standard SN/TS 3031.

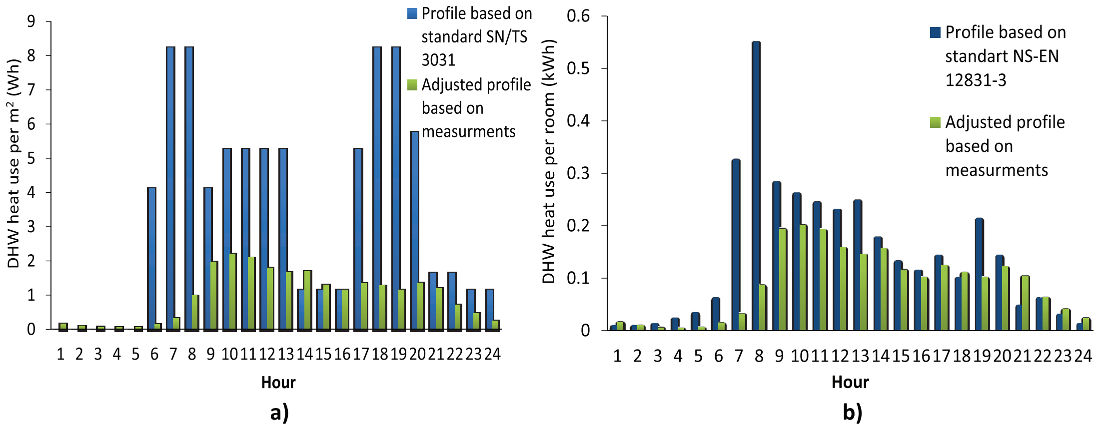

Fig. 10. Hourly profiles of DHW heat use according to the standards and measurements in the nursing homes, where a) standard SN/TS 3031 b) NS-EN 12831-3.

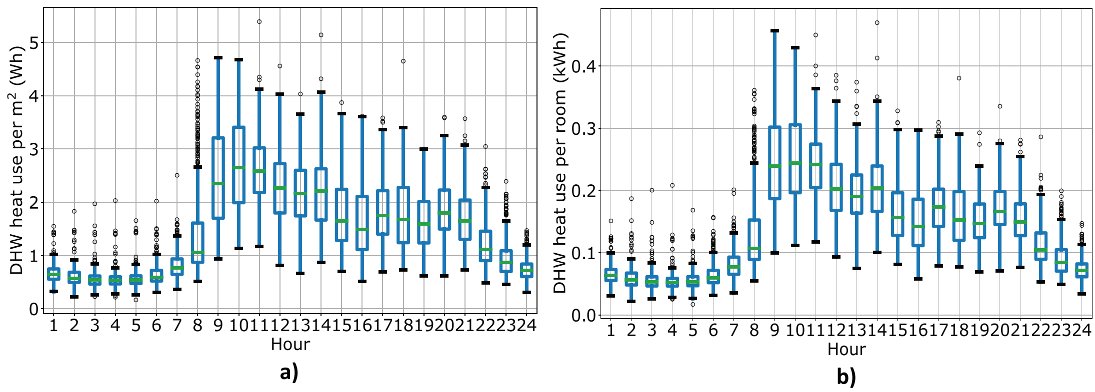

Fig. 11. Hourly profile of DHW heat use obtained by measurements, where: a) DHW heat use per m^2, b) DHW heat use per room.

There could be several reasons for the inaccuracy of the profiles in the standards. First, the majority of the standards are based on information and data obtained decades ago [17]. The introduction of new types of DHW appliances, changes in routines and behaviours in the nursing homes are also likely changing the assumed values from the standards. Consequently, standards cannot correctly display the current state of the DHW heat use in buildings, because the standards are developed to give limits and guidelines and cannot determine the real use. The other reason is that the profiles given in the standards are usually too simplified to enable their easier implementation by practitioners. These profiles were created for certain categories of buildings: nursing homes, school, hotel, offices, etc. However, even within one category of the buildings, the DHW heat use can behave differently. The location of the building in different parts of the country with specific temperature conditions is also factor that could lead to uncertainty.

The above mentioned standard profiles are commonly used for calculation of the building performance against national regulations. If the standard profiles deviates significantly from the reality, it may lead to unwanted effects. For example in Norway, there is a demand that above 60% of the energy demand for heating and DHW should be covered by a centralized system without fossil fuels. In cases with highly insulated buildings, the standard DHW heat demand may represent above 60% of the total heating demand. If the real DHW use is much lower than the standard calculation, the standard requirements on the system design will have unwanted effects on choosing energy supply systems and sizing the energy infrastructure.

Therefore, this study showed that dividing the DHW heat use profiles by season and days of the week is reasonable. These profiles should be based on accurate and up-to-date statistical data from real buildings and reliable methods of processing available information. The potential for energy saving, can be achieved by better DHW system sizing, introducing of demand-side management, and other energy saving measures. Representative profiles will form a basis for the proper implementation of energy saving measures and increasing the efficiency of DHW heat use in nursing homes.

5. Conclusions

DHW system is a significant consumer of energy in buildings. With the introduction of highly insulated building structures and technologies of passive houses, the share of the DHW heat use in the total energy balance of the buildings is continuously increasing. Accordingly, reducing the DHW heat use in buildings becoming a more important target.

The review of the literature showed that there is a gap in knowledge about actual DHW heat use in buildings. Specific heat use in the nursing homes is one of the highest comparing to other types of buildings. Therefore, analysis of the DHW heat use in nursing homes is particularly relevant for Norway. To increase energy efficiency in the DHW systems in Norway, an extensive analysis should be carried in various types of buildings. One of the most critical problems of such analysis is the development of up-to-day profiles of the DHW heat use. These profiles should accurately reflect DHW heaty use in the buildings and fill gaps in existing standards. In this article, the relevant problem was investigated for nursing homes located in the Eastern Norway.

Analysis of the measurements in three nursing homes showed a strong negative correlation between the monthly DHW heat use and the outdoor temperature. Consequently, seasonality is an essential factor that should be taken into account for DHW heat use profiles for nursing homes. The other significant factor identified in the article was the day of the week. For the DHW heat use analysis, the statistical approach that allowed us to develop unified profiles divided by months and days of the week with similar behaviour of DHW heat use was suggested. Based on this approach the months of the year for the nursing homes were divided into two groups: the cold season (January, February, March, April, November, December) and the warm seasons (June, July, August, September, October). Comparison of the profiles in different days of the week showed that weekends and working days should be considered separately. Furthermore, a method for determining the time zones with the peak, the minimum, and the average heat use in the daily profile of the DHW heat use was applied.

For the nursing homes, the profiles obtained by seasons showed that the DHW heat use in the cold season was higher than in the warm season. Besides, nursing homes used less heat for DHW in the weekends than in the working days. The maximum DHW heat use in nursing homes usually occurred from 9:00 o'clock to 11:00 o'clock, and minimum from 2:00 to 5:00 o'clock.

Finally, the DHW heat use profiles obtained from the measurements in the nursing homes were compared with profiles from national standard SN/TS 3031:2016 and international standard NS-EN 12831-3:2017. The comparison showed that the European standard, NS-EN 12831-3, overestimated the daily DHW heat use by 1.65 times, and the Norwegian standard, SN/TS 3031, overestimated it by 3.5 times. The magnitude and timing of the peak heat use in the buildings was also different from the standards. The European standard explains much better the actual DHW heat use in the nursing homes than the Norwegian standard. For practical application and relevant decisions related to building energy supply systems, preference should be given to profiles obtained on the basis of statistical data collected in real buildings.

The study in this work was limited to only three nursing homes. For this reason, in the future work, the analysis in larger amount of nursing homes and other types of buildings will be performed. For a larger amount of buildings, the application of different clustering methods for the analysis of DHW heat use will be tested. In addition, the question of predicting the DHW heat usage profiles will be considered in further studies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Dmytro Ivanko: Conceptualization, Methodology, Formal analysis, Software, Investigation, Writing - original draft, Visualization, Writing - review & editing. **Harald Taxt Walnum:** Data curation, Formal analysis, Writing - review & editing. **Natasa Nord:** Conceptualization, Formal analysis, Writing - original draft, Supervision, Writing - review & editing.

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Paper IX D. Ivanko, N. Nord, A.L. Sorensen, T.S. Plesser Wester, H.T. Walnum, I. Sartori, Identifying typical hourly DHW energy use profiles in a hotel in Norway by using statistical methods. *The 13th REHVA World Congress CLIMA 2019, E3S Web of Conferences*, Volume 111, 2019, 04015

Identifying typical hourly DHW energy use profiles in a hotel in Norway by using statistical methods

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Abstract. The aim of this research is to improve the existing approaches of domestic hot water (DHW) energy use analysis in buildings. A comprehensive statistical analysis of hourly DHW energy use for a hotel in Oslo, Norway, was performed. To recognize the trend of DHW energy use over several years, Centered Moving Average method was applied. To increase the accuracy of DHW energy use analysis, it was proposed to identify the months and days of the week with similar characteristics of DHW energy use and build unified profiles for them. For this purpose, the approaches based on the student's t-tests and Fisher's test was proposed. The analysis allowed us to detect two seasons of DHW energy use. In addition, it was revealed that behavior of DHW energy use on Mondays significantly different from other working days. To recognize the timing of peak and average and low DHW energy use, method of statistical grouping of the hourly energy use was utilized. The typical profiles of DHW energy in the hotel were obtained. The profiles proposed in the present article more reliably reflect the regimes of DHW energy use in the hotel and take into account factors that have influence on DHW use.

1 INTRODUCTION

According to the European Commission, buildings are responsible for approximately 40% of energy use and 36% of CO_2 emissions in the EU [1]. Energy efficiency saves money for buildings owners, reduces reliance on oil and gas and help protect the environment [2]. Through the Energy Performance of Buildings Directive (EPBD) an ambitious goal is set − to achieve very high energy performance in buildings, nearly zero-energy buildings, by 2020-2035 [3]. In order to achieve this goal, heating, cooling, and ventilation systems in buildings should be designed and operated to attain low energy use [4].

Traditionally, in countries with cold climate, energy used to heat domestic hot water (DHW) is much smaller than the energy use required for heating the building. For this reason, during the last decades, DHW energy use has had little focus in Norway and other countries [5]. Nowadays, with the introduction of energy efficient building technologies, the situation is changing. In energy efficient buildings, the energy use for heating is significantly reduced [6]. In meantime, the DHW energy use remains on the same level. Therefore, for future prospects in achieving energy efficiency in buildings − reducing DHW energy use is an important task. Additionally, global warming potential (GWP) and primary energy demand (PED) for a range of DHW systems has high carbon footprint [6].

The share of DHW tap system in the total energy use is approximately 25-35% [7] and varying from country to country and one type of building to another [5]. For instance, the average individual DHW use in Norway reaches 40 L/person/day [8], while in Denmark the average is at 20 L/person/day.

The study of Bøhm [7] shows that the efficiency of domestic hot water systems should be improved. Heat losses from the hot water tank and the circulation system in single-family houses, semi-detached houses, blocks of flats, schools and institutions are found to be very high, and equals approximately to 65% of DHW energy use.

For the sake of simplification, many methodologies propose to consider DHW energy use as a constant value [9]. Practical experience shows that the commonly used standards are based on assumptions of DHW energy use in the buildings, which do not correspond to the real state of the art [10]. These assumptions and simplifications could lead to oversizing of the components of DHW systems and additional financial and energy losses [11].

DHW energy use profiles are the primary instrument for understanding the process of DHW energy use in the buildings [12]. Analysis of DHW energy use profiles shows the changes in energy use in different time intervals [13]. The profiles of DHW energy use allow us to determine the hours of peak energy loads and other energy load characteristics of a building. The DHW profiles is the basis for achieving energy saving and better building operation, as well as the best strategies for designing DHW systems in new buildings. Traditionally, the analysis of DHW energy use is performed based on so-called "typical" profile. This type of profile is viewed as a profile that shows how the energy for DHW is used most of the time. The identification of the time intervals when peak energy use occurs during the day is one of the key information available by analysis of the "typical" profiles.

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Increasing the efficiency of DHW systems in buildings requires the implementation of effective demand-side management and energy conservation measures [14], as well as improvement of legislation and standards. Practical realization of smart management and energy saving measures in this field should be based on: 1) reliable knowledge about actual profiles [15] of DHW energy use in different types of buildings, 2) parameters that have a significant impact on DHW energy use, and 3) further analysis and processing of this information by statistical approaches. However, the knowledge about DHW energy use in Norwegian buildings currently remains at a relatively low level.

Statistical analysis is an effective tool for gaining in-depth knowledge about DHW energy use and other parameters of buildings performance [16]. The primary issues, which should be solved for deeper understanding of DHW energy use by means of statistical approaches, are: 1) collection and pre-processing of data, 2) analysis of DHW energy use profiles, 3) identifying variables that have a significant impact on DHW energy use 4) modelling of DHW energy use.

Scientific works on DHW energy use patterns mostly focus on, residential buildings. Non-residential buildings (hospitals, hostels, schools etc.) are less studied [5]. Nevertheless, Michopoulos, Ziogou [17] estimated that CO_2 emissions for hot-water use in the hotels remains quite high (2.87-3.2 kg-CO_2/(person-night)) and the problem of DHW energy use analysis in non-resident buildings are meaningful. A better understanding of the features of DHW energy use is a key factor in achieving energy savings in buildings.

The issue of DHW energy use analysis in buildings based on profiles is investigated by researchers in Norway and abroad [5]. However, due to differences in particular characteristic of each buildings, quality of available data, and calculation requirement, there is no a unique methodology of performing appropriate analysis.

Most of the present researches assume that the number of occupants, seasons, the day of the week and time of the day have significant influence on DHW energy use. Traditionally, the data are divided into weekdays and weekends, while other options of separating data by other days of the week are usually not considered.

It should be noticed that due to cultural tractions, technical and weather conditions the factors having influence on DHW energy use can vary from country to country, from building to building and from family to family.

In this article we present methods of profiles development and time series analysis of DHW energy use data from a hotel in Oslo, Norway. The data comprises five years of hourly measurements of energy use for DHW production. The aim of this research is to improve the existing approaches of DHW energy use analysis in buildings. The research is part of the research project "Energy for domestic hot water in the Norwegian low emission society". The possible benefits from using more accurate energy profiles are explained.

2 METHODOLOGY

To detect the tendency of the changes in DHW energy use over several years, the Centered Moving Average method was used [18].

The common practice in DHW energy analysis, is to split of the profiles into different seasons, as well as into working and non-working days. As experience shows, the division of profiles into working days and non-working days is not always justified. In this study, we are not assuming, beforehand, that the profiles can be split in certain ways. Instead, we are comparing the DHW energy use profiles from different days of the week and assessing the similarities. The method uses student's t-test and Fisher's exact test. The tests can be used for samples with standard normal distribution and t-distribution. It allows us to determine the days of the week for with similar DHW energy use profile. The method is described in detail in Section 2.1.

In Section 2.2, a method for determining the duration and boundaries of time zones with peak, minimum, and average energy use during the day is described.

Seasonality has a significant impact on DHW energy use. However, which months should be included in each season and how many seasons should be taken into account when analyzing DHW energy use is not a completely solved task. In Section 2.3. a statistical method for identifying the number of seasons, as well as the months included in each season was described.

2.1 Comparing similarity of DHW energy use profiles in different days of the week

To determine the days of the week with similar characteristics of DHW energy use, a method based on test statistics was proposed. The similarity of two DHW energy use profiles is checked based on the student's t-test and Fisher's exact test. Appropriate tests can be used for samples with standard normal distribution and t-distribution.

By applying the t-test, it is possible to check if the mean values of DHW energy from two days of the week are equal or not. To achieve this, the DHW energy use within each day is considered as a statistical sample with 24 elements, which represents the number of hours in the day. The t-test statistical value can be calculated as follows:

$$T_{cal} = \frac{\left[\bar{E}_{prof1} - \bar{E}_{prof2}\right]}{\sqrt{\frac{S_{prof1}^2}{n_{prof1}} + \frac{S_{prof2}^2}{n_{prof2}}}} \qquad (1)$$

where $\bar{E}_{prof1}$, $\bar{E}_{prof2}$ are mean values of DHW energy use in the first and second samples; S_{prof1} , S_{prof2} are standard deviations of DHW energy use profiles in the first and second samples; n_{prof1}, n_{prof2}–the number of elements in the first and second samples. The formula for standard deviation for i-th day is:

$$S_{profi} = \sqrt{\frac{\sum(E_{profi.j} - \bar{E}_{profi})^2}{n_{profi} - 1}} \qquad (2)$$

where i is the number of the sample, j is the number of element in the sample,$E_{profi.j}$ is DHW energy use in j-th element in i-th sample.

The obtained value of t-criteria (T_{cal}) is compared with the critical value (T_{cr}). T_{cr} can be found in reference literature for different sizes of samples and k degrees of freedom. The comparison can lead to three possible situations:

– If $T_{cal} \leq T_{cr}(n_{prof1} + n_{prof2} - 2, k = 0.05)$ – the mean values of the first and second samples are similar;

– If $T_{cal} \geq T_{cr}(n_{prof1} + n_{prof2} - 2, k = 0.01)$ – the mean values of the first and second samples have a significant difference;

– If $T_{cal} \leq T_{cr}(n_{prof1} + n_{prof2} - 2, k = 0.01)$ and $T_{cal} \geq T_{cr}(n_{prof1} + n_{prof2} - 2, k = 0.05)$ – the mean values of the first and second samples can be considered as similar, however the final decision should be done based on the knowledge of researcher.

Meanwhile, Fisher's criterion allows us to estimate the similarity of two samples by variances:

$$\mathrm{f_{cal}} = \frac{\max\left(\mathrm{S^2_{prof1}},\ \mathrm{S^2_{prof2}}\right)}{\min\left(\mathrm{S^2_{prof1}},\ \mathrm{S^2_{prof2}}\right)} \qquad (3)$$

The comparison of obtained by calculations Fisher criterion, f_{cal} with its critical value, f_{cr} leads to the follow results:

– If $f_{cal} \leq f_{cr}(n_{prof1} + n_{prof2} - 2, k = 0.05)$– the variances of the first and second samples are similar;

– If $f_{cal} > f_{cr}(n_{prof1} + n_{prof2} - 2, k = 0.05)$ – the variances of the first and second samples have significant difference.

The two profiles are considered to be similar if both student's t-test and Fisher's exact test show the same result. If at least one of two tests shows that the mean values or variances of profiles in first and second samples are not similar, we conclude that the profiles are dissimilar and should be analyzed separately.

Splitting DHW profiles by the days of the week should be made based on the large dataset, which represent DHW energy use during the year. Therefore, it was proposed to divide initial statistical data into separate weeks. Within each week, all combinations of daily DHW profiles should be compared among themselves by student's t-test and Fisher exact test. For instance, profiles for Monday and Thursday, Monday and Wednesday, Saturday and Sunday and so on should be compared. Afterwards, for all the combinations of days, the number of the week can be identified, when statistical tests show that profiles in considered pairs of days are similar. For further analysis, for each combinations of days the number of matches of DHW profiles in percentage can be found as:

$$\mathrm{n_{i.j}} = \mathrm{N_{i.j}} \cdot 100/\mathrm{N_{total}} \qquad (4)$$

where $n_{i.j}$ is number of matches in percentage, when DHW profiles on i-th and j-th days are similar, $N_{i.j}$ is number of weeks, when statistical tests shows that the i-th and j-th days are similar, N_{total} is total number of weeks in statistical data sample of DHW energy use, i is the day of the week of the first comparable profile (from 1 to 7), j is the day of the week of the second comparable profile (from 1 to 7).

For better clarity, the results can be presented in the form of matrix of the matches as in Table 1.

Table 1. The form of the matrix of matches

	Mo.	Tu.	We.	Thu.	Fr.	Sa.	Su.
Mo.	$n_{1.1}$	$n_{1.2}$	$n_{1.3}$	$n_{1.4}$	$n_{1.5}$	$n_{1.6}$	$n_{1.7}$
Tu.	$n_{2.1}$	$n_{2.2}$	$n_{2.3}$	$n_{2.4}$	$n_{2.5}$	$n_{2.6}$	$n_{2.7}$
We.	$n_{3.1}$	$n_{3.2}$	$n_{3.3}$	$n_{3.4}$	$n_{3.5}$	$n_{3.6}$	$n_{3.7}$
Th.	$n_{4.1}$	$n_{4.2}$	$n_{4.3}$	$n_{4.4}$	$n_{4.5}$	$n_{4.6}$	$n_{4.7}$
Fr.	$n_{5.1}$	$n_{5.2}$	$n_{5.3}$	$n_{5.4}$	$n_{5.5}$	$n_{5.6}$	$n_{5.7}$
Sa.	$n_{6.1}$	$n_{6.2}$	$n_{6.3}$	$n_{6.4}$	$n_{6.5}$	$n_{6.6}$	$n_{6.7}$
Su.	$n_{7.1}$	$n_{7.2}$	$n_{7.3}$	$n_{7.7}$	$n_{7.5}$	$n_{7.6}$	$n_{7.7}$

Based on the matrix of matches the groups of the days of the week with similar profiles of DHW energy use could be identified. Namely, the days of the week, which have $n_{i.j} \geq 100 - error$, have similar characteristics of DHW energy use and should be placed in one group and analyzed together.

The value of $error$ takes into account such factors as the accuracy of student's t-test (5%), Fisher's exact test (5%), and the percentage of days in the year when the building is not in operation such as holidays.

2.2 Determining the time zones with peak, minimum and average energy use in daily profile of DHW energy use.

It is known that DHW energy use changes during the day. In order to implement energy management in buildings, it is important to identify the typical duration and boundaries of time zones with peak load, minimum, and average energy use during the day.

To solve this issue, we are proposing to perform statistical grouping of the hourly capacity and consumer groups of the power system [19]. Initially this method has been used for identification of the tariff zones of electrical energy use in the power system. In this article, we have adapted the method for analysis of DHW energy use in buildings.

The method allows us to divide the hours of DHW energy use into several groups with statistically different mean values within each group. It is based on an iteration procedure and analysis of mean values of DHW energy use by applying student's t-test. In this case, DHW energy use profile was considered as a statistical sample e. The sample contains N=24 elements (hours) with DHW energy use in these hours equal e_j (where e_j is DHW energy use in *j-th* hour, j is the number of the element in the sample, N is number of elements in statistical sample e). The method includes the following steps:

1) The elements e_j in the sample e are sorted in the order of their increase. Such an arrangement of elements from smaller values of hourly DHW energy use to bigger values allows us to obtain the sorted sample E with N elements E_i (where $E_{i+1} > E_i$, i is the number of element in sample E).

2) Based on the sample E, an iterative procedure of generating of two statistical subsamples R_1 and R_2 with variable number of elements is applied. On each step of

iteration, sample R_1 contain M elements, while R_2 should have M+1 elements. The elements in samples R_1 and R_2 were taken consistently from the initial sample E. With each iteration, the number of elements M in these subsamples increases by one. The value of M varies from 1 to 23.

On each step of these iterations the value of student's t-test for two subsamples R_1 and R_2 are calculated using Equation (1).

For instance:

iteration 1) $R_1 = [E_1]$, $R_2 = [E_1, E_2]$, M=1, and T_{cal1};

iteration 2) $R_1 = [E_1, E_2]$, $R_1 = [E_1, E_2, E_3]$, M=2, and T_{cal2};

………..

iteration 23) $R_1 = [E_1, E_2 \dots E_{23}]$, $R_1 = [E_1, E_2 \dots E_{24}]$, M=23, and T_{cal23};

3) Based on the iteration procedure of the step 2, the series of t-criteria for all combinations of subsamples R_1 and R_2, T_{cal} =[T_{cal1},T_{cal2} … T_M] are found.

If an ordered sample of hourly DHW energy use is monotonous, then the numerical values of elements in this sample increase evenly. In this case, the series of t-criteria obtained by iteration procedure will also be monotonous. This means that values of t-criteria obtained by Equation (1) will decrease monotonically with each next iteration ($T_{cal1} > T_{cal2} \dots > T_M$).

If the ordered sample of hourly DHW energy use is uneven, then a monotonic decrease of the calculated values of t-criteria would be violated by periodic abrupt growth ($T_{cali} < T_{cali+1}$).

Thus, the identification of points of growth of the calculated values of t-criteria allows us to determine between which hours there is a noticeable statistical difference of DHW energy use. This assumption allows us to initially divide hours in the profile of DHW energy use into several groups. Each of these groups is the sample of data, where DHW energy use data varies monotonously.

Created in this way, neighboring groups of hourly DHW energy use can be checked in terms of the possibility for their further merge. For this purpose, the data samples of two neighboring groups are assessed by student's t-test (Equation (1)). As a result, the obtained by calculations value of t-criteria (T_{cal}) can be compared with critical value (T_{cr}). This comparison can lead to three possible situations:

– If $T_{cal} \le T_{cr}(n_{group1} + n_{group2} - 2, k = 0.05)$ – the mean values of two groups are similar and should be merged;

– If $T_{cal} \ge T_{cr}(n_{group1} + n_{group2} - 2, k = 0.01)$ – the mean values of two groups are different and they should be considered separately;

– If $T_{cal} \le T_{cr}(n_{group1} + n_{group2} - 2, k = 0.01)$ and $T_{cal} \ge T_{cr}(n_{group1} + n_{group2} - 2, k = 0.05)$ – the mean values of two groups can be considered as similar, however the final decision should be done based on the knowledge of researcher.

Step 3 is continued until the t-test shows that no groups can be merged together and that the total number of groups cannot be reduced.

4) Critical borders that separate DHW energy use profile into zones with peak, average and minimum energy use can be identified by the next formulas:

$$\mathrm{E_{min}} = \overline{\mathrm{E}}_{\mathrm{group.1}} + \\ +\mathrm{T_{cr.1}}(\mathrm{M_{group.1}} + 1 - 2, 0.01)\sqrt{\frac{\mathrm{S^2_{group.1}}}{\mathrm{M_{group.1}}}} \quad (5)$$

$$\mathrm{E_{max}} = \overline{\mathrm{E}}_{\mathrm{group.K-1}} + \\ +\mathrm{T_{cr.K-1}}(\mathrm{M_{group.K-1}} + 1 - 2, 0.01)\sqrt{\frac{\mathrm{S^2_{group.K-1}}}{\mathrm{M_{group.K-1}}}} \quad (6)$$

where $\bar{E}_{group.1}$, $\bar{E}_{group.K-1}$ are mean values of DHW energy use in the first group and next to the last group; $M_{group.1}$, $M_{group.K-1}$ are number of elements in the first group and next to the last group; $S^2_{group.1}$, $S^2_{group.K-1}$ are standard deviations in the first group and next to the last group; $T_{cr.1}$, $T_{cr.K-1}$ are critical values of t criteria for the the first group and next to the last group. The hours in which DHW energy use is below E_{min} should be considered as zone with the minimum DHW energy use. If DHW energy use is between E_{min} and E_{max} it can be assumed that in these hours DHW energy use is in a zone of average energy use. The hours with DHW energy use bigger then E_{max} lie within zone of maximum energy use.

2.3 Determining the seasons of DHW energy use

The method described in Section 2.2 can be applied in order to identify the groups of months with similar characteristics of DHW energy use. In this case, in contrast to the sample of 24 hours in daily profile, which was considered in Section 2.2, the initial sample contains 12 elements of monthly DHW energy use during the year. The basic principles and procedure of calculations in both hourly and monthly analysis is the same. As a result, the number of seasons of DHW energy use in the year and the months included in each season can be identified.

3 HOTEL DESCRIPTION

The characteristics of the hotel are typical for Scandinavian conditions and well aim to reflect the trends of DHW tap energy use in the similar types of buildings.

The hotel, located in Oslo, Norway, was built in 1938, and reconstructed in 2007. The total area of the building is 4 939 m^2, and consist of eight floors with 164 guest rooms. All guest have bathrooms with toilet facilities and shower. The rooms are cleaned daily. The maximum daily number of guests during the summer 2016 was 312 persons. Guests arrive between 15 p.m. to 12 midnight, and they check out before 12 noon. According to the hotel management, employees use hot water for cleaning the hotel, and guests use hot water for personal hygiene.

The hotel uses electricity to heat the water. The hot water is circulated to ensure fast delivery at taps. The circulation pump runs on fixed speed. In order to collect data of energy use in the building, electricity meters are installed, which allowed us to obtain hourly data of DHW energy use in the period 2013-2017. The meters measure electricity delivered to the DHW tanks, which mean that both DHW needs and heat losses in the DHW system is included in the presented DHW energy use. In addition, data about number of visitors were available from the hotel reservation system.

4 RESULTS

The results given in this section represent the practical application of proposed in the article methods and improvements, which were achieved. This section divided in several subsections that consider specific steps of investigation.

4.1 The analysis of the trend of DHW energy use in the hotel

Statistical data of energy use in the hotel substantiate that DHW tap systems have significant impact on energy use in the buildings. More specifically, in the hotel, DHW energy use constituted 19.5% of total energy use in 2016 and 23% in 2017.

The annual trends in DHW energy use was analyzed by calculating the Centered Moving Average. The trend of DHW energy use in the hotel (Fig. 1) shows permanent growth in energy use from year to year. For instance, in 2017 DHW energy use increased by 11.6% compared to 2016.

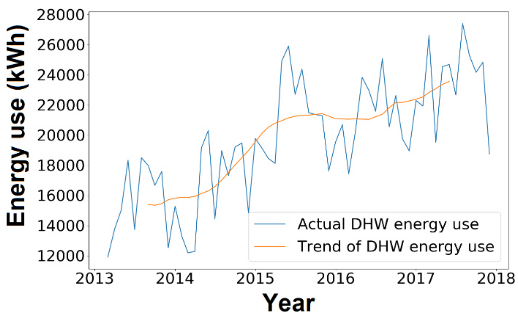

Fig. 1. Trend of DHW energy use in the hotel

A constant annual growth in energy use in the building may indicate a change in energy efficiency in DHW system, but could also reflect an increasing number of guests, changes in behavioral or administrative patterns related to the use of the building, or temperature changes.

DHW energy use per visitor for summer an early autumn in 2016 and 2017 years is shown in Fig. **2**. June through September are the months with the highest energy use. The average energy use per visitor increased by 15.5% in 2017 compared with 2016. From Fig. 3 we can see that average monthly temperatures did not change significantly between 2016 and 2017. This indicates that the increase in DHW energy use caused by changes in the behavior of visitors or a decrease in the efficiency of the DHW system, rather than changes in the outdoor temperature.

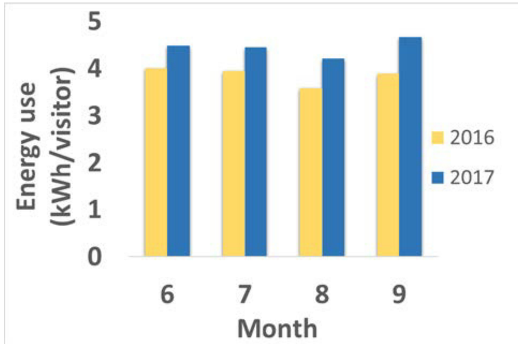

Fig. 2. DHW energy use per visitor in the warm season in 2016 and 2017

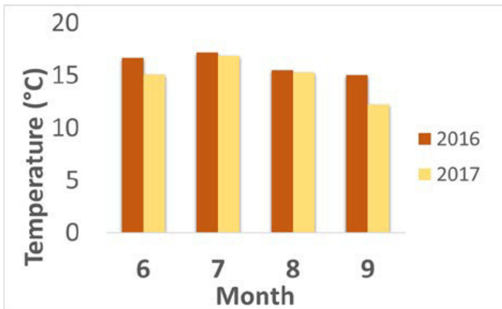

Fig. 3. Average monthly outdoor temperature in the warm season in 2016 and 2017

4.2 DHW energy use profiles aggregated by similar days of the weeks and seasons

The change of DHW energy between the months of June to September, within each year, is small, as shown in Fig. **2**. However, over a year the DHW energy use varies a lot more (Fig. 1). Therefore, it was necessary to identify the number of seasons of DHW energy use in the year, the months included in each season, and finally, develop separate profiles of DHW for each of these seasons.

In literature sources, it is suggested to consider separate DHW energy use profiles for working days and non-working days. However, this approach is simplified and may not give accurate results. Fig. 4 shows DHW energy use in representative week of 2016. From Fig. 4 we can see that DHW energy use on Mondays differs from that of the other working days. Taking the weekday into account allows us to obtain more accurate profiles of DHW energy use.

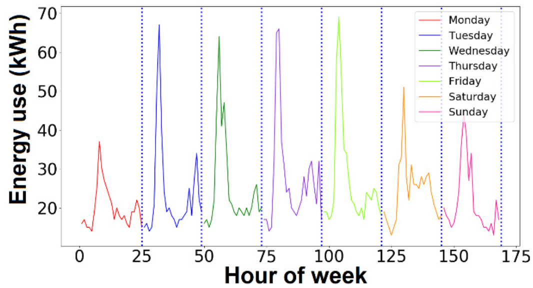

Fig. 4. DHW energy use during representative week of 2016

Seasons were identified in the average monthly DHW energy use data for last three years, using the method described in Section 2.3. Based on the t-criteria, the months of the year were divided into two groups with substantially different mean values of energy use within each group (Fig. 5). The groups represent the cold and warm seasons. The warm season includes the months May, June, July, August, September and October. January, February, March, April, November and December can be assigned to the cold season.

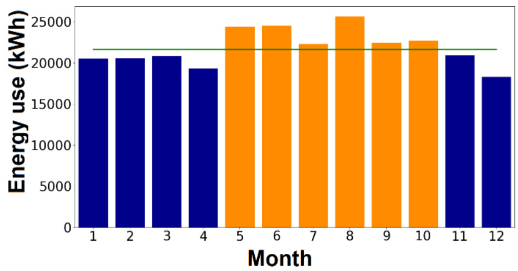

Fig. 5. Profiles of DHW energy use in the hotel divided by month and seasons

At the second step of the investigation, the days of the week were assessed for similarity. The available DHW use data was divided into separate weeks, in total 52 full weeks in the year. Within each week, all combinations of daily DHW profiles were systematically compared among themselves by student's t-test and Fisher exact test. The matrix of matching of daily profiles are shown in (Table 2).

In order to take in account the accuracy of student's t-test, Fisher's exact test, and the percentage of days in the year when the building is not in operation such as holidays, the value of error is accepted to be equal to 14%. Therefore, the days of the week that have statistically similar profiles in more than 86% of considered weeks (Table 2) were identified. Based on this information next groups of the days were identified: 1) Monday, 2) Tuesday, Wednesday, Thursday, Friday, 3) Saturday, Sunday.

Table 2 Matrix of matching daily DHW energy use profiles

	Mo.	Tu.	We.	Thu.	Fr.	Sa.	Su.
Mo.	100	42	30	30	34	22	20
Tu.	42	100	86	84	80	64	64
We.	30	86	100	92	86	78	70
Th.	30	84	92	100	90	84	68
Fr.	34	80	86	90	100	76	74
Sa.	22	64	78	84	76	100	92
Sun.	20	64	70	68	74	92	100

Detailed DHW energy use profiles aggregated by similar days of the weeks and seasons are shown in Fig. 6. The profiles demonstrate the time zones with a peak (Emax), minimum (Emin) and average (Eaverage) energy use of DHW. These time zones were identified based on average daily DHW energy use by the method explained in section 2.2. The application of the method allowed us to determine the following borders of time zones:

1) if DHW energy use is more than 29 kWh per hour, it corresponds to peak energy use;

2) if DHW energy use is less than 21 kWh per hour, it corresponds to minimum energy use;

3) if DHW energy use is between 21 kWh and 29.37 kWh per hour, it corresponds to average energy use.

The borders between time zones on Fig. 6 shown in the form of a straight lines.

Fig. 6 shows that profiles of DHW energy use in cold seasons and hot seasons are different by the shapes and maximum values of energy use. It can be seen from Fig. 6 that DHW energy use in the hot season is higher than in the cold season. This phenomenon can be explained by an increase in the number of guests in a summer period.

The analysis of profiles in Fig. 6 show than DHW energy use on Mondays is much smaller than in other days. For instance, the maximum energy use on Monday in a cold season was 40 kWh and 55 kWh in a hot season, meantime in other days it was equals 60 kWh and 70 kWh accordingly. A smaller number of visitors of the hotel on Mondays compared to other days of the week can explain these results.

The maximum energy use on working days usually occurs from 7 a.m. to 9 a.m. From 9 a.m. to 12 p.m. energy use tends to decrease, although it still remains quite high and corresponds to the pick energy use. The small spikes of energy use can also be observed in the hot season in the evening time from 21 p.m. to 23.00. Meantime, in a cold season, there is no peaks in energy use in the evening. Minimum energy use can be observed in midday and at night.

Peak energy use in weekends is shifted by one hour ahead compared to working days. The maximum energy use in weekends occurs from 9 a.m. to 11 a.m.

In general, the study shows that dividing DHW energy use profiles by season and days of the week is reasonable. The profiles obtained in this way are more informative and allow us retrieve additional information about DHW energy use in buildings.

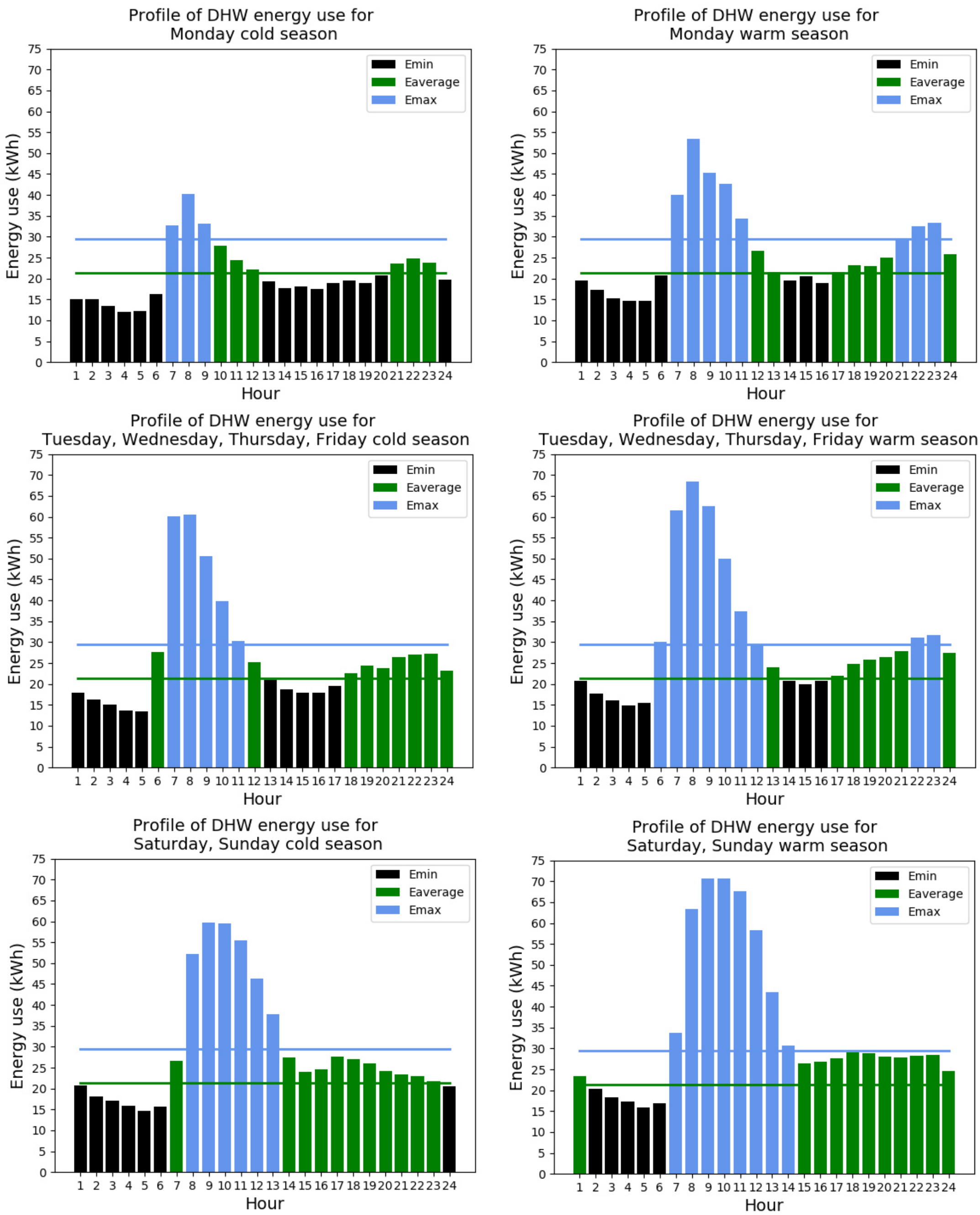

Fig. 6. Profiles of DHW energy use in the hotel divided by month and seasons

5 CONCLUSIONS

An important step in achieving energy efficiency in buildings is reducing the needs in DHW tap energy use. To solve this task we need reliable knowledge of DHW energy use in existing buildings. Analysis of DHW energy use profiles in different types of buildings is a powerful instrument for gaining appropriate knowledge.

The analysis described in this work show that the season of the year and the day of the week may influence DHW energy use. Therefore, in order to increase the accuracy of DHW energy use profiles, it is proposed to build unified profiles for months and days of the week with similar characteristics of DHW energy use.

A method, which identify the number of seasons of DHW energy use in the building and the months included in each season, is suggested. Based on student's t-criteria, the months of the year, for the hotel in this study, were divided into two groups: the cold season (January, February, March, April, November, December) and warm seasons (May, June, July, August, September, October).

Furthermore, a method for determining the time zones with peak, minimum and average energy use in daily profile of DHW energy use was applied.

For the analyzed hotel, the analysis of aggregated seasons and days of week, showed that DHW energy use in the hot season is higher than in the cold season. DHW energy use on Mondays is smaller than in other days. The maximum energy use in a working days occurs from 7 a.m. to 9 a.m., and from 9 a.m. to 12 p.m. remains high with a tendency to decrease. The results obtained in the article expand knowledge about methods of DHW energy use analysis in buildings.

Acknowledgement

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Paper X D. Ivanko, N Nord, A.L. Sorensen, H.T. Walnum, Analysis of monthly and daily profiles of DHW use in apartment blocks in Norway. *Nordic Symposium on Building Physics in Tallinn, Estonia, NSB 2020 E3S Web of Conferences,* Volume 172, 2020, 12002

Analysis of monthly and daily profiles of DHW use in apartment blocks in Norway

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Abstract. Profiles of domestic hot water (DHW) use give valuable information for achieving energy saving in buildings. In this article, analysis of monthly and hourly profiles in apartment blocks in Norway was performed. The aim was firstly to identify influencing factors on DHW use and afterwards to define typical DHW use profiles. Due to availability, two different data samples were used for monthly and hourly analysis. Monthly data from 49 apartments showed that approximately 30% of DHW was used in kitchens and the rest 70% in bathrooms. The influence of apartment sizes on DHW use was tested based on monthly profiles. Monthly profiles for three categories of apartments with 33 m^2, 51-52 m^2, and 68-72 m^2 floor area were developed. Cluster analysis allowed us to identify profiles for three groups of apartments with a typical number of residents. In addition, for comparison purpose, DHW hourly profiles in two social housings and two housing cooperatives were investigated. These profiles indicated that there was a difference in when DHW was used in these two types of buildings, with a higher daytime DHW use in social housing. Finally, the measured DHW heat use profiles are compared with the profile in the national standard.

1 Introduction

Nowadays, domestic hot water (DHW) systems are an essential part of residential buildings. They ensure a high level of hygiene and living conditions. DHW systems contribute to approximately 20% of the total energy use in buildings [1]. The projections of energy demand for residential buildings shows that DHW heat use tends to increase in the nearest future [2].

Primarily, the share of DHW energy use in Norway is growing due to the introduction of passive house solutions and technologies. Currently, these solutions reduce the energy need for heating. However, they do not affect DHW heat use. In this regard, DHW systems still have great potential for energy savings. Therefore, improving the operation and design of DHW systems is a topical issue for attaining more efficient and sustainable energy use in buildings.

Profiles of DHW and heat use are effective instruments for analysis and improvement of DHW systems performance. Monthly and hourly profiles are commonly used for design, modelling, simulations and management of DHW systems.

Many authors emphasise the importance of using accurate and reliable profiles for various purposes [1]. Application of proper DHW energy use profiles is an essential condition for accurate prediction of energy demand in buildings. The investigation [3] shows that application of profiles obtained from standards is not sufficient for accurate DHW heat use modelling in buildings.

The research toward the development of representative DHW use profiles is conducted in many countries.

The influence of DHW profiles on simulations for DHW and space heating solar combi-system in residential building is investigated in [4]. The simulations show potential for energy savings in the DHW system by applying more realistic DHW use profiles.

Profiles suitable for analysis of solar DHW systems in Canada is presented in [5]. To take variation in user's behaviour into account, the authors propose to use profiles divided by apartments with predominantly morning use, predominantly evening use, and use dispersed throughout the day. The simulations reveal that various DHW use profiles could lead to significant differences in the prediction of DHW system operation.

In Sweden, DHW use in 1,300 apartments within six years is measured [6]. These measurements are used as input for simulations. The simulations demonstrate the influence of the apartment's sizes and locations on the heat use. In addition, the authors found a strong correlation between the number of residents and DHW use. However, even within apartments with the same number of residents, a significant variation of DHW use is observed.

Analyses of one-year DHW measurements from 86 apartments with 191 occupants in Finland is performed in [7]. Representative DHW profiles for resident groups with 1, 3, 10, 31 and 50 occupants are developed. The authors

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assume that the actual profiles closest to the mean profile for each group and with similar shape are representative.

Weekdays and weekends load profiles for DHW heat use in Norwegian buildings, which use a heat supply from district heating, is investigated in [8]. For calculations, the authors use hourly measurements obtained by regular heat meters. The analysis of the profiles indicates that the DHW system efficiency should be improved through better pipe insulation.

In residential buildings, DHW is mainly used for showering and hygienic purposes, cooking, cleaning, dishwashing and laundry. Therefore, most of the existing publications report two main peaks of DHW use that occur in the morning and evening. These peaks indicate the typical time of food preparation and showering practices [9].

A number of articles propose to develop DHW profiles for apartments based on occupant activities and operating schedules for appliances (showers, baths, sinks, dishwashers etc.). Occupancy related parameters significantly affect the final energy demand in residential buildings. With the increase in the number of occupants, the relative share of DHW heat use in the total energy use for the apartment is also increasing. Mostly due to the increased DHW use, the number of occupants have a substantial impact on the heat used in residential buildings [3]. The DHW use is modelled by considering the probabilistic use of appliances in apartments in [10]. A DHW modelling approach that is coupling information about behavioural activities, energy balance models and stochastic modelling is presented in [11]. An Artificial Neural Network model for DHW energy use analysis is proposed in [12]. In this model, the occupant behaviour, appliance ownership, demographic conditions and occupancy rate are the main inputs.

Development of representative DHW profiles should be based on information gained from up-to-date data of DHW use in existing buildings. Due to the challenges in collecting and accessing statistical data about hot water and heat used in apartment blocks, the DHW use in these types of buildings in Norway is not fully investigated yet. Meanwhile, factors influencing DHW use (i.e. technical solutions, traditions, behaviour, weather condition etc.) are varying from country to country. For this reason, the profiles developed for other counties cannot be directly applied in Norway.

Investigation of both hourly and monthly data gives a deeper understanding of the process of DHW use in apartments. Traditionally, utility bills for heat and water use in residential buildings are paid monthly. Due to this fact, monthly data about DHW use could be accessed up to the apartment level. A study of monthly profiles for different apartments provides useful information on the structure of DHW use in buildings, seasonal variations, expected volumes of hot water use, and variables that have influence on DHW use. At the same time, hourly profiles are very important for system design, energy management and peak shaving. Therefore, this article aims to present an analysis of both monthly and hourly DHW use profiles in different types of apartments in Norway. For this purpose, two data samples were examined. Due to data availability, these data samples were obtained from different sources, however for similar apartment buildings.

First data sample contained data of monthly DHW use in 49 apartments in Norway. The available data had separate information about DHW use in both kitchens and bathrooms. This data sample was used for: identifying the share of DHW use in kitchens and bathrooms, investigating the seasonal variation of DHW use, analysing the influence of apartment's sizes on DHW use and developing monthly profiles of DHW use, taking the typical number of residents in apartments into account.

The second data sample contains 2-second DHW and heat use measurements in four apartment blocks. Two of these buildings belong to social housing and the other two to a housing cooperative with privately owned apartments. The measured data was applied to develop hourly profiles of DHW use for social housing and housing cooperative. Besides, the DHW heat use profiles for these types of buildings were further compared with the national standard. The main differences in these profiles were specified.

2 Description of apartment buildings

Data in 49 apartments that were used for the monthly analysis of DHW use were obtained from a company that specialised on measurements and billing of energy use in buildings in Norway. The considered apartments have the following sizes: 16 apart. - 33 m^2, 5 apart. - 51 m^2, 20 apart. - 52 m^2, 4 apart. - 68 m^2, 4 apart. - 73 m^2. For each of them, one-year data with DHW use in kitchens and bathrooms were collected in 2016-2017. The data were in liters of tapped hot water.

In addition, within the research project "Energy for domestic hot water in the Norwegian low emission society" 2-second measurements were performed in four apartment blocks. Table 2 shows the main properties of the observed buildings. Apartment blocks AB1 and AB2 are both social housing, while AB3 is part of a large housing cooperative with several blocks. AB4 consists of 4 smaller blocks. The average apartment size in AB1 and AB2 is significantly smaller than in AB3 and AB4. For all the buildings, the measurements were performed at the heating plant, giving the aggregated heat use of each block. Fig. 1 shows a principle drawing of the heating plant and measurements. In Fig. 1, the symbols for the temperature and water flow show the measurement places. In our analysis, heat losses from the circulation system were removed from the use data.

Table 1. Main properties of measured apartment blocks

ID	Area (m^2)	Number of flats	Heat source	Period of data collection
AB1	4400	96	Electric water heaters and heat pump	Oct. - Nov. 2018
AB2	2700	56	Electric water heaters	Oct. - Nov. 2018
AB3	3752	56	Electric water heaters and heat pump	Jan. – Mar. 2019
AB4	5100	86	Electric water heaters and heat pump	Mar.-Aug. 2019

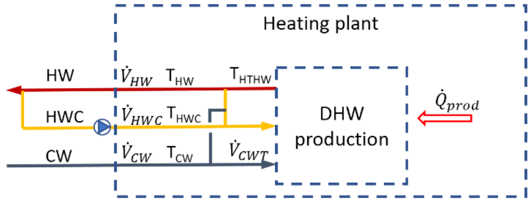

Fig. 1. Principle drawing of DHW heating plants with typical measuring points

3 Method

In this article, the analysis was primarily based on an investigation of monthly and hourly DHW use in apartment blocks. The entire approach in this study consisted of two parts: 1) identifying influencing factors of the total DHW use in apartments and analisys of monthly DHW use profiles 2) defining hourly profiles of the DHW use. Due to the availability of data and measurements, a different group of apartments were used for each of the above-mentioned analysis parts.

To identify influencing factors of the total DHW use in apartments, the DHW use data in 49 apartments were used to calculate the share of DHW used in bathrooms and kitchens for each month. In order to examine the influence of apartment size on DHW use, the monthly profiles for specific DHW use in three types of apartments with 33 m^2, 51-52 m^2, and 68-72 m^2 living areas were developed. Even though the sizes of apartments give essential information about DHW use, they do not take into account the number of people who lives there. In order to cover this drawback, hierarchical cluster analysis based on the K-means method was applied. By using this method, the groups of apartments with similar monthly DHW use were found. The applied clustering method is well known and presented in detail in [13]. The clustering was performed in Scikit-learn machine learning library for the Python programming language [14]. The number of residents in each obtained cluster was estimated based on the reference DHW use in apartment blocks per person in European standard "NS-EN 12831-3:2017: Energy performance of buildings" [15] and recommendations in [16]. In such a way, apartments with three different levels of occupancy were identified. Further, seasonal variations of DHW use were studied, taking into account apartment sizes and estimated number of people.

To define hourly profiles of the DHW use, the 2-second measurements in four apartment blocks were used. These apartments are used by social housing and housing cooperatives. The variation of DHW in different days of the week was studied through weekly profiles. Finally, the heat used for DHW in these building was compared with the Norwegian standard, "SN/TS 3031:2016: Energy performance of buildings. Calculation of energy needs and energy supply" [17], and the main differences were specified.

4 Results and discussion

This section is divided into two subsections. Section 4.1 investigates monthly DHW use in apartments of different sizes. Section 4.2 is dedicated to the analysis of hourly DHW use in social housing and housing cooperative.

4.1. Analysis of monthly DHW use in apartments

The average daily specific DHW use for different months for 49 apartments in Norway is shown in Fig. 2. The results were divided in DHW use in kitchens and bathrooms. The data showed that approximately 70% of hot water in these apartments was consumed in the bathrooms and 30% in the kitchens.

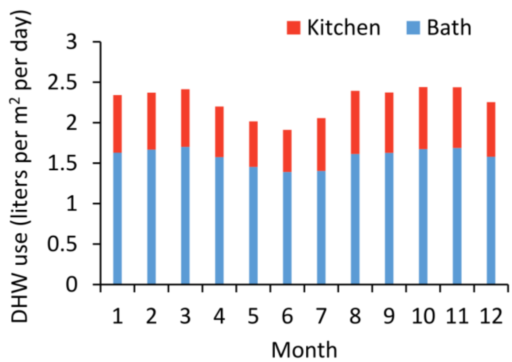

Fig. 2. Average monthly DHW use in 49 apartments

Monthly profiles in Fig. 2 display some seasonal variation of DHW use, with lower consumption from April to July, and higher in the remaining months. The decrease in DHW use in the spring/summer months may be related to the vacation time in Norway. Traditionally, the majority of Norwegian workers prefer to have vacations in July. In addition, April, May and June contain several holidays.

A more detailed investigation of monthly DHW use in the apartments showed that in some individual apartments, the DHW use decreased during the period of vacations, see June and July, while in others it increased, see Fig. 3. The two apartments in Fig. 3 with similar sizes were considered. The DHW use in Apartment 2 was higher than in Apartment 1, which can be explained by the different number of people living there.

This research indicated that a certain group of the apartment users left their apartments and travel during the holidays. Thus, these users reduced the DHW use in buildings, see Fig. 3, Apartment 1. Opposite, some people were at home during vacation time, which has the opposite effect on DHW use, see Fig. 3, Apartment 2). For this reason, the DHW use in summer months in the residential buildings in Norway were relatively uncertain and depended on how people intended to spend their vacations.

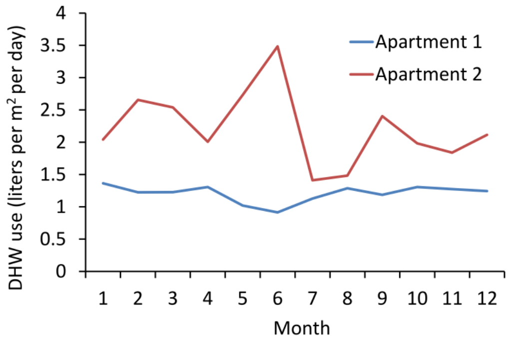

Fig. 3. Comparison of monthly DHW use of two apartments with 52 m^2 floor area

In order to estimate the influence of apartment sizes on the DHW use, the box plots [13] of average DHW use for apartments with 33 m^2 (Fig. 4), 51-52 m^2 (Fig. 5), and 68-72 m^2 (Fig. 6) floor areas were developed. Box plot is widely used method in descriptive statistics. It shows in a compact form, the median, first quartile and third quartiles, minimum and maximum, and outliers.

Apartments with 33 m^2 area show the highest average DHW use equal to 2.76 liters per m^2 per day, while the average in the 51-52 m^2 apartments is 1.78 liters per m^2, and the average in the 68-73 m^2 apartments is 2.5 liters per m^2, see Fig. 7.

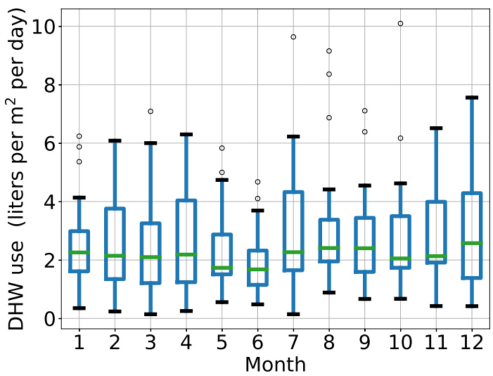

Fig. 4. Box plot of monthly DHW use in 33 m^2 apartment

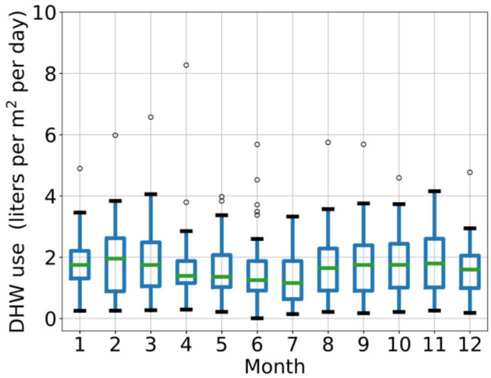

Fig. 5. Box plot of monthly DHW use in 51-52 m^2 apartments

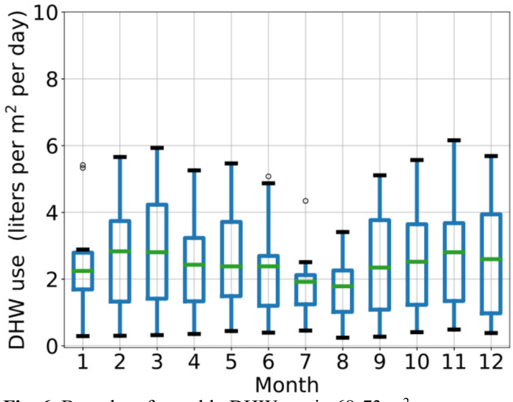

Fig. 6. Box plot of monthly DHW use in 68-73 m^2 apartments

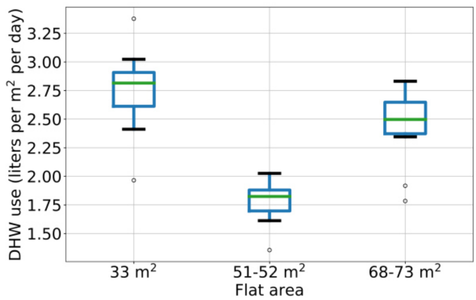

Fig. 7. Box plot of average monthly DHW use for different apartment sizes

The number of inhabitants was the main factor affecting the DHW use in apartments. However, information about this parameter was usually not disclosed. Therefore, it was proposed to find groups of apartments that have similar levels of DHW use based on cluster analysis. The assumption was that each of these clusters should represent DHW use in a group of apartments with a similar amount of people.

The clustering method showed three main clusters of the DHW use, see Fig. 8. Cluster 1 and Cluster 2 mainly contained apartments with 33 m^2 and 51-52 m^2, see Fig. 9. Fig. 9 shows that Cluster 3 included all types of apartments. Average DHW use in apartments within Cluster 1 was equal to 31 liters per day, while Cluster 2 – 76 liters per day and Cluster 3 – 167 liters per day.

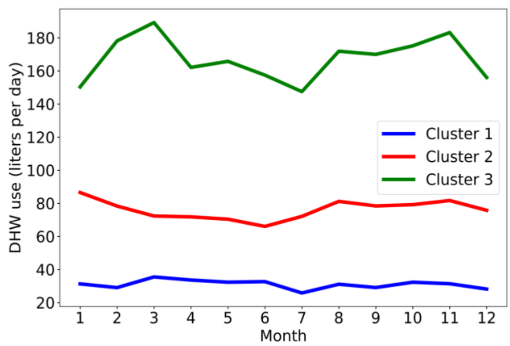

Fig. 8. Average DHW use within clusters of apartments

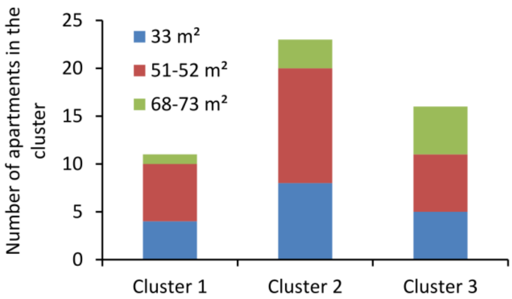

Fig. 9. Number of apartments of different sizes for each cluster

According to the European standard NS-EN 12831-3:2017: Energy performance of buildings [15], the average daily individual DHW use for residential buildings equals approximately 30 liters per person per day. This parameter is higher for Norway and reaches 40 liters per person as shown in [16]. By using this value to estimate the number of residents in the apartments, Cluster 1 might consist of apartments with only one resident, Cluster 2 apartments with two residents, and Cluster 3 families with three or more residents. However, this estimation did not take into account individual variation in DHW use, as observed in [6].

From Fig. 8, it may be noted that for all the clusters, DHW use in the cold season was higher than in the warm season. DHW use in the apartments within Cluster 3 was more uneven and showed bigger variations in DHW use. For Cluster 3, the highest DHW use was observed in November and March. There is observed significant drops in DHW use in months, which include long holidays and typical vocational time. To be able to draw further conclusions, it would be valuable to analyse DHW use in a higher number of apartments in a similar way, compared with holiday periods. This would increase the knowledge regarding seasonal variations in hot water use.

4.2 Analysis of hourly DHW use in apartment blocks

To recall, due to data availability, to identify hourly profiles of the DHW use, the other apartment buildings were used. However, building type and DHW heat use in these buildings were similar. In Fig. 10-13, the hourly DHW use for the four apartment blocks is represented as box plots. As was mentioned above, AB1 and AB2 are social housing buildings. These types of buildings are owned and managed by the state to provide affordable housing for people who need it. AB3 and AB4 are a housing cooperative, where residents normally own their apartment, representing a regular type of ownership in Norway. Fig. 10-13 display certain differences in DHW use profiles for social housing and the housing cooperatives.

In the housing cooperatives, the DHW use is mainly used from 7:00 to 22 o'clock. The increased DHW use occurs in the morning from 8:00 o'clock and lasted until 11:00 o'clock, see Fig. 12 and 13. From 13:00 o'clock to 16:00 o'clock, the reduction of DHW use could be observed. Evening peak occurred from 18:00 o'clock until 21.00 o'clock. The minimum DHW use arose at night time from 1:00 o'clock to 6:00 o'clock.

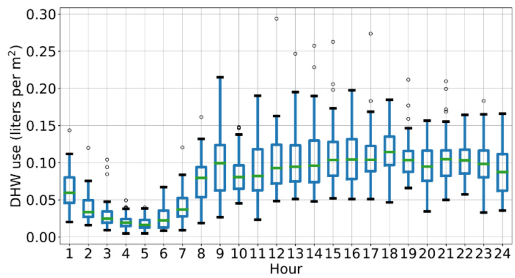

Fig. 10. Box plot of hourly DHW use in AB1 (social housing)

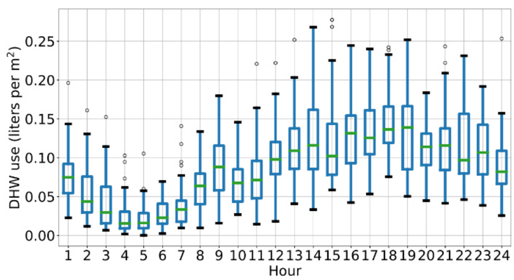

Fig. 11. Box plot of hourly DHW use in AB2 (social housing)

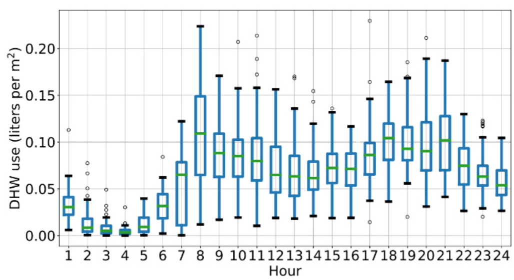

Fig. 12. Box plot of hourly DHW use in AB3 (housing cooperative)

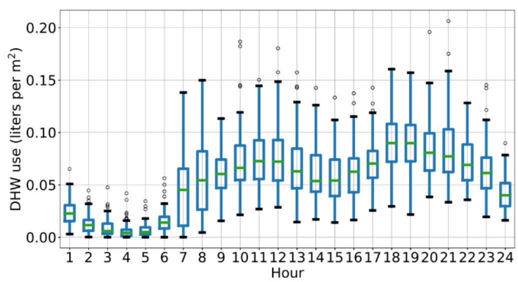

Fig. 13. Box plot of hourly DHW use in AB4 (housing cooperative)

The DHW use profiles for social housing are more even through the day and with a morning peak, about one hour later than in the housing cooperative. Evening peak in social housing took place before 20:00 o'clock. Unlike a housing cooperative, social housing profiles had increased DHW use in the daytime, from 13:00 to 16:00

o'clock. An explanation of this might be that a larger share of the residents in social housing was staying home during the day-time.

Both social housing and housing cooperative showed a weekly variation of DHW use, see Fig. 14. From Fig. 14, it is clear that the DHW use at the weekends in apartment blocks is higher than during the working days.

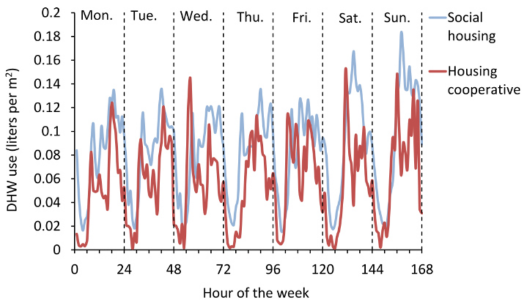

Fig. 14. Weekly average DHW for apartments in social housing and housing cooperative

The profiles of the DHW heat use for social housing and housing cooperative is shown in Fig. 15. The reference profile presented in the Norwegian technical specification, SN/TS 3031:2016: Energy performance of buildings. Calculation of energy needs and energy supply are shown in Fig. 16 [17]. The shape of the average hourly DHW heat use corresponds to the DHW use profiles in Fig. 10-13. A comparison of the measured DHW heat use profiles with the SN/TS 3031:2016 standard showed a significant difference between them. Especially, this difference was noticeable for social housing.

The standard SN/TS 3031:2016 assumes that the DHW heat use from 1:00 o'clock until 6:00 o'clock equals to zero. In considered apartment blocks, a certain amount of heat use was measured even during the night. In addition, the standard profile significantly underestimated DHW heat use during the day time, especially for the social housing.

It should be mentioned that the standard SN/TS 3031:2016 shows precisely the morning and the evening hours with the highest DHW heat use for a housing cooperative. In addition, the peak values of DHW heat use presented in the standard quite well corresponds with the measured values. Thus, we could conclude that standard SN/TS 3031:2016 gives useful information about the peak values of DHW heat use. However, the timing of heat use in the standard does not explain DHW heat use in actual apartment blocks. This reference profile is especially inaccurate for social housing.

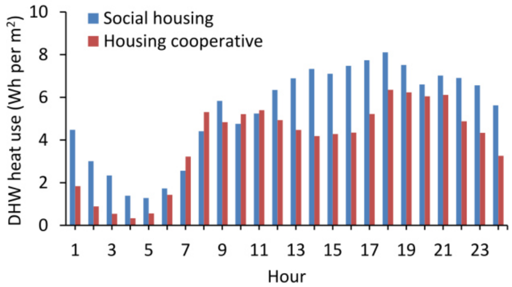

Fig. 15. Average hourly DHW heat use for social housing and housing cooperative

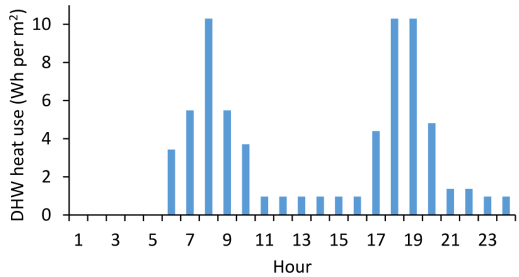

Fig. 16. Hourly profiles of DHW heat use according to the standards SN/TS 3031

3 Conclusions

Improving the performance of DHW systems is a critical issue for achieving further energy savings in buildings. Using accurate and representative profiles is essential for the design, modelling, simulations and improving the operation of DHW systems. In this article, both monthly and daily profiles for apartment blocks in Norway were investigated.

Examination of monthly profiles for 49 apartments revealed that kitchens contributed to approximately 30% of the DHW use in Norwegian apartments and the remaining 70% were used in bathrooms. The analysis of monthly data from three types of apartments with 33 m^2, 51-52 m^2, and 68-72 m^2 living area indicated that the highest specific DHW occurred in 33 m^2 apartments.

Well known, that the main influencing factor on DHW use is the number of people who live in apartments. Despite this fact, quite often, this information is not available. Apartment sizes did not allow us to estimate the number of inheritance in a particular apartment. For this reason, hierarchical cluster analysis based on the K-mean method was used to identify three clusters of apartments with different levels of DHW use. It was assumed that these clusters represented the apartments with one resident, two residents and families with three or more residents. Obtained in such a way, profiles within each cluster were studied on seasonality.

At the next step of our research, the hourly profiles of DHW and heat use for social housing and housing cooperative apartment blocks were examined. The profiles showed differences in the timing of DHW use in these types of buildings. Compared to the housing cooperatives, the social housing buildings had an increased DHW use during the daytime and not a pronounced evening peak.

The profiles of the DHW heat use for social housing and housing cooperative were compared with the reference profile presented in the national technical specification SN/TS 3031:2016 [17]. SN/TS 3031:2016 provides valuable information about the peak values of DHW heat use. However, compared to the four apartment buildings analysed, the reference profile is not accurate enough and should be considered modified. In addition, it may be relevant to take into account the difference between social and regular housing.

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Paper XI D. Ivanko, Y. Ding, N. Nord, Analysis of heat use profiles in Norwegian educational institutions in conditions of COVID-lockdown. *Submitted to Journal of Building Engineering (Status 17/2/2021: Minor revision)*

Analysis of heat use profiles in Norwegian educational institutions in conditions of COVID-lockdown

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Abstract

The COVID-19 pandemic at the beginning of 2020 has significantly affected the energy demand in Norway. In order to avoid unnecessary energy use and ensure the proper functioning of buildings, it becomes essential to have a better understanding and planning of heating use for different building types under possible pandemic conditions. Despite this fact, the literature review showed a lack of awareness about heating system performance in buildings during the COVID-lockdown. This article addressed the problems of heat use profiles analyses and scenario development for schools, kindergartens, and university campuses in Norway. The comparison of heat use profiles in these educational institutions during both the previous year and the COVID-lockdown showed that the operation of the heating system remained on the same level, although the occupancy was largely reduced. Moreover, the month after the reopening of the buildings was characterized by a remarkable increase in heat use, regardless of the warmer weather conditions. For heat use planning in educational institutions, the following scenarios were developed: Scenario 1 − operation according to a normal year setting; Scenario 2 − reducing the heating to the level of the night heat use; and Scenario 3 − using settings that were applied during the lockdown. The results showed that the application of Scenario 2 might allow us to reduce daily heat use up to 261 Wh/m^2.

Keywords: heat use in educational buildings, COVID-19 pandemic, heat use profiles, energy efficiency, scenario-based analysis, data analysis

1. Introduction

COVID-19 is a potentially fatal coronavirus disease that may cause severe problems with the human respiratory system [1]. Since the beginning of 2020, this disease has begun to spread rapidly around the world [2]. In March 2020, the World Health Organization (WHO) declared that COVID-19 outbreak is a global pandemic. Social distancing and personal hygiene are proved to be the primary measures that may help to prevent the spread of COVID-19 [3]. Therefore, in order to avoid people gatherings and crowds, most countries have imposed a partial or full lockdown of educational institutions and commercial and industrial companies. Many people were compelled to stay at home and work remotely. Such drastic changes in the behavior of energy users have a significant impact on energy demand and lead to substantial problems in the energy sector. Some crucial problems and challenges for energy systems are discussed in the publications below.

Several authors investigate the problems related to changes in energy loads of the energy system during the COVID-19 pandemic. The weekly electricity loads in the Brazilian power system and its subsystems (Northeast, North, South, and Southeast-Midwest) are compared in the periods before and after the isolation [4]. Statistically, significant decreases are observed in the levels of electricity use. The average daily electricity loads in 26 cantons in Switzerland are analyzed in [5]. In these cantons, the reduction of energy use was varying and reached a decline up to -16.5 % of the energy use compared to the previous year. The analysis of the hourly electricity loads amidst the pandemic in Ontario, Canada, is performed in [6]. The electricity loads show a noticeable curve flattening during the pandemic, especially during the peak hours of from 7:00 till 11:00 o'clock in the morning and from 17:00 till 19:00 o'clock in the evening. The effect of restrictions on energy demand in the EU countries is investigated in [7]. The EU countries have individually approached the restrictions associated with the COVID pandemic. The analysis of energy use showed that countries that imposed stricter restrictions experienced a higher reduction in energy demand.

A regression model is used to forecast the peak electric load in the Kuwaiti power grid according to climatic data [8]. The influence of the pandemic on the power grid in the Kuwaiti power grid is investigated by comparing the actual demand during 2020 with the predicted demand for the same year in normal conditions. The full lockdown resulted in 17.6% drop in energy use compared to the 2020 prediction. A comprehensive review of the electricity use in Italy, Japan, USA, and Brazil shows that the pandemic leads to uncertainty in the electricity demand and causes problems for the system operators [9]. To conclude, changes in the energy demand profiles during the COVID period creates difficulties for accurate load forecasting.

The investigation of power system operation in [10] states that during the COVID-lockdown, the total electricity demand in many countries reduced by around 10 – 30%. A set of recommendations should be introduced to overcome the current crisis and achieve a sustainable operation of the power systems. Governmental policies and actions considering the discounts for electricity bills in commercial and residential buildings in G20 countries were investigated in [11]. The authors argue that in addition to the applied discounts, it is necessary to provide energy users with guidance on energy conservation for the pandemic outbreak and especially lockdown.

The impact of corona lockdown on energy systems and pricing in Italy is evaluated in [12]. The energy generation systems in this country faced problems related to the regulation capabilities and flexibility. Combined heat and power plants were compelled to work close to the minimum. A nearly doubled increase in the ancillary market costs for system operations during the last week of March 2020 was observed in Italy [12]. The global renewable energy sector was also affected by pandemic restrictions and experienced additional difficulties and risks related to the operation of existing installations, as well as the implementation of new projects [13]. The additional expenses during the COVID-19 pandemic are related to the need for the energy systems to achieve load balancing, frequency control, and to reserve margins formation.

The negative influence of COVID-19 pandemic on the energy sector can be mitigated by ensuring the energy efficient functioning of end-users, better energy planning, quick adaptation to new conditions and introduction of proper operation measures. The deployment of demand-side management for the residential, commercial, and industrial energy users is essential to ensure a smooth operation of the power system in the pandemic period [9, 10]. Energy use profiles provide us with valuable insights to analyze changes in energy use and take actions to respond to these changes. Moreover, the regimes of work of residential energy consumers are different from non-residential consumers, and therefore pandemic affected them differently. Thus, the ability to isolate residential from non-residential electricity profiles during COVID-19 is considered as an essential aspect for planning and operation of the electricity systems. For this reason, it is necessary to understand the changes in energy use profiles related to COVID-19 that occurred in each category of energy users.

The comparison of the energy use profiles before and after the COVID-19 pandemic was performed publications [14-18]. The main results of these studies are presented below.

In a study [15], data obtained from energy management systems (HEMS) in 632 apartments in New York were used to investigate the dynamics of energy use patterns during the COVID pandemic. The research is based on the comparison of the energy use profiles in the same months between the normal time and the COVID lockdown [15]. The authors found that the morning peak of energy use was shifted later, and the previous energy decrease during daytimes became non-existent. Moreover, most of the residents are experiencing much higher electricity use than before [15].

During the COVID-19 pandemic, the energy demand in the industrial and commercial sectors showed a significant decrease, while in the residential buildings, an increase in energy use was observed [16]. For example, energy use in residential buildings in the USA rose by 6-8% [16]. Similar to the article [16], research is performed for Southeast Asia [17]. The investigation in [17] finds that the lockdown measures reduced the energy needs in the industrial sector and increased the energy demand in the residential sector. In addition, the daily energy demand in these Asian countries has been found close to the Sunday electric load curve.

The electricity load profiles for residential, commercial, and industrial consumers are respectively shown under three cases: 1) business-as-usual case without a lockdown; 2) the case of a partial lockdown; 3) the case of a total lockdown in [18]. The research in the mentioned study is performed based on data from 259 electrical energy users located in the Lagos metropolis, Africa. Compared to the business-as-usual case, no change in the percentage of electricity demand by sectors under a partial lockdown case was detected. However, under the total lockdown, the authors discover a sharp increase of electricity demand in the residential sector, a 6% decrease in the industrial sector, and almost no changes in the commercial sector [18].

Data from 3.8 million electricity users in Illinois, USA, was examined in [14]. This study shows that the onset of COVID-19 shifted weekday load profiles for residential buildings was similar to weekend profiles from previous years.

The literature review [14-18] shows that efficient energy use in buildings becomes a crucial problem during the COVID-19 pandemic. The study [19] is dedicated to the prior cases of pandemic diseases and challenges that they brought to society. It shows the results similar to publications [14-18] and emphasize that the COVID measures will lead to more attention to sustainable and energy efficient solutions in buildings design and operation. The post-COVID recovery agenda is developed by the International Renewable Energy Agency (IRENA) [20]. This report states that in the post-COVID period buildings are expected to receive the most significant share of energy efficiency investment [20].

Mostly, the articles [14-18] demonstrate that currently the existing publications are focused on the residential buildings, while research on non-residential buildings is lacking. For the educational institutions, office buildings, and other commercial buildings that experienced lockdown, it is usually assumed that the demand profiles for weekdays during the pandemic are similar to weekends of the reference week in 2019 [7]. However, the data-based evidence for energy use profiles in these types of buildings is missing.

In order to achieve efficient energy use in buildings during the COVID-19 outbreak and the post-pandemic period, it is necessary to understand and forecast the changes in energy use in the main technical systems of buildings. Out of all the technical systems in buildings in the EU, space heating (SH) and domestic hot water (DHW) are often the most significant consumers of energy. According to [21], before the pandemic, SH and DHW heat use together has accounted for more than 20% of the total EU energy demand annually. The heat use profiles in normal conditions are well established and presented in [22]. However, the building heat use has been significantly affected by the pandemic. For instance, the energy data from 352 households in a Chinese region which had a similar energy composition to the EU before the pandemic, showed a 60% increase in cooling and heating demand during the lock-down [23]. The current heat use profiles for normal conditions are not descriptive in pandemic circumstances. Nevertheless, the heat use in buildings during the COVID-19 pandemic is not studied enough, especially for non-residential buildings. Currently, there are only a few publications that give some information or recommendation for heat use in buildings in pandemic time.

The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) presents guidance [24] for buildings operation in epidemic conditions. This guidance does not recommend to completely shut off HVAC systems in a temporarily unoccupied building. It proposes to use the special "Unoccupied Mode" that maintains the building within a reasonable range of temperature and humidity conditions, while reducing energy use during the shutdown. For example, the number of operating boilers should be reduced to the minimum needed. However, to avoid further problems with the system operation, the boilers and DHW circulation systems should operate at least once per week for a minimum of 1 hour in a normal regime.

In [25], several conditions of energy use in a typical household in Serbia are considered: S1 – Reference case, S2 – Mild protection measures, S3 – Semi-quarantine measures, S4 – Complete quarantine. The numerical modelling for the household is performed in EnergyPlus. As an input for the simulation model, the occupancy profiles in the building for the considered scenarios were used. The simulations show that an increased presence of inhabitants in their households during the corona pandemic has led to an increase in heating use. In normal conditions before declaring the state of emergency, the energy use for heating in March was 3 414 kWh. However, in conditions of mild protection measures, semi-quarantine measures and complete quarantine, it could be increased to 4 509 kWh, 4 487 kWh and 4 465 kWh, respectively. In total, heating energy demand reached up to 62% of the total demand [25].

Our study aimed to improve the existing knowledge about heat use in buildings in Norway during the period of the COVID-19 pandemic. The literature review showed a lack of awareness about the changes in heat use in non-residential buildings. Among non-residential buildings, the performance of educational institutions was highly affected by the pandemic. Therefore, this research was focused on the analysis of heat use in educational institutions: schools, kindergartens, and universities. First, our study compared profiles in buildings during the COVID-lockdown and the post-lockdown period with the profiles obtained before the pandemic. The second part of the study was devoted to the development of scenarios for heat use in buildings in conditions of the pandemic lockdown. The following scenarios were considered: 1) Scenario 1 − Modelling based on behavior in a normal year (i.e. the previous year), 2) Scenario 2 − Modelling based on heat use in night hours, 3) Scenario 3 − Modelling based on the current settings that were used in the buildings during COVID-lockdown. The proposed scenarios represented the different settings for the heating systems and gave important information for further efficient utilization of heating systems in buildings. Such a study creates the basis for achieving energy saving in the educational building in Norway.

The paper was structured as the following. Section 2 introduces the methods for the scenarios-based modelling of heat use during the COVID-19 pandemic. Section 3 explains the main characteristics of the buildings that were used for the analysis in our study. In Section 4, the methodology was implemented on the real data, and the main results of this investigation were presented. The profiles of heat use in periods before the pandemic, during the COVID-lockdown, and the post-lockdown were compared. The adequacy of heating systems settings in buildings during lockdown was checked. The scenarios for heat use in Norwegian educational buildings were proposed. Finally, the limitations and conclusions of the study were highlighted in sections 5 and 6.

2. Methods

This chapter consists of three subsections. The subsections represent the methods for developing scenarios of heat use in buildings during the pandemic. Subsection 2.1 considers Scenario 1 when the settings of the heating system did not change and remain the same as for the normal year. Subsection 2.2 shows Scenario 2, where the heating system was set to the night heat demand of the normal year. Subsection 2.3 shows Scenario 3 when the settings that were applied during the lockdown in March-April 2020 were used for the entire year heat use prediction.

2.1. Scenario 1 - Modelling heat use for based on behavior in a normal year

When the building is operating in a regular regime, not affected by unexpected changes in occupancy, the outdoor temperature may be treated as the main factor that explains the variation of heat use in buildings [26]. The model that expresses the relationship between the heat use in an observed building and the outdoor temperature is called the Energy Signature Curve (ESC) [27].

The ESC is widely used for energy planning in buildings [28]. Usually, the ESC contains two sub-models divided by the change point temperature (CPT). The CPT is a critical temperature that sets the boundary between the start and the end of the heating season. Piecewise regression is a method that can be used to build the ESC model. By piecewise regression method, the two separate sub-models for ESC are identified by using the following:

$$f(x) = \begin{cases} \beta_0 + \beta_1(x - CPT) + \varepsilon & \text{If } x < \text{ CPT} \\ \beta_0 + \beta_2(x - CPT) + \varepsilon & \text{If } x > \text{ CPT} \end{cases} \tag{1}$$

where $f(x)$ is a model for the ESC, x is the outdoor temperature, β_0, β_1, β_2 are the coefficients of the piecewise model, and ε is the residual error.

It is well known that heat use in buildings also varies depending on days of the week and hours of the day [22]. Due to the diverse schedules of work, in working days at hours when the main activities are held, the heat use in educational buildings is much higher comparing to the rest of the time. For this reason, in order to plan the heat use in a regular regime, we developed the separate ESC models for each hour of the weekdays and weekends. In such a way, based on the data obtained for 2019, we developed the 48 ESC models that explained how the heat use in a building would behave if the settings of these considered buildings remain the same as before COVID-19 pandemic.

In order to formulate heat use in Scenario 1, the outdoor temperature data for the typical cold and warm meteorological years (TMY) were applied as an input to the ESC models. The temperature data for the typical meteorological years for different locations may be found at the website of the European Commission information system [29]. The temperature data is produced by choosing each month with the most "typical" conditions out of the last 10 years [29]. By this means, using the typical cold and warm temperatures allowed us to obtain expected boundaries of heat use for each hour of the typical year in Scenario 1 (i.e. for normal conditions when no changes were made in the operation of the building heating system).

2.2. Scenario 2 − Modelling based on hours of night heat use

Compared to Scenario 1, Scenario 2 considered better operation settings for the heating system during the lockdown. In this scenario, it is assumed that during the lockdown, the buildings' heat use should be kept at the level of night heat use under the normal pre-pandemic conditions. In the educational institutions, the lowest heat use can be usually observed at the night time from 1:00 o'clock to 5:00 o'clock in working days, when there are no people in buildings and the heating system is working with the minimum energy load required to maintain the lowest acceptable temperatures.

In order to express the possible reduction of heat use in the buildings, the ESC model based only on nighttime heat use was developed. After that, in a similar way to Scenario 1, the ESC model was applied to the outdoor temperature data for the typical cold and warm meteorological years. In such a way, possible boundaries of the heat use for each hour of the typical year in Scenario 2 were obtained (i.e. for conditions when the heating system was operating at the night level).

2.3. Scenario 3 − Modelling based on current settings that were used in the buildings during COVID-lockdown

Scenario 3 was intended to explain how building heat use would behave if the settings that were actually applied to the heating system during the COVID-lockdown in Norway would be continuously used to the typical year. Scenario 3 was developed based on the average monthly heat use that was observed before and during the COVID-19 pandemic. The flowchart of the algorithm applied to Scenario 3 is shown in Fig. 1.

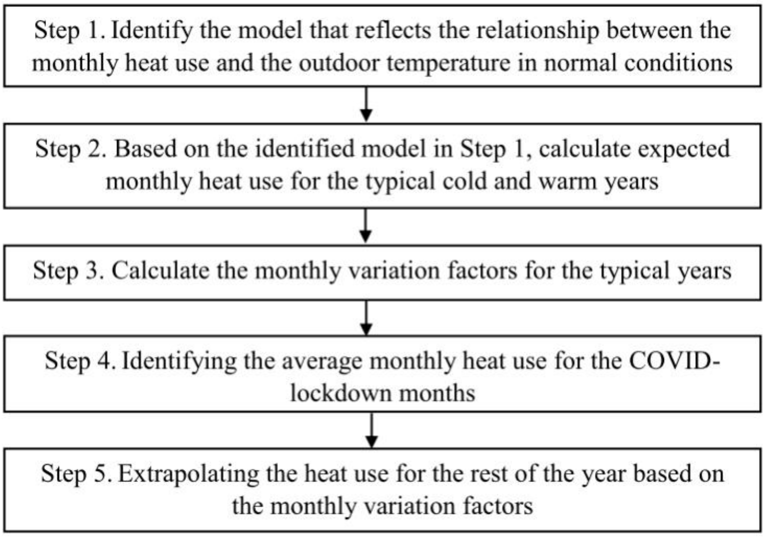


Fig. 1. Flowchart for the algorithm for determining the heat use in Scenario 3

The detailed algorithm for determining boundaries of the heat use under Scenario 3 was as the following:

Step 1. Identify the model that reflects the relationship between the monthly heat use and the outdoor temperature in normal conditions

It is well known that monthly heat demand in buildings varies throughout the year due to changes in the outdoor temperature [28]. The average monthly heat use and the outdoor temperature are linearly dependent as stated in [30]. In order to explain these relationships, a linear regression model was developed based on data from 2019.

Step 2. Based on the identified model in Step 1, calculate expected monthly heat use for the typical cold and warm years

At this stage, the average monthly outdoor temperatures for typical years were used as the input to the regression model (see Step 1). Thus, the values of the expected monthly heat use for a typical cold and warm years were obtained.

Step 3. Calculate the monthly variation factors for the typical years

In accordance with the expected monthly heat use for a typical year, the monthly variation factors for the heat use was calculated as:

$$K_i = E_{t.i}/\bar{E}_t \tag{2}$$

where K_i is the monthly variation factors for i-th month, $E_{t.i}$ is the expected heat use for i-th month of the typical year, $\bar{E}_t$ is the average monthly heat use for the typical yearly.

Step 4. Identifying the average monthly heat use for the COVID-lockdown months

Relying on data in 2020, the actual monthly heat use when the COVID-19 lockdown occurred were identified. The analysis showed that the difference between the monthly outdoor temperatures in March 2020 and the typical warm year was only 0.4 K. On the contrary, in the outdoor temperature in 2020 April was closer to the cold year with the temperature difference of 1 K. For this reason, it was assumed that heat use in March for a typical warm year was equal to heat use in March 2020, and heat use in April for a typical cold year was equal to heat use in April 2020.

Step 5. Extrapolating the heat use for the rest of the year based on the monthly variation factors

By using the monthly variation factors, the average monthly heat use when the COVID-19 lockdown occurred were extrapolated for the typical cold and warm years. In such a way, we obtained boundaries of the average monthly heat use in Scenario 3 (i.e. for conditions when the heating system was expected to operate under settings that were used in the buildings during COVID-lockdown).

3. Description of the observed educational buildings

The investigations in this article were performed based on data obtained from educational institutions located in Trondheim, Norway. University buildings are presented by the Geology and Mineral Resources Engineering building at the campus of Norwegian University of Science and

Technology (NTNU). This building was built in 1953 and it underwent several renovations afterwards. It has an area of 3 516 m^2. A more detailed description of the buildings properties and energy use at the entire NTNU campus are given in [31]. The heat use data for this building were collected from the energy management system of NTNU. The information of the heat use in eight kindergartens and 12 schools were obtained from the energy monitoring platform of the Trondheim municipality. Among these schools, nine schools are for junior pupils, two schools are secondary schools, and one is the mixed school. The area of kindergartens are within 779 - 2 086 m^2, and the area of the schools are within 3 206-8 449 m^2. All the buildings in the analysis are using district heating system (DH) as the main heating supply carrier. In order to compare buildings of different characteristics, the average heat use per heating area (per m^2) was used as a physical indicator.

The influence of weather conditions on heat use was considered in the investigation. For this purpose, data obtained from the nearest meteorological station located in Trondheim were used [32].

4. Results

This section is divided into two subsections. The analyses of heat use profiles before and during the COVID-19 restrictions is given in Section 4.1. The several scenarios for heat use in the educational institutions are shown in Section 4.2.

4.1. Analysis of heat use profiles in educational institutions before and during the COVID-lockdown

Norway is among the countries that had imposed strict restrictions when the COVID-19 pandemic began to spread in early 2020. One of these restrictions was the temporary lockdown of educational institutions. Following the recommendations of the government, schools and kindergartens were closed from March 13th to April 23rd 2020. The universities in Norway also stopped their regular operation starting from March 13th. Unlike schools and kindergartens, classes at the university buildings were resumed only from August 2020. However, a significant share of employees returned to physical presence on campuses in May 2020. Accordingly, this chapter is focused on comparing heat use in March, April, and May 2019 and 2020. In addition, in our investigation, March and April included only days when the lockdown was imposed.

Energy use profiles are a powerful instrument that allow us to display the changes in heat use at different time intervals. In our work, the profiles were used for the analysis of heat use variability before and during the COVID-19 pandemic. Although the outdoor temperature influence heat use [28], it was decided to compare the real profiles rather than the temperature adjusted values in this work. This enables us to focus on real data without making any biased suggestions. The temperature adjustment of heat use was introduced in the scenario analysis (See Chapter 4.2). Nevertheless, in the analysis of the profile, the outdoor temperatures in 2019 and 2020 were considered. It was considered that the average outdoor temperature in March 2019 was 0^{o} C, and in March 2020 it was 1.7^{o} C. In April 2019, the outdoor temperature was 7.2^{o} C, and in April 2020 it was 3.9^{o} C. Whereas in May 2019 it was 7.9^{o} C, and in May 2020 it was 6.4^{o} C. As it may be noted, April and May in 2020 had slightly colder temperatures than in 2019, while March a bit warmer.

Since weekdays and weekends have different patterns of heat use, their profiles were considered separately. The average daily heat use profiles for kindergartens, schools, and university campus of 2019 and 2020 are compared in Fig. 2 - Fig. 4, respectively. In Fig. 2 - Fig. 4, WD denotes working day and WE denotes weekend, and the dashed lines stand for 2019 and the solid lines for 2020. Typically, on weekdays, the main heating load follows the opening hours of the educational institutions. The heat use generally increased from 7:00 to 16:00 o'clock with the peak of the heat use at 9:00 o'clock, and a significant heat reduction persists from 20:00 to 6:00 o'clock next morning. From Fig. 2 - Fig. 4, it may be observed that the shape of the heat use profiles before and during the pandemic in educational institutions remained almost the same. The profiles show that for kindergartens, this working schedule did not change during the COVID-lockdown in 2020. For schools, there was a slight change of the peak load that was shifted backwards by an hour in March and April 2020 and forward by an hour in May 2020. For the university campus, the peak heat was moved backwards by an hour in April and two in May, while much lower heat demand during the off-work time in March 2020 was noticed.

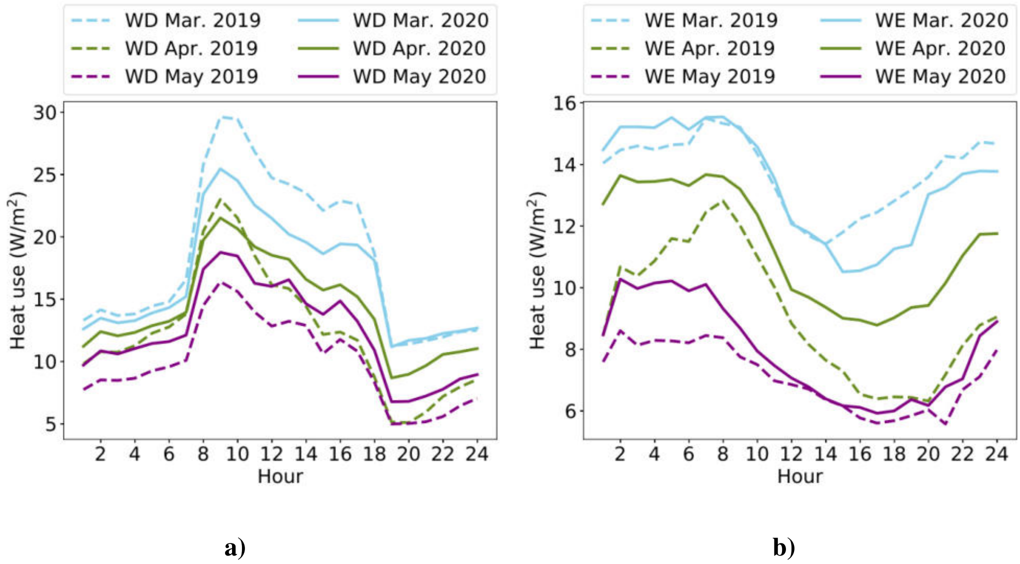


Fig. 2. Heat use profiles for kindergartens, where: a) profiles for weekdays, b) profiles for weekends

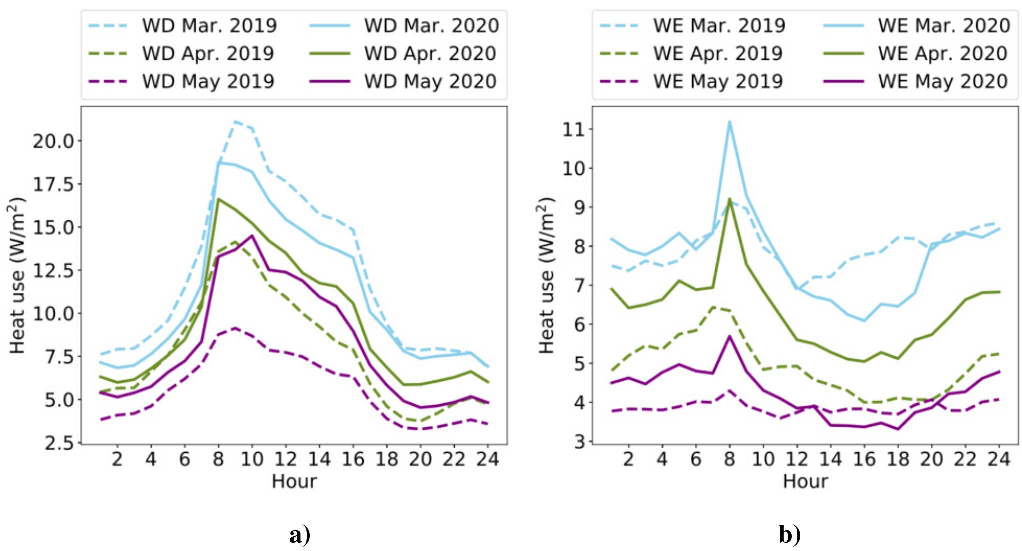
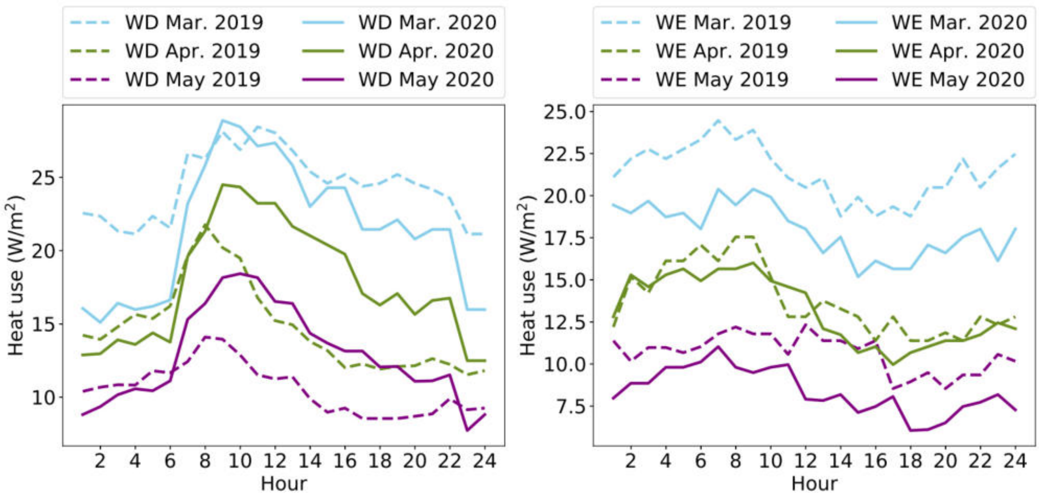


Fig. 3. Heat use profiles for schools, where: a) profiles for weekdays, b) profiles for weekends



a) **b)**

Fig. 4. Heat use profiles for the university campus, where: a) profiles for weekdays, b) profiles for weekends

In Norway, teaching activities are not carried out in educational institutions on weekends. Thus, the heat load on weekends was much lower than on weekdays and is more in line with the heat load on weekdays at night. In Fig. 2 - Fig. 4, it may be noted that ehe minimum heat use on weekends was from 12:00 to 20:00 o'clock. It is likely that during this period, the heating system was operating at the minimum load, and the indoor temperature in the building was maintained mainly by thermal inertia.

Fig. 2 a)- Fig. 4 a) show that during the weekdays in March 2020 heat use was reduced compared to the same period of 2019. However, unlike the assumptions made in [7], the profiles in the working days 2020 were not identical to the weekends. One of the reasons for this could be that some institutions may have operated during the COVID-lockdown. In order to support parents who are working in the critical positions such as medical systems, transportation, police stations, and others, kindergartens and junior schools (See Appendix Fig. A1) remained open during the pandemic. On the other hand, our analysis also showed that some buildings were using energy inefficiently and did not reduce heat use, regardless of the transition to distance learning. For example, the profiles for the secondary schools (See Appendix Fig. A2) showed that they did not decrease heat load in the buildings.

Despite the lockdown, in April 2020, the heat use was slightly higher than in April 2019. This fact can be explained by several reasons. Firstly, from April 18th to 22nd 2019, there were public holidays in Norway, and most educational buildings were closed in these days. The second reason is that April 2019 was warmer than April 2020, which led to less energy use in 2019. The third reason is preparation for buildings reopening at the end of April 2020. For example, it required cleaning and disinfection work, and testing of the heating system performance, which resulted in increased heat use.

After buildings reopening in May 2020, we can observe an increased heat use comparing to May 2019. This phenomenon may be associated with an increase in DHW use for regular disinfection of buildings and personal hygiene.

For many buildings, the profiles showed that the operation of heating systems during lockdowns should be changed to be more efficient. In order to achieve this goal, it is therefore necessary to develop recommendations and scenarios for operation of heating systems in various conditions.

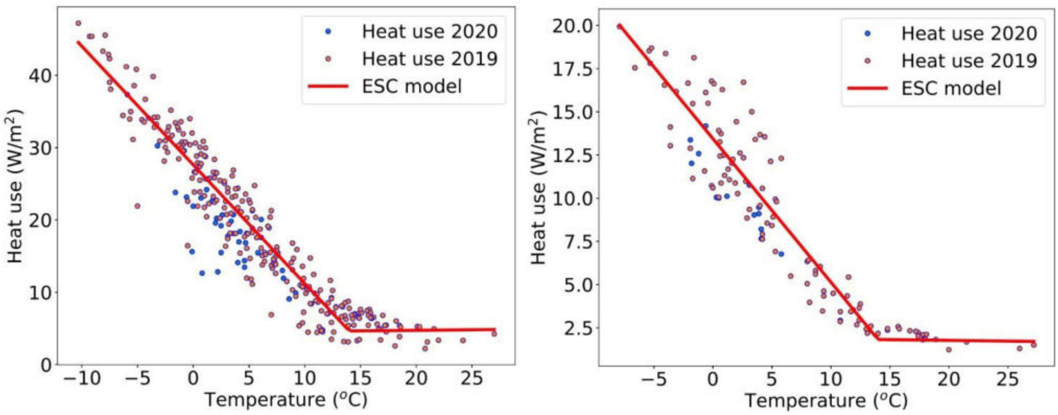
4.2. Analysis scenarios of heat use in educational institutions

This chapter explores three scenarios for the operation of the heating system in educational institutions during the pandemic. All the scenarios were developed by employing real statistical data obtained from schools, kindergartens and university campus.

Scenario 1 investigated the heating system operation in the same regime as before the pandemic. This scenario was developed based on the method presented in Section 2.1. The ESC models for every hour on weekdays and weekends were developed with the data for 2019. Thus, the heat use for each building type was represented by 48 ESC models. For all these ESC models, the CPT of 14 $^{\circ}$ C showed the best approximation.

An example of the ESC models for the heat use at the 13-*th* hour in kindergartens is shown in Fig. 5. For a more detailed analysis, the actual heat use in 2019 and during the lockdown in 2020 was also plotted in Fig. 5. As it may be seen from Fig. 5, the heat use during the COVID-lockdown lies close to the pre-pandemic data and models. This fact proves that the operation of heating systems in kindergartens remained practically unchanged during the lockdown in 2020. For other educational institutions, the ESC models demonstrated similar results.

It should be noted that at certain hours on weekdays, the line after CPT had a slight positive slope (See Fig. 5 a)). From a theoretical point of view, with an increase in outdoor temperature, heat use should decrease. This positive slope can be explained by the use of the cooling system during the hot days.



a) **b)**

Fig. 5. ESC models for 13-th hour for kindergartens, where: a) ESC for weekdays, b) ESC for weekends

Table 1 shows that the application of 48 ESCs allowed us to obtain quite accurate models for normal conditions of the heat use. For kindergartens and schools, the R^2 was around 0.94, while for the university campus R^2 was 0.83, meaning that all met the requirement of ASHRAE guidelines for achieving a satisfying regression model. In order to develop Scenario 1, the outdoor temperatures for the typical cold and warm meteorological years were applied as the input to the 48 ESC models. In such a way, the possible boundaries of the heat use in buildings for Scenario 1 were identified.

The boundaries of the heat use in Scenario 1 for the schools, kindergartens, and university campus are shown in Fig. 8 - Fig. 10. The potential of energy savings can be assessed by comparing Scenario 1 with the other scenarios that represent more efficient settings of the heating systems.

Table 1. Accuracy of the model based on 48 ESC for Scenario 1

Building type	CPT (° C)	R^2	MAE	MSE
Kindergarten with DH	14	0.94	1.04	4.38
Schools	14	0.94	1.68	11.15
University campus	14	0.83	2.28	20.03

Scenario 2 assumed that during the lockdown, the heat use in the buildings should be kept at the level of night setting under normal conditions. The heating system operation under such conditions may be explained by the ESC model determined based on the heat use in 2019 at the nighttime. An example of the ESC model for the kindergartens is shown in Fig. 6. This model represents periods when the heating system was operating at the minimum load due to the low occupancy in the buildings.

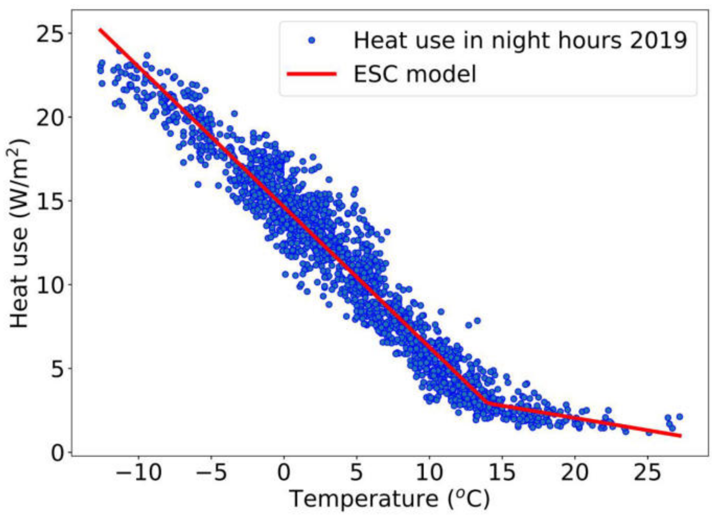


Fig. 6. ESC for kindergartens for night settings of heat use

The accuracy criteria for the ESC models in Scenario 2 are given in Table 2. They indicated that the models explained the heat use reasonably well. For instance, for the kindergartens R^2 = 0.93, for the schools R^2 = 0.88, and for the university building R^2 = 0.78. The typical cold and warm temperatures were applied to the ESC models in order to identify possible boundaries of heat use in Scenario 2. The heat use over the entire year for this scenario is presented in Fig. 8 - Fig. 10. Comparing to Scenario 1, Scenario 2 presented a reasonable approach to reduce heat use during the lockdown when buildings are not occupied.

Table 2. Accuracy of the ESC models based on night heat use for Scenario 2

Building type	CPT (° C)	R^2	MAE	MSE
Kindergartens	14	0.933	0.83	1.99
Schools	14	0.883	0.66	1.29
University campus	14	0.78	2.28	16.27

Scenario 3 demonstrated the average monthly values of the heat use in conditions when the heating system was operated under the settings that were really applied during the COVID-lockdown in March-April 2020. Similar to the previous scenarios, Scenario 3 was adjusted with the typical cold and warm years. For the development of Scenario 3, the monthly heat use model for 2019 was determined. The study revealed that the relationship between the average monthly heat use in educational buildings and the outdoor temperature could be described by a linear regression model, as shown in Fig. 7. Table 3 shows the validation criteria for the monthly heat use models. The R^2 criteria in Table 3 were from 0.94 to 0.98. These values indicated that models were accurate enough to be used for the investigation.

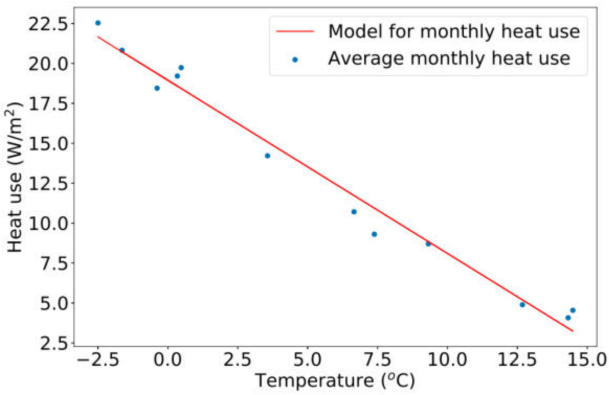


Fig. 7. Monthly model of heat use for kindergartens

Table 3. Accuracy of the monthly heat use model for Scenario 3

Building type	R^2	MAE	MSE
Kindergartens	0.98	0.87	0.87
Schools	0.97	0.56	0.58
University building	0.94	1.85	5.85

The average monthly outdoor temperatures for typical cold and warm years were used as the input to the model for Scenario 3. In such a way, the expected monthly heat use for typical years was determined. After employing Equation 2, the monthly variation factors of heat use were identified. The variation factors for the typical cold and warm years are presented in Table 4 - 5.

Table 4. Monthly variation factors for a typical warm year

Building type	Month											
	1	2	3	4	5	6	7	8	9	10	11	12
Kindergartens	2.1	1.63	1.42	0.9	0.66	0.6	0.35	0.29	0.41	1.14	0.98	1.48
Schools	2.22	1.7	1.48	0.9	0.62	0.56	0.28	0.21	0.34	1.16	0.98	1.54
University building	2.35	1.78	1.53	0.88	0.59	0.51	0.2	0.13	0.27	1.17	0.98	1.59

Table 5. Monthly variation factors for a typical cold year

Building type	Month											
	1	2	3	4	5	6	7	8	9	10	11	12
Kindergartens	1.83	2.02	1.84	1.14	0.64	0.27	0.23	0.3	0.41	0.82	1.20	1.27
Schools	1.93	2.14	1.94	1.16	0.6	0.18	0.14	0.21	0.34	0.79	1.22	1.29
University building	2.03	2.27	2.04	1.18	0.55	0.1	0.06	0.13	0.27	0.78	1.24	1.33

The monthly variations factors present the seasonality of the heat use. They showed that the highest heat use in the educational buildings occurred in January, March, and December. The lowest heat use was observed in the summertime, when space heating system was not used, and DHW use reduced due to summer holidays. For a typical cold year, the difference between the heating season and the summer months was more significant than for a typical warm year. This phenomenon may be explained by the fact that the heat use was significantly affected by the outdoor temperature and the DHW use due to the colder inlet water temperature. Therefore, the warmer outdoor temperatures caused lower heat use in buildings and vice versa.

The boundaries of the heat use under Scenario 3 for schools, kindergartens, and the university building are presented in Fig. 8 - Fig. 10. Scenario 3 indicated also months that have the highest variation of the heat use between the typical cold and warm year. Among these months January, October, and December were the most noticeable ones, which may be seen with the large shadowed squares in Fig. 8 - Fig. 10.

Scenario 3 was created using the monthly average values, and therefore, it was not as accurate as Scenarios 1 and 2 with the hourly values. This issue is discussed in Section 5. However, when considering the average monthly values, Scenario 3 would require higher heat use than Scenario 2, because it did not follow the advantageous energy-saving setting of the heating system.

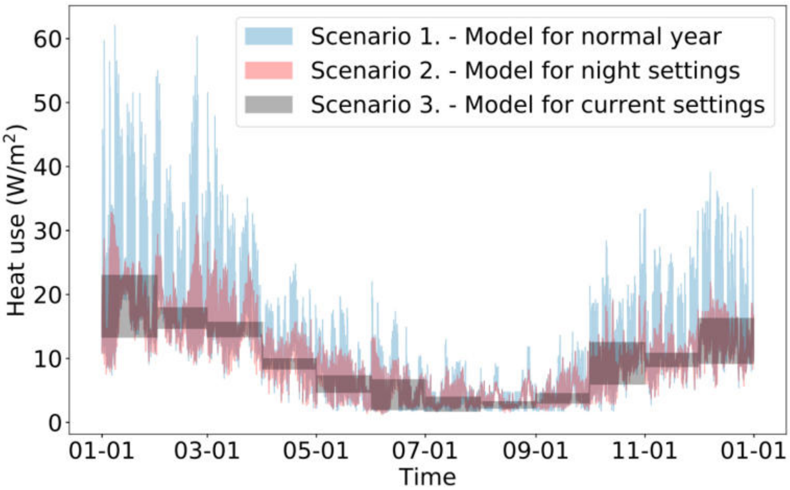


Fig. 8. Three scenarios for the heat use in kindergartens

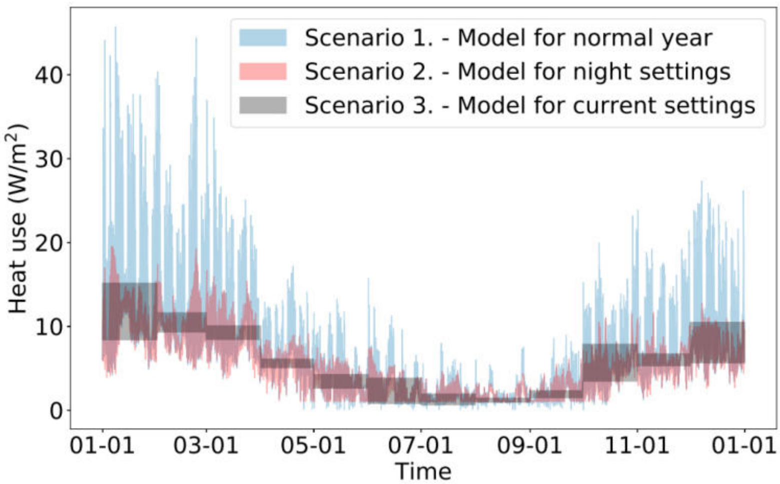


Fig. 9. Three scenarios for the heat use in schools

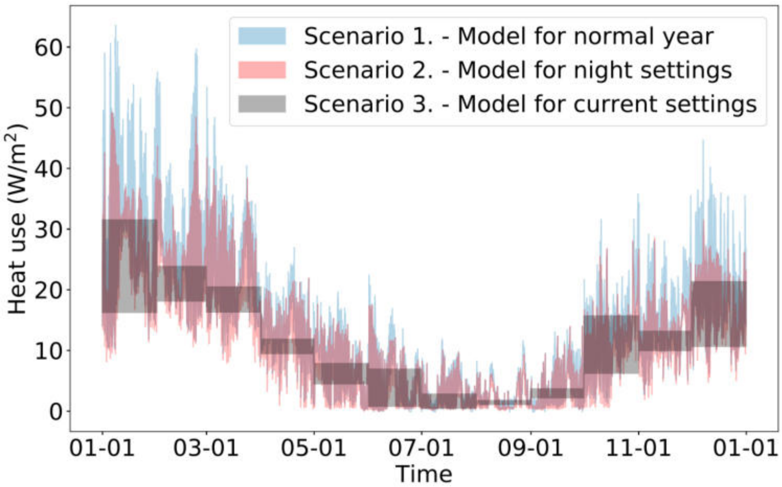


Fig. 10. Three scenarios for the heat use in the university building

The above analyses showed that the application of the night setting for the whole day, see Scenario 2, might reduce the daily heat use up to 54% compared to the settings when the heating system was working in the normal conditions, see Scenario 1. For kindergartens, it might be reduced up to 261Wh/m^2, for schools – 236 Wh/m^2, and for university building –248 Wh/m^2. This fact indicates that there is a significant unrealized potential for energy conservation during lockdown. By applying the proper setting of the heating system during a pandemic is expected to reduce energy use and save money.

5. Discussion and limitations of the study

The COVID-lockdown in the educational institutions in Norway lasted for about two months. In this regard, the amount of the data collected over this period was limited for a comprehensive analysis. The comparison of the heat use profiles in this work was performed only for March, April, and May. The analysis of the annual data would be more useful and provide a better understanding of changes in the heat use. Due to the lack of data, it is challenging to forecast the heat use for the entire year. Furthermore, due to restrictions that were gradually imposed, the patterns of the heat use may be changed several times during and after the lockdown.

For this reason, this work focused on developing different heat use scenarios during a pandemic. These scenarios were adjusted to the outdoor temperatures of the typical cold and warm meteorological years. Typical temperatures are an approximation for the last 10-years and therefore may differ from the actual temperatures in subsequent years. Accordingly, they can be used only for estimation of possible boundaries of heat use in buildings rather than accurate forecasting. Scenarios 1 and 2 were developed based on actual heat use for the entire 2019. No noteworthy assumptions were made in these scenarios. Contrarily, Scenario 3 was based on monthly heat use in March and April 2020 that was extrapolated for the typical cold and warm years. Such extrapolation was based on several assumptions. First, it was expected that monthly variation factors identified based on the data from 2019 would be applicable for the pandemic conditions. Despite the consistency of this assumption, it is impossible to confirm it with the available data. The second assumption used the fact that the monthly outdoor temperatures in March and April 2020 were close to temperatures for the same month in the typical years. However, even due to minor differences in the temperatures, the particulate inaccuracy of Scenario 3 might occur. For this reason, if the additional data could be collected, further work shall be performed for improving Scenario 3. In addition, better scenarios may be identified.

The analyzed buildings in this study are using DH as the main heating supply method and electricity for electric appliances. Meanwhile, there are also many Norwegian buildings having electricity as the main energy supply method, including electric heating without submeters. It would be interesting to investigate the energy changes of these buildings during the lockdown or other circumstances in further research.

6. Conclusions

The COVID-19 pandemic poses significant challenges to the energy sectors both in Norway and many other countries. These challenges are primarily related to fluctuations in energy use of buildings caused by restrictions that aim to stop spreading of the infection. The operation of educational institutions was significantly affected by lockdown in March-April 2020 and other restrictions. Understanding the changes in energy use triggered by the pandemic is essential for further energy planning, avoiding excessive energy use, and ensuring the proper operation of buildings. Among all technical systems in buildings, the heating system is the biggest energy user in Norway. Despite this fact, the literature review showed that the operation of heating systems and the heat use in educational buildings during and after the COVID-lockdown is not investigated enough yet. This article highlights the issue of the analysis of the heat use profiles and scenario development for schools, kindergartens, and university buildings in Norway.

Many publications assume that during the lockdown, the operation of educational institutions would follow the weekend patterns. However, our research rejected this hypothesis. The investigation found that the shape of the heat use profiles on weekdays before and during the pandemic remains almost unchanged and differs significantly from the weekend profiles. The profiles revealed that in March 2020, the heat use was lower than in the same period of 2019. In April 2020, the heat use was slightly higher than in April 2019. Differences between the profiles in March and April were mainly influenced by changes in the outdoor temperature, instead of changes in the heating system settings. Therefore, it can be stated that during COVID-lockdown, the energy system in many buildings was operated inefficiently. After the educational buildings were reopened in May 2020, the profiles showed an increase of the heat use. Such an increase might be explained by introducing strict requirements for regular buildings' disinfection and personal hygiene.

The short-term lockdown in Mach-April 2020 did not allow us to collect enough statistical data about the heat use. The available data were not adequate for accurate prediction of the heat use. For this reason, instead of performing model prediction, this article suggested scenario-based modelling for possible settings of the heating system. The following scenarios were developed for educational institutions: 1) Scenario 1 − Modelling based on the settings for a normal year, 2) Scenario 2 − Modelling in accordance with night settings of heat use, 3) Scenario 3 − Modelling based on settings that were used during the lockdown. All the scenarios were adjusted with the outdoor temperatures of the typical cold and warm years. The ESC method showed high accuracy in modelling Scenarios 1 and 2. Scenario 3 was developed by monthly variation factors of the heat use. These factors were used in order to project the seasonal variations of the heat use in the COVID-lockdown conditions. The proposed scenario can be used for planning the heat use and estimating the potential energy savings. For example, the analysis showed that application of night setting, Scenario 2 might allow us to reduce daily heat use up to 54% compared to the normal settings, Scenario 1. For kindergartens, it might be reduced up to 261 Wh/m^2, for schools − 236

Wh/m^2, and for university building – 248 Wh/m^2. The methods and outcomes of the study may be applied to similar types of buildings when temporary lower attendance or shutdown will appear.

Acknowledgement

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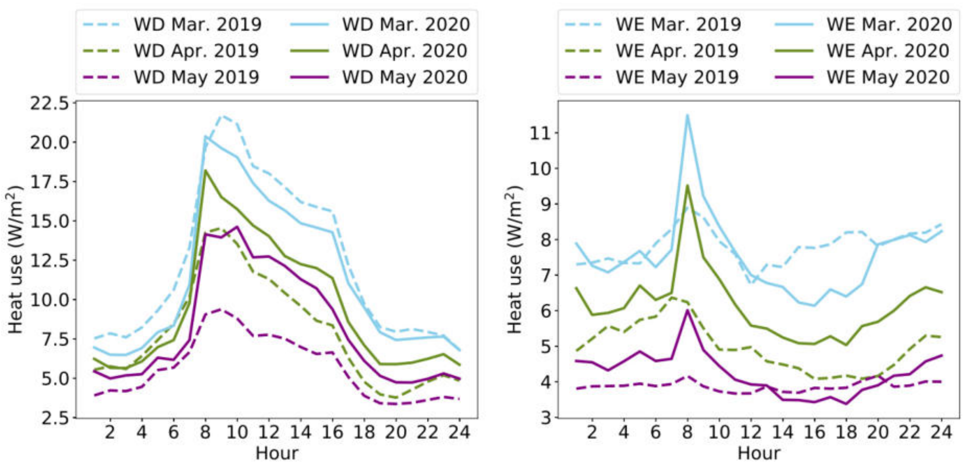
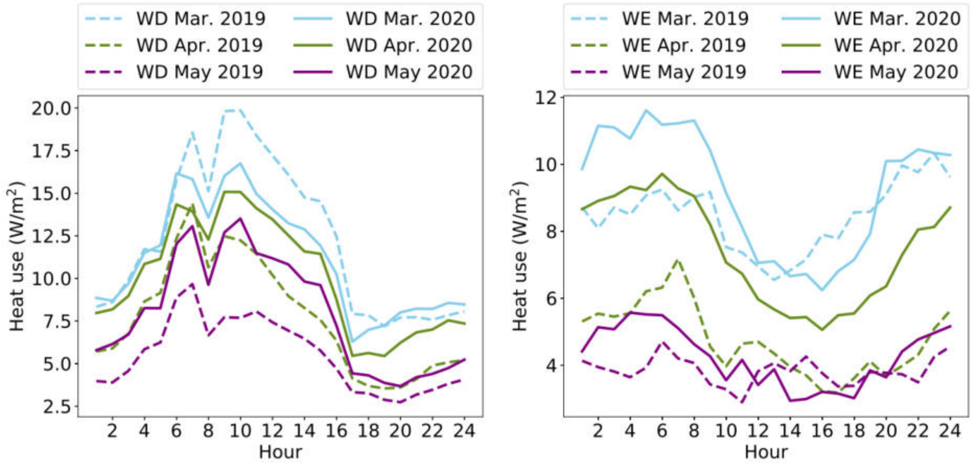
Appendix A



a) **b)**

Fig. A1. Heat use profiles for junior schools, where: a) profiles for weekdays, b) profiles for weekends



a) **b)**

Fig. A2. Heat use profiles for secondary schools, where: a) profiles for weekdays, b) profiles for weekends

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