Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Engineering
Department of Energy and Process Engineering

Maria Solomon Langeland

Parameters relevance in data-driven models for building energy prediction

Master's thesis in Energy and the Environment
Supervisor: Bjørn Austbø
Co-supervisor: Gaurav Chaudhary
June 2021

NTNU
Kunnskap for en bedre verden

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Preface

This report represents my master thesis, conducted in the spring semester of 2021 at the Department of Energy and Process Engineering at the Norwegian University of science and technology, NTNU, in Trondheim, Norway. The master thesis accounts for 30 ECTS credits and is a continuation of the project work[1] “Data-driven models for building energy prediction, assessment and control”, conducted the Autumn semester of 2020.

The object of this master thesis is to examine the relevance of variables in data-driven models for building energy prediction, with a focus on indoor air temperature prediction. The evaluation of different parameters has been done by making changes to the building simulated in IDA ICE and the data-driven model. The data-driven model utilized in this thesis is a hybrid MOMO LSTM model developed by PhD candidate Gaurav Chaudary.

The head supervisor for the project is Bjørn Austbø, Associate Professor at the Department of Energy and Process Engineering at NTNU, With PhD candidate Gaurav Chaudhary as co-supervisor. I want to thank them both for valuable feedback and guidance throughout the work with this master thesis. I am thankful for all the time they both have set aside to help me and their availability throughout the process.

Maria Solomon Langeland
Trondheim, June 10, 2021

Abstract

Buildings account for 40 % of the world's energy use and 36 % of the greenhouse gas emissions. A large share of the energy is related to heating, ventilation, and air-conditioning (HVAC) systems. Intelligent technologies, such as black-box models, for optimizing these systems will be an excellent resource for reducing energy use without compromising human comfort.

The thesis aims to examine the parameter relevance related to data-driven models for predicting indoor temperature. The findings in this thesis can lead to increased performance of black-box models, with more accurate and less computational expensive predictions. The investigations of parameters include both the black-box input parameters and the parameters of the building.

The back-box model utilized is a hybrid multiple-input and multiple-output (MIMO) Long short-term memory (LSTM) model. The data used as input for the LSTM model is generated from buildings simulated in IDA Indoor Climate and Energy (IDA ICE). The building will be tested for different internal gains, envelopes, and locations to get a wide variety of data. The most utilized building is an office Passive House located in Trondheim, Norway. The importance of input parameters for the data-driven model is evaluated by utilizing a feature elimination method and the wrapper method.

The results show that a stable indoor temperature is crucial for prediction accuracy. Buildings with stable temperatures often have a high thermal mass, heavy insulation, little glazed envelope, and/or external shutters. A characteristic not suitable for prediction is variable set-points in the HVAC system. The variation in the desired temperature is challenging to predict and is amplified when the temperature difference between indoor and outdoor increases.

Regarding input parameters, daily time-index, equipment, and solar radiation are essential for office buildings. The type of solar radiation varies based on the climate, where direct normal radiation is suitable for cool climates, and solar radiation on a horizontal surface for temperate climates. For buildings located in cool climates and/or has lower insulation meteorological parameters are of more importance. Especially, outdoor temperature, and wind when little insulation is utilized.

Time-indexes were the most essential input parameter, and the use of advanced time-indexes will be the best measure to improve prediction accuracy in the model. Time-index is a number that gives information regarding time, day, or similar. The time-indexes are strongly related to the patterns of occupants, which further are strongly related to the use of HVAC systems, lighting, and other appliances. The time-indexes are also strongly related to meteorological values due to the sun's correlation to the hourly time-index and the other parameters affected by the sun. A sufficient time-index can therefore give information related to multiple factors affecting the building energy use.

Another finding of this thesis is that there is little or no communication between zones in the hybrid MIMO LSTM model. The lack of communication can be a drawback for either the building utilized as input or the LSTM model. If the building was not perfectly heated or had less internal insulation, the model might have captured the dynamic between zones. This due to an increase in heat transfer through internal walls. It is also possible that another data-driven model would be able to capture this interference without increasing the heat transfer between zones.

Summary in Norwegian

Bygninger står for 40% av verdens energiforbruk, og 36% av drivhus gassene. En stor andel av denne energien er knyttet til bygninger, mer spesifikt, systemer for varme, ventilasjon, og kjøling (HVAC). Intelligente systemer, som data-drevne modeller kan optimalisere disse systemene og være en god ressurs for å redusere energiforbruket relatert til bygninger.

Målet ved denne oppgaven er å undersøke relevansen til parametere brukt i data-drevne modeller for energiprediksjoner av bygninger. Funnene i denne rapporten kan derfor lede til økt prestasjon av data-drevne modeller, hvorav modellene kan bli raskere og mer nøyaktige. Parameterne som undersøkes i denne oppgaven er både inngangsparameterne til den data-drevne modellen, og parameterne til bygget predikert.

I rapporten er det brukt en hybrid flere-inngang og flere-utgang (MIMO) Long short-term memory (LSTM) modell. Data brukt som inngangsparametere til modellen er generert fra en bygning designet i programmet IDA Indoor Climate and Energy (IDA ICE). Inngangsdataen er generert i ulike versjoner, hvorav bygningskonvolutt, lokasjon, og rutiner endret for å teste modellen på et bredt utvalg senarioer. Bygningen mest brukt i testingen er et kontorbygg med Passiv hus standard, lokalisert i Trondheim, Norge. Utgangsparameterne brukt gjennom hele rapporten er innendørstemperatur. Evaluering av inngangsparametere er utført ved hjelp av en elimineringsmetode og Wrapper metode. Resultatene i denne oppgaven viser at en stabil innendørs temperatur er nødvendig for nøyaktige predikasjoner. Bygninger med stabile temperaturer har ofte høy termisk masse, mye isolasjon, få vinduer, og/eller persienner. Et særtrekk ved bygg som ikke er passende for predikasjoner er at de har varierende set-punkt temperatur. Variasjoner i temperaturen er utfordrende å forutse, som igjen øker med differansen mellom innendørs og utendørs temperatur.

Funnene relatert til inngangsparameterne indikerer at daglig tidskonstant, teknisk utstyr og solradiasjon er de viktigste inngangsparameterne. Typen solradiasjon varierer med klima, hvorav direkte normal stråling er egnet for kjølig klima, og solstråling på en horisontal overflate i temperte klima. Når bygg er lokalisert i kjølig klima og/eller har lite isolasjon er meteorologiske parametere av større betydning. Da spesielt utendørs temperaturen, og vind dersom bygget har lite isolasjon.

Tidsindeks er inngangsparameteren av størst betydning, og forbedring av tidsindeks er det beste tiltaket for å øke nøyaktigheten til prediksjonene. Tidsindekser er sterk relatert til forbrukerens rutiner, som videre er sterkt relatert til rutinene til HVAC systemer, lys og annet teknisk utstyr. Tidsindekser er også sterkt knyttet til meteorologiske verdier, da solen er sterkt korrelert med klokken. Andre meteorologiske verdier som temperatur og fuktighet blir sterkt påvirket av solen, noe som også kobler disse verdiene til en tidsindeks. En god tidsindeks kan derfor gi informasjon om ulike faktorer som påvirker bygningers energiforbruk.

Et annet funn i oppgaven er at det er lite eller ingen kommunikasjon mellom sonene i den hybride LSTM modellen. Mangelen på kommunikasjon kan være grunnet mangel i den data-drevne modellen, eller grunnet bygningen. Dersom bygningen ikke hadde vært perfekt temperert eller ved mindre isolasjonene i de interne veggene, kunne utfallet vært annerledes. Dette grunnet en økt varmetransaksjon mellom interne vegger, som kunne gjort det lettere for modellen å oppdage samspillet mellom sonene.

Contents

Abbreviations

AE	Autoencoder
ANN	Artificial neural network
BEM	Building energy modeling
BPNN	Back-Propagation Neural Networks
CAV	Constant air volume
Comb. nr.	Combination number
Comp.	Compressor
COP	Coefficient of performance
d	Day of the week
D.	District
DD	Degree day
DHW	Domestic hot water
DT	Decision tree
DHW	Domestic hot water
Env.	Envelope
El.	Electricity
Eq,i	Equipment load in zone i
GDP	Gross domestic product
GNP	Gross national product
h	Hour of the day
Hd,i	Heat demand in zone i
Hist.	Historical
HT	Heat transfer
HVAC	Heating, ventilating and air-conditioning
i.e.	id est, synonym of "that is"
IDA ICE	IDA Indoor Climate and Energy

IQR	the interquartile range
IT,i	Indoor temperature in zone i
LI	Light insulation
Li,i	Lighting load in zone i
LSTM	Long Short Term Memory
MAE	Mean absolute error
MAPE	Mean absolute percentage error
Mech	Mechanical
MIMO	Multiple input multiple output
MISO	Multiple input single output
Occu,i	Occupancy in zone i
OT	Outdoor dry-bulb temperature
P	Proportional
PCA	Principal Component Analysis
PD	Peak demand
PI	Proportional integral
RH	Relative humidity
RMSE	Root mean square error
RNN	Recurrent Neural network
SC	Sky cloud cover
STD	Standard deviation
SR	Solar radiation
SR_{Nor}	Direct normal radiation radiation
SR_{Hor}	Diffuse radiation on horizontal surface
SVM	Support vector machines
T	Temperature
VAV	Variable air volume

W_x	Wind speed - East to West
W_y	Wind speed - North to South

Figures

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1 Introduction

The first section of the introduction includes the background and motivation for this thesis. The following section describes the problem statement, approach, and structure of the thesis.

1.1 Background and motivation

Challenges related to climate change stand before us. The increasing amount of greenhouse emissions resulting from human industrial activities has lead to less biodiversity, ocean acidification, and rising sea level [2]. The emissions causing these climate changes are strongly related to energy production, and a global initiative to reduce greenhouse emissions is stated in the Paris Agreement [3]. By 2030 Norway has a goal to reduce greenhouse gas emissions by 55% [4].

The building sector is the world's most energy-demanding sector worldwide [5], accounting for more than 40% of the energy use and 36% of the greenhouse gas emissions of the world [6]. In the U.S., the annual electricity use of buildings has increased from 25% of the country's electricity use in 1950, to 76% in 2012 [7, 8]. In 2017 buildings in the U.S. accounted for 13% of the world's total primary energy use [7], while Norwegian buildings accounted for 22% of the country's total energy use. Reducing energy use in this sector is therefore essential to reach the climate goals.

For cold climate countries, heating is one of the most energy-demanding sectors regarding building energy use [9]. As a consequence of reducing energy use related to space heating and cooling in buildings, the buildings became tighter and more compact. Thus, ventilation systems became an essential component in buildings to ensure a good indoor environment. The energy use of heating, ventilation, and air-conditioning (HVAC) systems has increased over the years [6], and have become one of the most energy-demanding sectors within a building. Nevertheless, an adequate HVAC system is essential since humans spend 90% of their time inside [10].

Prediction of indoor air temperature is an excellent tool to reduce the energy use related to HVAC systems without compromising human comfort. On the contrary, information about future temperatures can help increase human comfort by customizing the occupants' temperature to a more extensive degree. The customization will reduce energy by avoiding overheating and heating and cooling when zones are not in use. To implement accurate and reliable predictions, engineering methods are of great importance.

1.2 Problem statement

The objective of this thesis has been to examine parameters' importance in data-driven models for building energy prediction. The parameters' importance will be evaluated by testing a data-driven model for multiple data-set and investigating the different sets' performances. The following tasks are answered:

- Literature study on the use of data-driven models for building energy prediction will be included to define the state-of-the-art. A literature study of parameters affecting the energy use in buildings will also be included, and the parameters' effect on building energy prediction.

- Generation of training data-sets using IDA-ICE for a given sample building and preliminary data analysis. These data-sets need to be large and rich.
- Testing and evaluation of a promising black-box modelling technique will be conducted. Testing and evaluation of input parameters for black-box models for building energy prediction will also be conducted.
- Discussion, examination, and assessment on improving performance for data-driven models for building energy prediction will be included. These improvements include evaluating necessary parameters and the date utilized as input. Discussion and evaluation of buildings suitable for temperature predictions will also be included.

1.3 Scope

This thesis presents a literature review of building energy modeling. There are two different approaches for estimating energy used in buildings: the building-physics approach and the data-driven approach. The building-physics approach models the building behavior and simulates it to calculate the energy use and the indoor climate conditions. The data-driven approach is purely empirical, and the input and output variables are used to define a mathematical description of the system. This type of model is efficient and easy to build but requires training data based on historical data of the building[8]. This thesis will focus on the data-driven approach and utilize the building-physics approach to generate testing data for the data-driven model. [5]

Literature regarding energy use in buildings will also be presented in the thesis. The literature will contain information about building envelope, outdoor climate, indoor climate, and different forms of internal gains, in addition to data-driven models. Literature of energy use in buildings not related to building energy prediction will not be included, such as the power market, costs, power consumption, and similar topics mostly occurring outside the building's boundary. The literature regarding building energy modeling (BEM) will be included, here are both white- and grey-boxes included, but black-box models will be emphasized. Information regarding the development (except training, validation, and testing) and implementation of data-driven models will not be included. The literature study also includes methods for evaluating parameter importance in data-driven models.

The experiments conducted are done with a Long short-term memory (LSTM) model, a hybrid multiple-input and multiple-output (MIMO). The model utilized revived input data from nine of total 26 building zones and generated outputs for each zone. Since not all zones are included, the model can not be classified as a full MIMO model from a building energy prediction perspective. To limit the thesis only 24h prediction is included in the various tests.

The input data is generated from a small office building made in the white-box program IDA ICE. The experiments involve testing the model's reliability and how it is affected by different internal gains, building envelopes, and climates. Evaluation of different zones is conducted during all the different cases. Throughout the experiment, the indoor air temperature is the output temperature of the data-driven model. The data-driven model was not developed by me and has not been applied for control but can be used for it. The thesis will only evaluate the given data-driven model. The different input files for the data-driven model were developed in context with this thesis, and the process of the development will be included and evaluated.

The changes done regarding internal gain include PI and P controller, office and residential schedules for occupants and equipment, and seven different occupants schedules for an office. In addition, tests splitting one zone into two and reducing the number of output parameters were also conducted. All these experiments were only conducted for a Passive House envelope located in Trondheim, Norway.

The different building envelopes tested are designed after the Norwegian building standard for Passive House, TEK 17, and TEK 87. In addition, a Passive house with high thermal mass and tests related to windows location and shutters are included. The different envelopes tested are only tested for the office building located in Trondheim, Norway.

The building generated is also tested for different locations. To limit the results, only three locations are included: Trondheim, Norway; Oslo, Norway; and Malaga, Spain. An experiment where the orientation of the building is changed is also included. This was only conducted for the Trondheim location. The prediction for the different locations is only conducted for the Passive House envelope, set up as an office.

Regarding parameter relevance, a feature elimination method is conducted with detailed results of the Passive house located in Trondheim, Norway, with an office schedule. The wrapper method is also conducted for this building. In addition, the feature elimination is conducted for different internal gains, envelopes, and climates, but to a smaller extent. The wrapper method is conducted for the TEK 87 envelope and the Malaga location, in addition to the Trondheim Passive House.

1.4 Hypothesis

Before conducting the experiments, some assumptions about the upcoming results were made. These assumptions were based on acquired knowledge from Section 2. The assumptions are as followed:

- The most important parameters for one building are most often the same for other buildings. Since the energy behavior of buildings most often is affected by similar parameters related to energy use.
- Buildings with less insulation and thermal mass are more weather dependant. Therefore it is assumed that meteorological parameters are more important for these buildings.
- Office buildings are more dependant on occupancy than residential buildings due to the short period of occupancy.
- Buildings in temperate climates are less weather-dependent than cool climates due to smaller temperature differences between indoor and outdoor temperatures.

1.5 Structure and content

This paper is divided into six chapters. The structure is as follows:

Chapter 1 - Introduction
This chapter includes an introduction to the study, including motivation and scope.

Chapter 2 - Literature review
Literature on energy use in buildings and BEM is included in this chapter. Regarding energy use in buildings, energy features are included and their importance in modeling. Out of the BEM models, data-driven models are emphasized, with detailed information about Artificial neural networks (ANN) and Support vector machines (SVM). Further on, the study focus on the state of art, development of models, and findings in other studies.

Chapter 3 - Method
This chapter holds information about the approach utilized when making the white-box models utilized in the black-box model. Detailed information about the buildings is included for all the different variations of the building. A general description of the black-box model is also included, combined with detailed information about the approach utilized for the different experiments with the black-box model.

Chapter 4 - Results
The results will be presented here, and include information regarding experiments where different input parameters are utilized, changes in internal gains, building envelope, and climate. During all these experiments, the accuracy of temperature prediction will be the primary target. MAPE and indoor temperature will mainly present the results visualized with box plots and bar charts.

Chapter 5 - Discussion
In this section, the results will mainly be discussed and connected to the literature. Most of the experiments will be discussed and validated separately, followed by a general sum up, where the relation between all the results will be drawn.

Chapter 6 - Conclusion
A conclusion of the experiments conducted is presented, along with suggestions for further work. The conclusion includes the most important parameters and characteristics of buildings suited for temperature predictions.

2 Background

This section includes a literature study of data-driven models for energy predictions. The section starts with a review of energy use in buildings, its effect on buildings, and how the parameter is utilized in data-driven models. Further, building energy modeling (BEM) is introduced, including white-, grey-, and black-box models. Further, the most popular data-driven models are presented, followed by general information of data-driven models, a review of previous studies, and methods for finding parameter relevance. The section ends with information regarding modeling accuracy.

2.1 Energy use in building

This section will explain each building variable and its effect on buildings' energy use and energy modeling. Building energy use is mainly influenced by six factors: climate, building envelope, energy systems, operation and maintenance, occupant activities, and indoor environmental quality provided [11]. All of these parameters affect the energy use of buildings in different ways. The average energy use related to each energy sector for a TEK 10 office building in Norway is illustrated in figure 2.1.

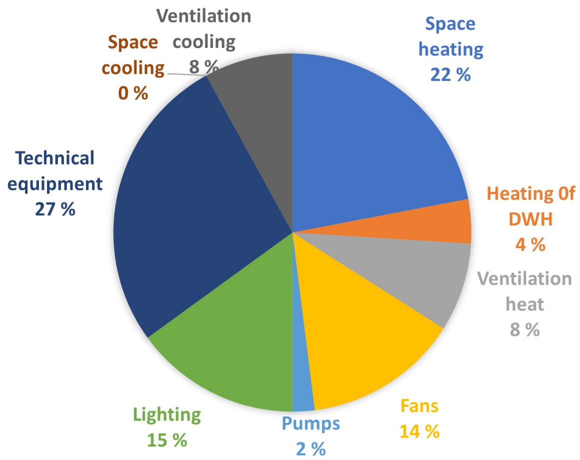


Figure 2.1: *Average energy use related to each sector in Norwegian TEK 10 office buildings[9]*

2.1.1 Building envelope and characteristics

Building envelope mainly includes walls, windows, roof, foundation, air leakage, and shading[12]. The performance of building envelopes has a very close relationship with building energy use regarding space heating and cooling, which is the majority of global building energy used. An energy-efficient building envelope is therefore essential to reduce the total energy use. [12]

The designation "building characteristics" includes the parameters related to the building envelope, orientation, heat transfer coefficient, absorption coefficient, and solar radiation [13]. These parameters affect the heat flow through the building's boundary and the building's ability to store heat and cold.

Building standard

The Norwegian building standards have evolved throughout the years, and as it evolves, the share of energy used for heating decreases. Figure 2.2 illustrate the average share of energy used in each energy sector for different Norwegian building standards. The decreasing proportion of energy used for heating is mainly based on improvements in insulation and building structure, decreasing the thermal time constant of the building. As the building structure gets more insulated and thermal bridges are minimized, heat is better kept inside the building's boundary.

> **thermal time constant**
> The *thermal time constant* describes the building's response to changes in internal and external conditions [14], and is the time it takes for the indoor temperature to change by 63.2% of the absolute difference between initial and final body temperature. [15].

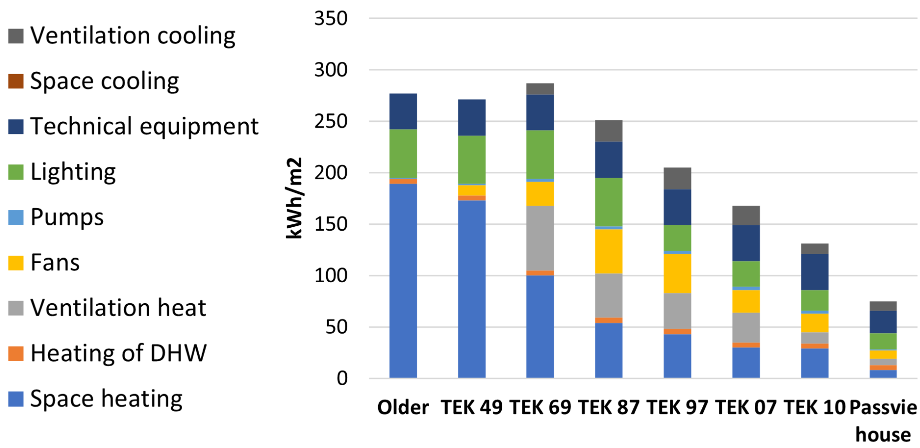


Figure 2.2: *Energy used for each energy sector in various building standards for Norwegian office buildings. [9]*

U-value represents the thermal transmittance through a construction [16] and is often used to evaluate the insulation of a building. Another parameter often used to evaluate the building's ability to keep heat is *thermal mass*. Thermal mass is the materials' ability to absorb and store heat energy [17]. Buildings with low U-value often have a low energy demand for heating.

Importance in modeling

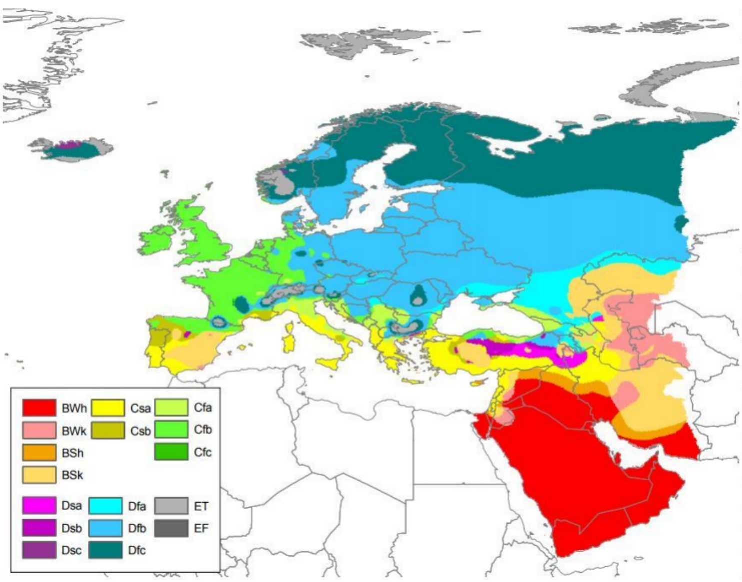
After a building is constructed, the building parameters remain relatively constant. Therefore, they are irrelevant when using data-driven models for a specific building since historical data often is necessary. However, when the study is based on multiple buildings or the model is transferred between buildings, this data is beneficial. [13] However, when using a white-box, these values are crucial and play a critical role in modeling the building. For grey-box models, the importance of these input parameters varies from model to model, based on which part of the model is black and which is white.

2.1.2 Location and climate

Climate is defined as the average weather in a given area over a more extended period of time[18]. A climate can be described by values, such as average temperature, rainfall, and sunshine. *Weather* is defined as a combination of meteorological values for a given area for a short period of time[19]. These meteorological values take many forms, such as temperature, both ambient, dry-bulb, and wet bulb, solar radiation, humidity, rainfall, air pressure, and wind velocity [13, 20]. However, it is essential to note that not all of these parameters are independent.

Climate classification

In 1900, the Russian/German climatologist Wladimir Köeppen made a climate classification system for the whole world. This classification system is one of the world's most utilized climate classification systems and classifies the world into different climate zones based on various criteria. An updated version of this classification system was made by Peel et al. [21] in 2007. The updated European climate classification is illustrated in Figure 2.3. This updated classification map is based on meteorological data gathered from 4279 locations spread worldwide and is made to have an accurate classification system where recent climate changes are included. [21]



1st	2nd	3rd	Description
A			Tropical
	f		Rainforest
	m		Monsooon
	w		Savannah
B			Arid
	W		Dessert
	S		Steppe
		h	Hot
		k	Cold
C			Temperate
	s		Dry summer
	w		Dry winter
	f		Without dry season
		a	Hot summer
		b	Warm summer
		c	Cold summer
D			Cold
	s		Dry summer
	w		Dry winter
	f		Without dry season
		a	Hot summer
		b	Warm summer
		c	Cold summer

Figure 2.3: *Updated climate classification of Europe[21]*

Importance in modeling

The outdoor environment affects buildings to a great extent [22], mainly resulting in temperature changes. Each building reacts differently to weather influences, depending on the construction materials, internal load from occupants, provision of heating, ventilation, air-conditioning systems, and control strategies [13]. Solar radiation and indoor temperature are the most commonly utilized meteorological input parameters, primarily due to their effect on the thermal demand and easy accessibility from weather forecast[13]. [1]

Studies have been made in an attempt to simplify the impact weather has on building energy prediction. White and Reichmuth [23] predicted a buildings' monthly energy use by using the average monthly temperature. This procedure was more accurate than predictions based on heating and cooling degree days, which is the standard procedure for energy predictions. [20, 23] Wei et al. [24] predicted the occupancy level and energy use in an office building. Their thesis identifies outdoor temperature as the most crucial input parameter.

Degree days
A *Degree days* compares the average outdoor temperature of the location to a standard temperature, where a more extreme temperature lead to higher degree days [25]. A high level of degree days usually results in a high level of energy use for cooling or heating [25].

Westphal and Lamberts [26] used simplified weather data to estimate the thermal loads of non-residential buildings. The simplified data consisted of monthly average maximum and minimum temperatures, atmospheric pressure, relative humidity, and cloud cover [20]. Their results had certain limitations regarding the representation of thermal inertia influence on annual cooling and heating load, but was good on low mass envelopes [26].

The connection between building loads and weather variables has also been researched. Cai et al. [27] used deep learning and time-series techniques to conduct one-day ahead forecasts of load levels. The paper concluded that outdoor temperature is the most valuable input parameter among the meteorological ones regarding the prediction of building load. The correlation between the other variables and building loads is insignificant. [13, 27]. Alberinia et al. [28] examined the residential hot water and electricity demand in Italy. Their thesis found that the outdoor temperature is irrelevant regarding electricity load in Italian residential buildings below 24.4°C. The irrelevance is due to the common use of natural gas for heating, in contrast to cooling, which utilized electricity. [28]

Zeng et al. [29] conducted a comparative study of data-driven models for building energy prediction. This study states that the dry-bulb temperature, wet-bulb temperature and enthalpy are the most influential meteorological parameters, while other factors, including humidity level, etc., have negative or an insignificant effect on the energy usage [29]. The study also states that the standardization of the parameters are beneficial to improve the reliability of original data and dimension reduction, resulting in reduced computational complexity.

2.1.3 Occupancy and usage

Occupancy information can be divided into two categories; occupants behavior and occupancy conditions. Occupancy behavior include the control occupants have over thermal environment, windows, artificial lighting, shading devices, and appliances. [30, 31] The energy use in buildings is, therefore, influenced by the behavior of occupants in various ways[32], depending on the number of occupants, habits, and type of activity. The occupancy varies from building to building, mostly dependent on the buildings area of use. Office buildings are mostly used between 08.00-16.00; shops often have longer opening hours and consist of multiple working shifts and varying occupation of costumers; factories may have occupants working around the clock. The occupancy schedule greatly impacts the energy use of the building due to heating, electricity plug, office equipment, and air-conditioning devices that occupants often use. Figure 2.4 and 2.5 illustrate the average daily power profile for different industries for both weekdays and weekends. [33]

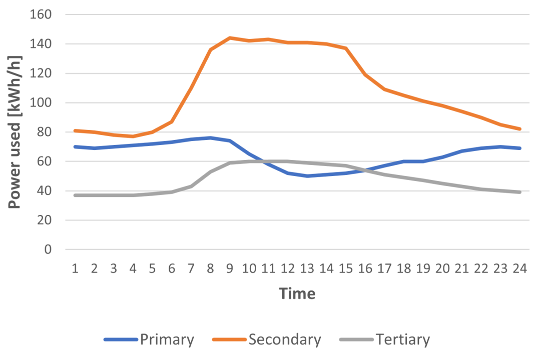


Figure 2.4: *Average power used hour by hour by various businesses during weekdays[34]*

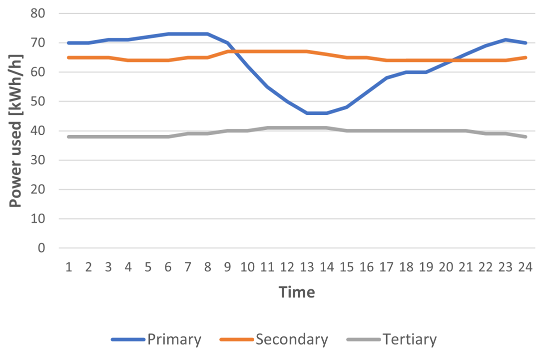


Figure 2.5: *Average power used hour by hour by various businesses during weekends[34]*

For residential buildings, the profile often looks a lot different. This power profile is often characterized by the working hours of the occupants and has high peaks before and after the regular working hours. Figure 2.6 illustrates a typical power profile for a weekday of a household where both adults are not homemakers.

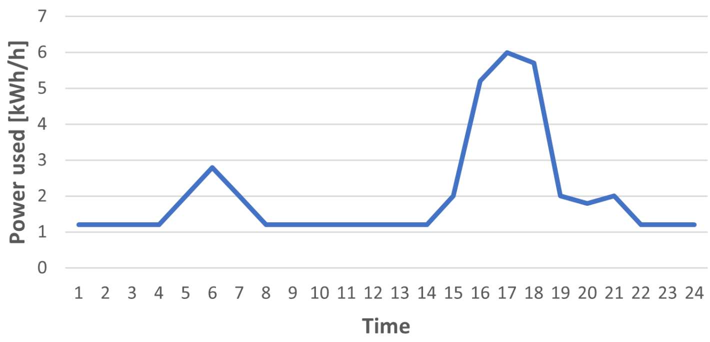


Figure 2.6: *Average power profile for households where adults are not homemakers. The power usage is represented hour by hour for a typical weekday[35]*

Area of use

Studies have been made to investigate the relationship between the area of use, insulation, and climate, Figure 2.7. The study shows that insulation makes the most significant impact on the heating load, while climate makes the most significant impact regarding the cooling load. When the insulation is poor, the climate makes an immense impact on the heating load. Regarding the area of use, the energy profile is relatively constant for each case, and offices come off as the most energy-intensive building of the three categories. [19]

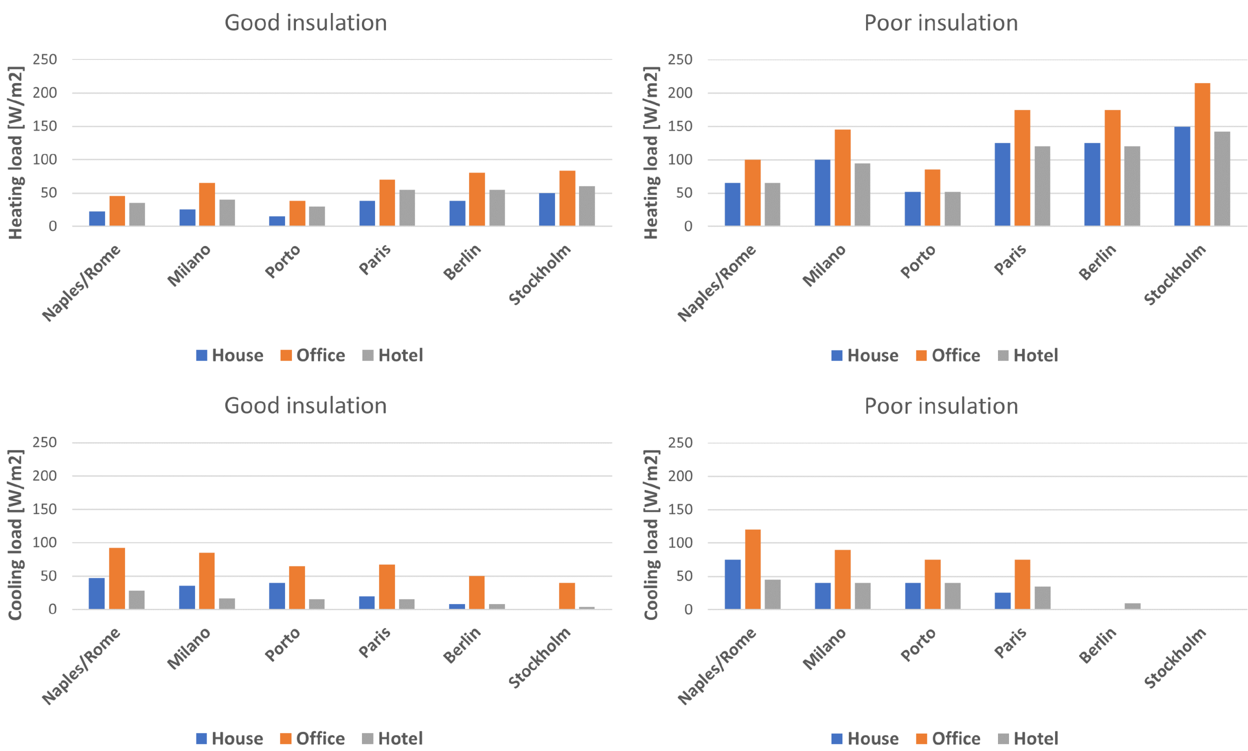


Figure 2.7: *Heating and cooling load for different building purposes in different climates[19]*

Importance in modeling

The number of occupants, activity level, and routine play a valuable role in building energy prediction [36]. Occupancy-related data often affect the internal heat gains in zones and the pattern of energy use. BEM tools usually include the effect of occupants in a simplified form, for example, using a fixed schedule or multiplying a fixed value for metabolic heat gain with the number of occupants. *Metabolic heat* is the heat evaporated from a body in a specific activity [37]. Therefore, the BEM tools used in other studies and designs have varying accuracy, and the results can be deterministic. [13, 22] Due to these simplifications, the study of incorporating occupancy information into prediction models has a more significant potential to improve [36]. However, short leave of occupants and small deviations from the simplifications may not affect the consumption to a large extent [13].

Accurate occupant data can be achieved by accessing detailed occupant-related data such as occupancy and socio-economic data. However, acquiring relevant data related to occupancy is challenging due to the lack of occupancy sensors and other privacy concerns. Even if the occupancy information is acquired when establishing the model, it is challenging to obtain during the use of the model. In addition to violate privacy concerns, the collection of occupancy data is time-consuming and laborious in some situations. Therefore, an occupancy indicator such as time-index is often utilized in studies to reveal the patterns and conditions of occupants. [31]

Multiple studies have examined the impact occupants have on building energy use. Wei et al. [24] proved that the number of occupants is more important than meteorological and indoor climate information, in context with data-driven energy prediction. Wang et al. [38] found a strong linear relationship between plug loads power and occupants for working days. *Plug loads* refer to energy used by equipment that is plugged into an outlet [39]. Sala-Cardoso et al. [40] improved the prediction of the heating, ventilating, and air-conditioning (HVAC) thermal power demand by predicting the activity indicator of occupants. This approach was validated suitable to increase accuracy in energy prediction. [13]

In the study of Zeng et al. [29] various data-driven models were tested for energy prediction on two separate offices, hotels, and shopping centers. The study showed that the accuracy of the models depended on the building predicted. Comparing the accuracy for all models on all the different buildings, all the models perform the best on hotels and worst on offices. [29]

2.1.4 Indoor environmental information

Building indoor climates include thermal-, atmospheric-, acoustic-, actinic- and mechanical environment [10]. The main goal of a good indoor climate is to provide healthy and comfortable conditions for occupants. In addition to comfortable conditions, a good indoor climate is also proven to increase the efficiency of the occupants by more than 3% [41]. Therefore good indoor climate is essential, and in Norway also required by Direktoratet for Byggkvalitet [42], to achieve a good building [10].

Ventilation

To achieve good indoor air quality, ventilation is essential. The ventilation can be either natural or mechanical, whereas natural ventilation is driven by pressure difference due to temperature difference or wind. Mechanical ventilation often uses fans to move the air through the building and can be split into two categories, constant air volume (CAV) and variable air volume (VAV). VAV ventilation is often connected to sensors and has a set-point for when to ventilate and when not to. The ventilation can be triggered by occupancy, CO_2 level, or temperature. CAV ventilation ventilates with a constant air volume. [10]

For buildings in Norway, there are several requirements regarding air quality and ventilation. As for the CO_2 level, it must not exceed a limit of 1000ppm CO_2 [43]. To achieve this, the supply air often needs to be filtrated in bigger cities, due to outdoor air pollution.

A high humidity level can lead to fungus and mold growth, which poses risks to humans [10]. A relative humidity (RH) of 40-60% is therefore acceptable in building to avoid this, whereas 50% RH is the most optimal for most cases [19]. For colder climates, a lower RH is preferable to avoid condensation on windows, which further also can lead to mold and fungus. [10]

Relative humidity
When referring to humidity, the phrase *relative humidity*(RH) is often used. The relative humidity is defined as the amount of water vapor in the air, expressed as a percentage of the maximum amount that cold air can hold at a given temperature [44].

In-office buildings, a gross area of $15\,\mathrm{m}^2$ is required per person. Regarding ventilation, a minimum airflow of $2.5\,\mathrm{m}^3/\mathrm{h}$ per square meter is required when the room is attended, and $0.7\,\mathrm{m}^3$ per square meter when not. In addition, an airflow of $26\,\mathrm{m}^3/\mathrm{h}$ has to be added per person attending the room. These values are when “light activity” is assumed for the occupants. [42]

Heating and cooling

In Norway office buildings have an average specific energy use of 230 kWh/m^2 per year[6]. Meaning that they are very energy-intensive buildings. A great share of this energy is used for space heating, Figure 2.1. The Koepper Climate Classification classifies Norway as a cool country[21], which explains why the large amount of energy used for heating is necessary.

Heating of buildings is currently done by ether boilers, direct electrical heating, or central heating systems [16]. Boilers can use solid, liquid, and gas as fuel. *Electrical heating* is a practical and efficient system that can be improved by connecting to heap pumps. Central systems generate heat centrally and transport it by a heat-carrying medium. [16]

TEK 17 is currently the newest building standard in Norway and gives regulations on technical requirements and minimum standards for buildings to be built legally. Table 2.1 holds the recommended indoor dry-bulb temperatures for various activities. When cooling is utilized, a value close to 22°C is recommended. [42]

Dry-bulb temperature

Dry-bulb temperature is the most frequently used temperature expression and means the ambient air temperature. This temperature is measured by a thermometer that is not affected by the moisture of the air. [45]

Table 2.1: *TEK17 recommended indoor dry-bulb temperature for various activity levels [42]*

Activity group	Light work	Medium work	Heavy work
Temperature [°C]	19-26	16-26	10-26

Importance in modelling

Studies have shown that the activity level of occupants affects buildings with lower energy use to a large degree. Both the user behavior and lifestyle can affect energy use up to a factor of three. Their behavior related to heating can affect the energy use by changing the temperature set-point, the number of heated rooms, and heating duration. These factors often have a strong relation to gender, age, knowledge of control functions, and meteorological conditions. Regarding cooling, the occupancy makes a significant impact on the system. Often, the choice of a cooling system, duration and frequency of usage, choice of set-point temperature, and maintenance frequency. It is also indicated that shading devices and lighting have a strong influence on the HVAC system's energy use. [46]

Due to the significant possible variations based on the specific occupant's peregrinations and habits, there is a considerable amount of potential error in this category. Wrong interpretations of the occupants' behavior can lead to enormous consequences on energy use and indoor temperature. A case study conducted in China shows that the set-point of indoor air temperature, the RH of the outdoor air, and the operation time of air handling units are the factors most influential on the HVAC system [46].

2.1.5 Equipment

Equipment includes all electronic devices not incorporated in the building, i.e., lighting and plug loads. Appliances used for achieving a good thermal environment and air quality will not be reviewed in this chapter.

Lighting
Artificial lighting usually does not affect energy use, primarily since energy use for lighting is insignificant. The technology within lighting has a wide variety, with many low energy demanding alternatives. Today, LED lighting is among the least energy-demanding technologies. [47] However, in an energy-efficient building, the energy used for lighting plays a more prominent role, and intelligent solutions must be made. An example of solutions that will decrease the energy demand for lighting is daylight sensors, dimming the light as needed. This solution takes advantage of natural light and is, therefore, energy efficient. [16]

The use of artificial lighting in buildings is influenced by both occupants' behavior and the building design[46]. There is a close link between the start of daily occupancy and switching-on lighting in large open space offices[46]. Peak lighting hours are usually between 10.00 to 18.00, with an average lighting use of more than 90% during weekdays. This peak information is based on case studies from Norway, China, and Belgium. [46]

In small space offices, the occupant behavior plays a more important role in terms of lighting. Studies show that occupants easily use more natural lighting in individual offices compared to large open space offices. [46]

Appliances
Office appliances include computers, displays, copiers, printers, and similar plug-in loads. [46]. These appliances are usually switched on during office hours. The distinct difference regarding energy-saving relies on the occupant behavior during office hours. Studies show that offices with higher turn-off rates for appliances during off-hours save more energy. [46] For residential buildings, the appliances are different and involve appliances for cooking and cleaning.

Importance in modeling
In the study of Wei et al. [24] it was found that the electricity use of appliances is the most crucial input parameter when predicting the power used by air-conditioning (AC) systems. In the project work[1] introductory to this study, the electricity used for lighting was found as the third most crucial parameter input, F.4.

2.2 Building energy modeling

Building energy models (BEM) can be split into three different categories. Purely physics-based, “white-box”, purely empirical,“ black-box”, and a combination of these two, “grey-box” . For all of these categories, there are multiple subcategories and sub-subcategories. [1, 13, 48, 49] An overview of the main categories within the focus of this study is given in Figure 2.8. The emphasized models are related to the model tested in this thesis.

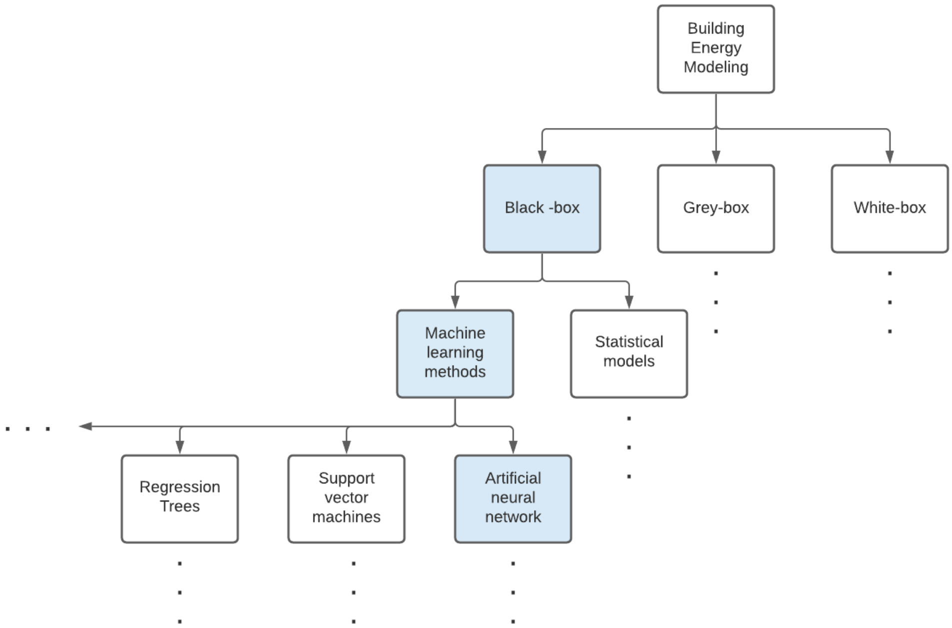


Figure 2.8: *Classification of building energy models for building energy prediction [50]*

White-boxes are purely physics-based, making it possible to track all the output parameters through thermodynamic equations based on the input parameters. This property gives the user full insight into the model, making the model fully transparent. The black-box is purely empirical and models the building based on patterns in data. Therefore these models require training with historical data from the same building. Due to the use of patterns in input data, the actions taking place inside the model are impossible to track and out of reach for the user. Grey-box models are a hybrid of black- and white-box models, meaning some outputs can be traced and are based on equations and others not; which part and the amount of the model that is black and white depends on the model. The concept of transparency of the models and the amount of insight given to the user is illustrated in Figure 2.9. [5, 13, 51]

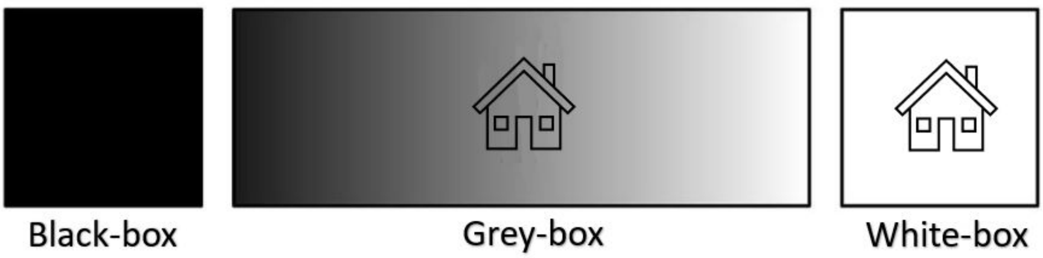


Figure 2.9: *Transparency within the BEM models [52]*

2.2.1 White-box models

White-box models are based on the laws of thermodynamic and physic. The models rely on detailed physical parameters as inputs and are used to model details of building components [5]. The models can capture the building dynamic well; however, this detailed modeling is pretty computationally expensive and time-consuming to develop and simulate [8, 33]. There have recently been multiple attempts to simplify the white-box-based approaches, but these simplifications are error-prone and often overestimate energy-saving of buildings [33].

IES VE, TRANSYS, IDA ICE, EnergyPlus, and SIMIEN are examples of BEM models utilizing the white-box-based approaches. The models need detailed physical properties as input data, making them suitable for buildings in the design phase, compared to data-driven modes, which need historical data as input. These programs are often used for energy calculations in the planning phase of new buildings. This type of modeling is also very informative and helpful regarding operation strategy assessment [8], and optimization and control [53]. However, these models do not perform well for the prediction of energy use for occupied buildings. This is mainly due to insufficient knowledge about occupants' interaction with the building, which is a complicated phenomenon to predict. [54]

The pros of this kind of modeling are that it is easy to discover hidden errors, it is suitable for small data sets, and they are very reliable [53, 55]. However, the models are complex, require many parameters, a high number of iterations, a fast computer, and a large amount of memory [8, 53], making them unsuitable for near real-time applications [54]. The advantages and disadvantages of the model are summarized in Table 2.2.

Table 2.2: *Strength and weaknesses related to the BEM White-box models [1]*

Strengths	**Weaknesses**
• Easy to discover hidden errors [55] • Can provide good estimation accuracy [8] • Insight into physical processes [53] • No need for training data [53] • Usable for optimization and control [53] • Very reliable [53] • Suitable for small data sets [53]	• Restricted by the degree of understanding of fundamental principles [53] • Mathematical solutions methods are often complex [53] • Model complexity and debugging increases with the size of the building [53] • Requires fast computers and large amounts of memory [53] • Time consuming to design test cases [55] • Require many parameters and high number of iterations [8]

2.2.2 Grey-box models

Grey-box-based approaches are modifications of white-box-based approaches, using a combination of physical- and empirical approaches [33, 51]. Due to this combination, the model needs both physical properties and historical data as input parameters. However, which specific physical and historical data required depends on the model, making these models good for situations where the information is partly known. One primary issue in current grey-box models is computational inefficiency due to uncertain inputs and complex interactions between elements [33]. [20]

The models are well suited for analyzing building energy behavior when the data is incomplete or uncertain [20, 50]. All these scenarios are possible with good accuracy and high calculation speed [53]. However, it is tricky to discover hidden errors [55]. The grey-box approach is more simple compared to white-box models; the approach also allows to capture the buildings dynamic more efficiently compared to pure empirical models [56].

Xingji Yu et al. [57] studied low order grey-box modeling of a building. In this study, the black-box part of the model is based on linear time-interval, which considers the input parameters; outdoor temperature, solar radiation, and heat gain. The output parameter for the black-box part for the model was indoor dry-bulb temperature. The rest of this model was “white”, and based on physical properties. General strengths and weaknesses related to grey-box models are listed in Table 2.3.

Table 2.3: *Strength and weaknesses related to BEM Grey-box models [1]*

Strengths	Weaknesses
• Designing test cases can be done in a short period of time [55] • Good at handling problems related to small samples and missing data [50, 53] • High calculation speed [53] • Good accuracy [53] • Transferable [53]	• Difficult to discover hidden errors [55] • Need training data [53]

2.2.3 Black-box models

Black-box models, also called data-driven models, are purely empirical bases and uses the correlation between operation data and statistical models for prediction [8]. To circumvent the above shortfalls of white- and grey-box-based approaches, black-box-based approaches can conduct a building energy consumption analysis based only on historical data without the detailed knowledge of on-site physical information [33]. Feeding the model historical data is called “training”, and is a big part of completing the model, combined with “validation” and “testing”. The data used for training need to be on-site, covering a longer time. This is to make the model able to predict the building behavior during various conditions [51].

Black-box models are widely applied in studies regarding building strategies for energy and cost reduction [51]. This model is also suitable for energy prediction for existing building stock. The black-box models can get hourly feedback from the HVAC module, making the AI-based models predict the future behavior of energy use, being one of the significant advantages with these models. [36]

Black-box models hold certain advantages compared to white- and grey-box models, such as model simplicity, calculation speed, and learning capability. Due to the simple model structure, the model is also easy and rapid to develop. The necessary input data are often convenient to collect. Indoor temperature and similar data can be updated hourly using feedback from HVAC modules. Furthermore, using time series data, black-box models can predict the future behavior of energy use. Whereas white-box models use a forward approach offering energy estimation for a known structure only. [36]

Leading to the main advantages of black-box models, they only require a small number of parameters that adequately represent the building's performance. The white-box model requires known structure and known parameters as they are subjected to input variables for estimation. [36] More information about advantages and disadvantages connected to the black-box model are given in Table 2.4.

Table 2.4: *Strength and weaknesses related to BEM Black-box models*

Strengths	Weaknesses
• Easy to build and computationally efficient [8] • Need few parameters [53] • High calculation speed [53] • High complexity of calibration [53] • High accuracy [53] • Transferable [53]	• No transparency in terms of physical interpretation [49, 53] • Require long training period and are bounded to building operating conditions [8, 53] • Not accurate when training data does not cover all the forecasting range [8] • Extremely complex [20] • Very difficult to discover hidden errors [55] • Can not guaranteed to always comply with physical laws. Most common in cases with small training data. [57]

2.3 Data-driven methods

Black-box models, also called data-driven models, can be separated into two different main categories, machine learning models and statistical models, Figure 2.8 [50]. Statistical models often consist of a collection of probability distributions used to describe patterns of variability where random variables or data may display [58]. Machine learning models are a method of data analysis that automates analytical model building [59]. It is based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention [59].

Many black-box models were established to predict the energy consummation, particularly electricity usage, of buildings. Estimating the energy usage for long-, medium, or short-term is of great importance for energy market planning and investments. Very short-term (i.e., minutes or hours ahead) estimation of energy use can significantly influence the final dispatch for the national el. market. A precise prediction would therefore lead to more efficient energy management. [33]

Artificial neural networks (ANN) and Support vector machines (SVM) are the two promising data-driven approaches used for the prediction of building energy consumption [5, 33]. These models are good at solving non-linear problems, making them very suitable in building energy prediction [20]. Both these methods require data for training, but their performance is in most cases better than statistical models [5]. Due to this, it is chosen to only focus on machine learning models, particularly ANN and SVM, in this study.

2.3.1 Artificial neural network (ANN)

Artificial neural network (ANN) are designed to mimic the basic architecture of the human brain [5, 33]. The model consists of three main layers, which further can hold a large number for layers [33, 48]. Inside each layer, there are many process units arrayed connected across layers [33]. The main layers are the input layer, the hidden layer, and the output layer [48]. Figure 2.10 illustrates the schematic of a typical ANN. In this study, the input layers consist of the training data generated in IDA ICE and listed in Chapter 3.3.3, where one input parameter equals one layer. The output layers are the predicted indoor dry-bulb temperature for each zone, where the output for one zone equals one of the output layers.

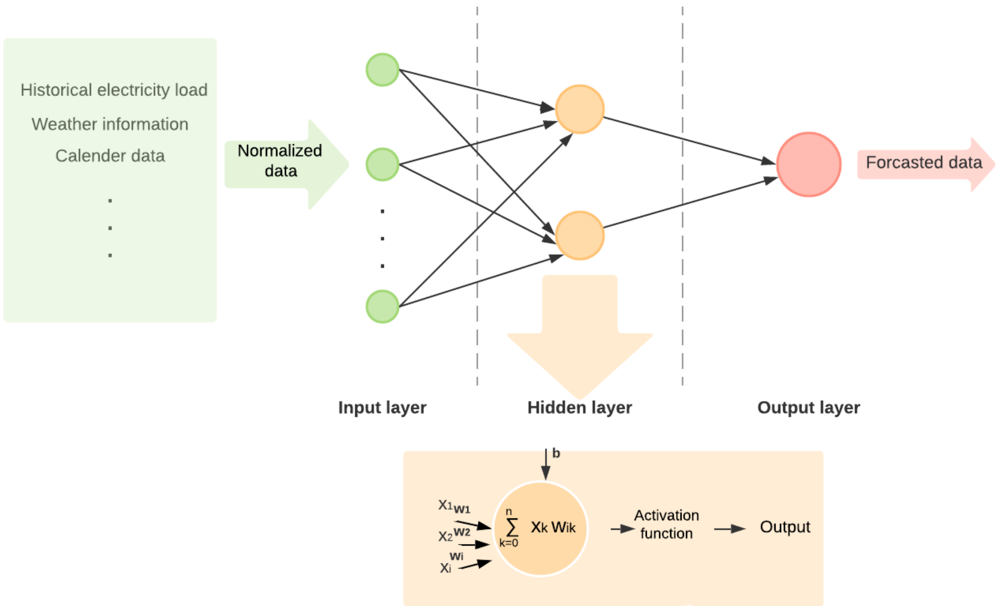


Figure 2.10: *Schematic of typical ANN model [60]*

The model employs data-driven, self-adaptive methods to perform non-linear modeling without knowledge about relationships between inputs and outputs [22]. These properties are due to the training process, which specifies all needed connection weights and biases before conducting predictions [33]. The training will take advantage of available historical data, which will be used as benchmarks to cultivate the proper response of the model for given inputs [33]. Due to the training, ANN models can learn the relationship between the different input parameters and capture fundamental information through training based on historical information [33].

The process units in ANN are arranged in a layer structure and have different process units in every layer, as mentioned above. The connection between these units is based on a designed architecture [33]. Figure 2.10 illustrates an example of a simple feed-forward ANN, where the information flows in one direction through the three layers. To more effectively approximate human brain activities, the model's architecture can be arranged in a different order [33]. Two representations are back-propagation neural network (BPNN), Figure 2.11, and recurrent neural network (RNN), Figure 2.12 [33]. These models compute the error related to every output and further propagates this information as negative feedback to tune the incoming connection weight, and bias [33].

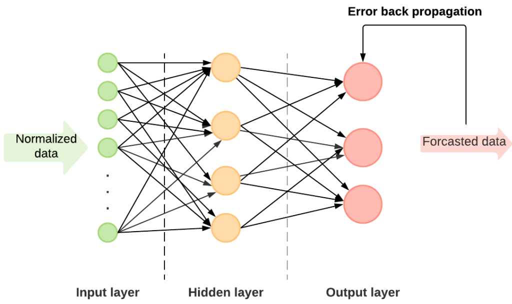


Figure 2.11: *Schematic of a three layer-BPNN [33]*

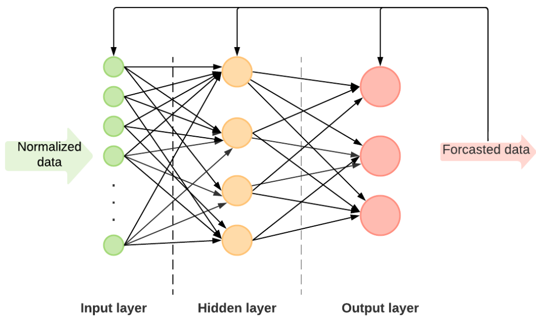


Figure 2.12: *Schematic of a three layer-RNN [33]*

ANN is the model with the best performance and most widely used within data-driven models for building energy prediction [5, 20, 49]. The adaptability of the self-tuning process during operation makes the model able to take accurate decisions during disturbances [8]. Researchers have applied ANNs to analyze various types of building energy use in a variety of conditions during the last twenty years [20]. These are parameters such as energy use, heating load, cooling load, and optimization. However, there are still some disadvantages connected to the model. Table 2.5 holds the strength and weaknesses related to the model.

Table 2.5: *Strengths and weaknesses related to the data-driven model ANN*

Strengths	**Weaknesses**
• Able to to implicitly identify all non-linear relationships between inputs and outputs [13, 50] • Can solve the problems with some failed element on the Neural Network [61] • Can be applied and implemented in any type of application [61]	• Limited ability to explicit relationships between variables [50] • Not cost effective [50] • Can not directly deal with uncertainties [53] • Might consider noise as part of the data pattern [50] • Can not be generalised to different buildings during different conditions [50] • Not flexible [50] • Exposed to over-fitting [50] • Required long time for training models with a large number of networks [13]

2.3.2 Support vector machines (SVM)

Another popular data-driven model is support vector machines (SVM). The method utilized by SVM is attempting to separate categories of data by maximizing the margin between them, Figure 2.13. This separation aims to find a function that predicts the results from the actual target with some deviation [13]. This function can be used to solve classification and pattern recognition problems [20, 62], to find underlying relationships between the nonlinear inputs to the continuous actual values [33]. When SVM is used for regression problems, support vector regression (SVR) is an essential tool for energy prediction of buildings [33].

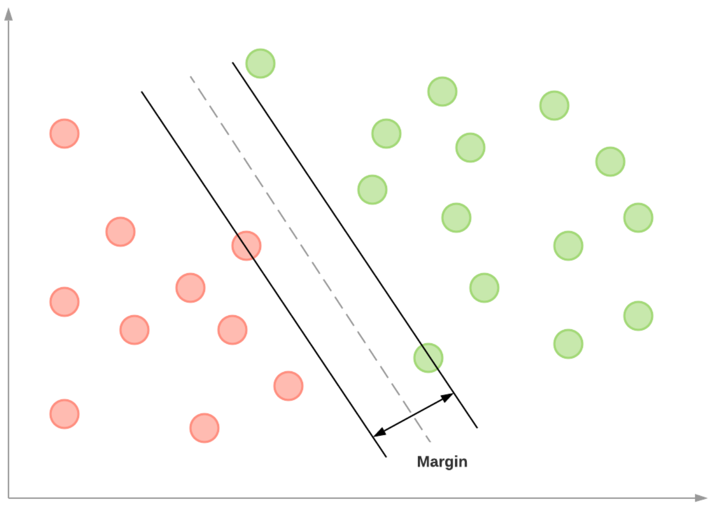


Figure 2.13: *Schematic illustration of SVM [13]*

The main task of SVR is to construct a decision function through the training process based on historical data [33]. This is necessary to be able to represent the behavior of the system [50]. The given input of the historical data must ,therefore, not deviate from the actual target more than the threshold [33].

Regarding the framework, SVM is superior compared to other models [33]. The framework is easily generalized for different problems, and it can obtain globally optimal solutions [33]. In addition, the model is capable of dealing with nonlinear relations in a unique way [33]. However, the model is rather time-consuming for large-scale problems [33].

SVM models are used in research and industry to a great extent, primarily due to their high efficiency in solving nonlinear problems, even with small training data [20]. SVMs are one of the most robust and accurate algorithms [5], and the models' have been widely applied in building energy analysis [20]. A complete list of the advantages and disadvantages related to SVM is given in Table 2.6.

Table 2.6: *Strengths and weaknesses related to the data-driven model SVM*

Strengths	Weaknesses
• Accurate in classification [48] • Rapid in learning [48] • Useful for big data-sets with multiple input parameters [13, 48] • Considers data being close to the opposite class, giving a reliable classification [48] • Comparative to existing artificial intelligence approaches in terms of accuracy [20, 50] • Less prone for over-fitting issues compared to ANN [50] • Not sensitive to the noisy data [13] • Able to solve global minima instead of local minima [13]	• Lack of universal method for selecting appropriate Kernel function [50] • Not cost-effective [50] • Not flexible in assessing energy conservation measures [50] • Adoption by urban planners is complex [50]

2.4 General information about data-driven models

This subsection includes information of different data-driven models, time-stamp of prediction, input- and output parameters, and finalizing the model.

2.4.1 Models

The study of Zhao and Maloules [20] from 2012 examined models used for energy prediction of buildings. Their study reviewed scientific papers regarding data-driven models and made a comparative analysis of the models used to predict building energy use. A summary of their results is presented in Table 2.7.

Table 2.7: *Comparative analysis of data-driven models [20]*

Methods	Model complexity	Easy to use	Running speed	Inputs needed	Accuracy
Satistical	Fair	Yes	Fairly high	Hist. data	Fair
ANNs	High	No	High	Hist. data	High
SVMs	Fairly high	No	Low	Hist. data	Fairly high

In 2018 Amasyali and El-Gohary [5] reviewed the field of energy predictions in buildings. Their study investigated the use of different data-driven models in the field. The study found that 47% of the studies review used an ANN model, making this model the most widespread model.

25% of the studies reviewed in the study utilized SVM to predict energy use, making this model the second most popular model.

In 2020 Sum et al. [13] did a similar study reviewing data-driven models in the field of energy prediction for buildings. Their study also showed that ANN was the most used data-driven model in the field of study, used in approximately 65% of the studies reviewed. SVM was the following most popular model, used in approximately 40% of the studies reviewed. In the study of Sum et al. [13] more than 80% of the studies reviewed utilized multiple data-driven models, while this was not given in the study of Amasyali and El-Gohary [5].

2.4.2 Prediction

After the models are trained and validated, the developed model can be used for real-time energy prediction [13]. Amasyali and El-Gohary [5] reviewed the utilized prediction time within the field of energy prediction for buildings. Their results showed that hourly prediction was most utilized, 57% of the time. Their findings are illustrated in Figure 2.14. The findings of Amasyali and El-Gohary [5] correspond to the findings of Sum et al. [13], and Daut et al. [61], regarding the widespread utilization of one-hour prediction.

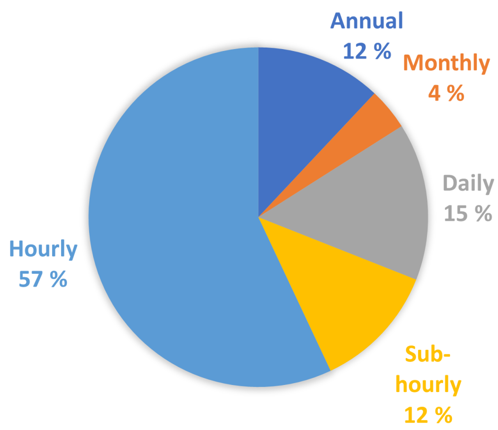


Figure 2.14: *Statistic over utilized prediction for data-driven models [5]*

Multi-step prediction

Multi-step prediction is when more than one prediction is made at a given time. Example in the study of Li et al. [63] 16 steps ahead was predicted at each time-step, equals to a 4 hour ahead prediction with data for every 15 minute. Multi-step prediction is useful for continuous control, and monitoring of the system [13], and can efficiently capture the dynamic behavior of the building [63]. Compared to one-step prediction, multi-step prediction is more complex and can accumulate errors when increasing prediction step size [63]. Multi-step prediction is utilized in most studies, including this one [13].

2.4.3 Output parameters

In 2017 Wang and Srinivasan [36] reviewed the field of energy prediction for buildings. Their study found that the total building energy use was the most utilized output in the field of study. Other outputs often utilized were energy used for heating & cooling, heating demand, and cooling demand. Figure 2.15 illustrated the distribution of utilized output. [36] In 2018 Amasyali and El-Gohary [5] did a similar analysis. Their findings were similar. A large share of the studies uses total energy use as an output, followed by cooling demand and heating demand. The results of this study are illustrated in Figure 2.16. [5]

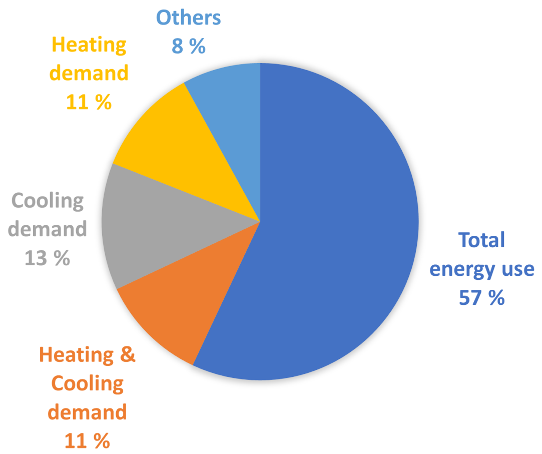


Figure 2.15: *Statistic over utilized prediction output based on Wang and Sirnivasan [36], 2017*

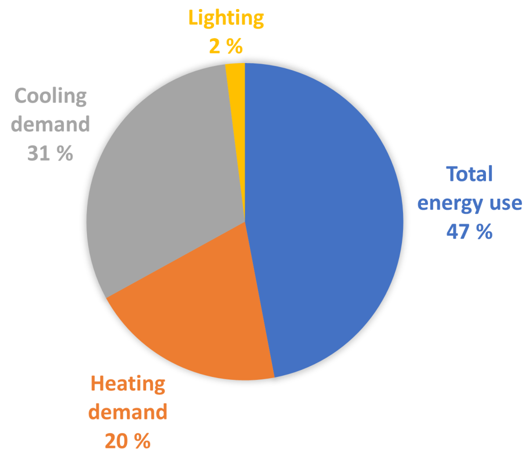


Figure 2.16: *Statistic over utilized prediction output based on Amasyali and El-Gohary [5], 2018*

2.4.4 Input parameters

Meteorological information, historical data, and time-index are the three most important factors for building energy prediction according to Sum et al. [13]. Air-conditioned buildings often have constant indoor conditions, being one of the main reasons indoor environmental information is not commonly used. Occupancy data are often difficult to collect, making this parameter hard to utilize. However, this input parameter can be replaced by time-index data since the behavior of occupants tends to occur in patterns. Building characteristics are usually constant through a building's life cycle, and due to this, they are often ignored in data-driven models. [13] For residential buildings, studies have shown that the main factor affecting the thermal load of the building are outdoor temperature, solar radiation intensity and historical load [64]. An overview of the deviation of utilized parameters is given in Figure 2.17. Most studies the figure is based on include multiple input parameters.

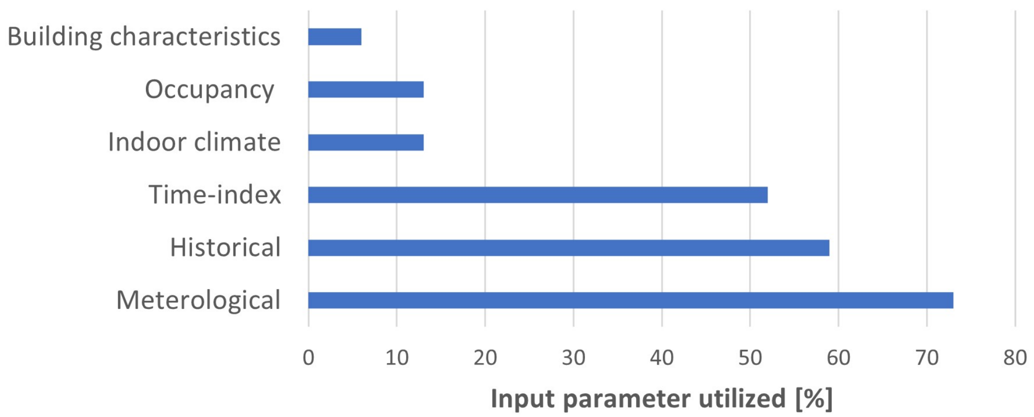


Figure 2.17: *Deviation of input parameters utilized in studies [13]*

Historical data
Data-driven models use data patterns to execute prediction. Therefore, the model has to be fed with information for a certain amount of time to learn the patterns. When the model is ready for predictions, the pattern utilized is based on the data given earlier in the training period, i.e., historical data. In recent years, historical data have been a more utilized parameter in data-driven models due to its ability to increase prediction accuracy [13].

This historical data can, for example, consist of heat demand, electricity use, or occupancy information. Since the building characteristics most often are constant after build, heat loads and similar information can be based on the historical information [13]. Wang et al. [31] found that the historical energy use for heating is the most crucial input for heat demand predictions. Ahmad et al. [54] found that the previous hour electricity use is the most crucial parameter for energy prediction.

Time-index
Time-index means the stamp series for time [13]. It can, for example, be the hour of the day, day of the week, or week of the month. The schedule of occupants tends occur in patterns, meaning that the user tends to have the same pattern of energy use on the same day, weekday, 14-days, or similar [13]. A time-index is, therefore, an excellent option to use when occupants-related data is out of reach. Fan et al. [65] states that there is a correlation between the occupants' time-index and energy use. However, Wang et al. [31] state that the time-index is negligible in residential buildings with district heating.

Wei et al. [24] found in their study that multiple data-driven modes, including ANN, tend to deteriorate prediction accuracy when utilizing too many auxiliary input variables. Therefore, feature extraction using PCA or similar methods plays an important role for energy prediction models. [24] Mtibaa et al. [66] confirms this for LSTM models. More information about input parameters utilized in building energy prediction is given in Chapter 2.5.

2.4.5 Training, validation and testing

The process of completing the models consists of three steps, training, validation, and testing, which all rely on three different sets of data [49]. The data needs to be large, covering all seasons, and rich, covering all possible scenarios [51]. Figure 2.18 illustrates an example of how to divide available data into the three different sets of data required.

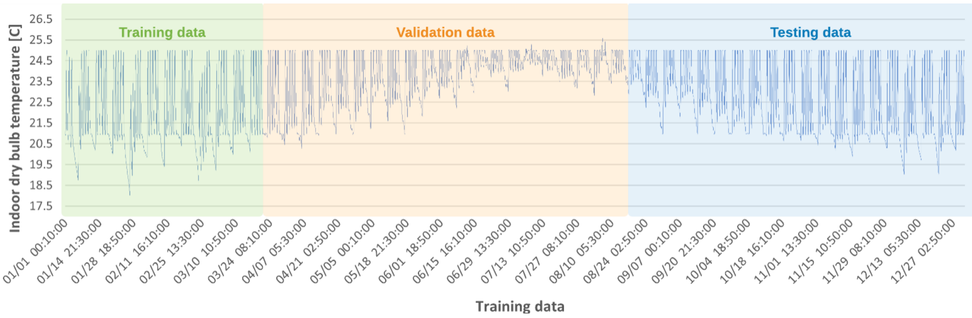


Figure 2.18: *Example of how to divide available data*

Training the algorithm is the first step. In this step, the model is fed with the "training data-set", to try to find a pattern in the data given. The results accumulated in the training are compared to the original data and adjusted if necessary. [49]

The next step is **validation**. The data-set for validation is used to provide an unbiased evaluation of the implemented algorithm, already fit on training data, and tune its key modeling parameters to enhance the fitting of the model [49]. The validation data must be different from the training data. This difference is to avoid that the model only works for some data sets and to prevent over-fitting, explained in Figure 2.19. [49]

The last step is **testing**, where the algorithm developed is run on the remaining data to provide a final, unbiased evaluation of the model [49]. The model parameters and structure should not be modified based on the result from the testing[65]. Therefore, the model is complete during this step, and the testing is only performed to evaluate the performance of the model. As the model is used, the data-driven models get more information, and the performance increases.

Distribution of data-sets

The data sets used to train, validate and test the model can be divided into multiple ratios. The ratio used in most studies is a share of 50-90% for training, or training and validation [49]. Meaning a ratio of 50-10% for testing [49]. It is also common to have an equal share of data for testing and validation [49].

In the project work [1], tests were conducted to find a good distribution of data for training, validation, and testing. During these tests, the data distribution resulting in the best performance was 20% for testing, 40% for validation, and 40% for testing. All tests carried out related to this experiment were done on one constant building, with the same data-driven model, and the ratio for validation and testing was equal at all times. Some deviation may occur for other cases, and it can not be stated that this is the best data distribution.

Type of data

In connection to the project work [1] an experiment regarding the type of data used for training, validation, and testing was also conducted. In this experiment the available data, an entire year, was split into equal parts, and the data used for training, validation, and testing varied between them. However, training, validation, and testing were executed in that order, no matter the data used.

In this experiment, the best performance was when the data from Jan. - Apr. was used for training, May - Aug. for validation, and Sept. - Des. for testing. This experiment was also conducted for one building only, using one data-driven model. Some deviation may therefore occur. The full results from this experiment are enclosed in Appendix F.2.

2.5 Review of previous parameter studies

Other studies are reviewed to capture the state-of-the-art and the parameters utilized for various outputs. The review is conducted for ANN and SVM models, where only the most relevant information about each study is included.

2.5.1 Parameters used in SVM models

The overview of the review is illustrated in Table 2.8. The review shows that the most utilized input parameter is historical data, often as historical electricity use. As for output, the most utilized ones are energy use and cooling load.

Table 2.8: *Overview of reviewed articles using SVM models [33]*

Building type	Location	Data-driven model	Output	Input
Four commercial buildings [67]	Singapore	SVM	Monthly energy use	- OT - RH - SR - Hist. el. use
Multiple [68]	NSW, Australia	SVM, BPNN	Predicted el.load	- Hist. el. use
100 Office buildings [69]	Paris, France	Parallel SVM	Heating D., el. load	- El. heating - Total El.
Institutional building [70]	Singapore	GA + SVM	Energy use	- Energy use
Campus building [71]	Guangzhou, China	SVM + FCM	Cooling load	- Cooling load
Seven residential buildings [72]	Knox County, Tennessee	LS-SVM	Energy use	- Enviro. info. - Time-index - Hist. el. use
Office building [73]	Guangzhou, China	SVM, BPNN	Cooling load	- Hist. cooling - T - RH - SR

Note: BPNN = back-propagation neural network, Comp. = Compressor, D. = demand, El. = electricity, Enviro. info. = environmental information, FCM = Fuzzy c-means clustering, GA = genetic algorithm, Hist. = historical, LS-SVM = Least-squares support-vector machines, OT = outdoor temperature, RH = Relative humidity, SR = Solar radiation, T = temperature

2.5.2 Parameters used in ANN models

The overview of the studies utilizing ANN models is included in Table 2.9. The table illustrated that the studies reviewed often uses four or fewer input parameters, and the most common input parameters are outdoor temperature and historical data.

Table 2.9: *Overview of reviewed articles using ANN models [33]*

Building type	Location	Data-driven model	Output	Input
Holiday Passive House [74]	44° latitude	RNN - BPNN	Energy use	- Season - Insulation - wall thickness - HT coefficient - Time index
Multiple within a nation [75]	Turkey	BPNN	Net energy use	- GDP - GNP - Population
Offic building [76]	Montreal	ANN	Dynamic chiller el. D.	- OT - Outdoor RH - Chiller water T - Comp. status
Office building [77]	Turkey	BPNN	El. power use one day ahead	- Previous load - Hist. T, - Occupancy - Sin and cos of the hour
Multiple within same region [78]	NSW, Australia	MIMO - FFNN	El.D. halv-hour ahead	- Hist. el. use
Seven residential buildings [79]	China	BPNN	Energy used for heating and cooling	- Building Env. - Heating DD - Cooling DD
Commercial building [80]	Not documented	BPNN	Cooling D.	- Hist. cooling D. - Air T - RH
Seven residential buildings [81]	Umeå, Sweden	BPNN	Indoor-outdoor T difference	- Supp. heat D. - El. domestic D. - Flag parameter
University building [82]	Pennsylvania	BPNN	Energy used for heating and cooling	- OT - RH - Set-point T - Occupancy
University/Office building [83]	Sao Paulo	BPNN	Energy use	- OT - time-index

Note: Comp. = Compressor, DD = degree day, D. = demand, El. = electricity, Evn. = envelope, GDP = Gross domestic product , GNP = Gross national product , Hist. = historical, HT = heat transfer, OT = Outdoor temperature, RH = relative humidity, T = temperature

2.5.3 Parameter relevance

Investigation of parameter relevance has been conducted in other studies. This subsection will review some studies in this field, which have utilized one or multiple methods for evaluation of parameter relevance in regard of building energy use. Their approach and results will be highlighted, as well as the building type. The studies in focus are "Prediction of occupancy level and energy consumption in office building using blind system identification and neural networks" by Wei et al., "Multi-criteria comprehensive study on predictive algorithm of hourly heating energy consumption for residential buildings" by Wang et al., "Trees vs Neurons: Comparison between random forest and ANN for high-resolution prediction of building energy consumption" by Ahmad et al., and "Selecting the model and influencing variables for DHW heat use prediction in hotels in Norway" by Ivanko et al.. None of these papers have the main focus on parameter relevance in building energy prediction but all have included it in their research.

The study of Wei et al. [24]
Building type: Commercial building
Location: Beijing
Occupancy data: Calculated from actual CO_2 level
Output: Power used by AC system
Parameter ranking method: Feature extraction method - PCA

The study of Ahmad et al. [54]
Building type: Hotel
Location: Madrid
Occupancy data: Actual data from reservation system
Output: Total energy use
Parameter ranking method: Feature elimination - Compare results where the relevant parameter is missing using accuracy matrices.

The study of Wang et al. [31]
Building type: High-class commercial skyscraper (ICC)
Location: Hong Kong
Occupancy data: Hourly time-index from actual data
Output: Total energy use
Parameter ranking method: Feature extraction method - Embedded method

The study of Ivanko et al. [84]
Building type: Hotel
Location: Oslo, Norway
Occupancy data: Actual data from reservation system
Output: DHW heat use
Parameter ranking method: Feature extraction method - Wrapper method

The results from the studies are listed below. The output parameter for Wang et al. [31] and Ahmad et al. [54] are equal, which may explain why the importance of input parameters are corresponds.

Wei et al. [24]

1. Electricity use of appliances
2. Number of occupants
3. Electricity use of lighting
4. Solar radiation
5. Electricity use of fresh air appliances
6. Outdoor dry-bulb temperature

Wang et al. & Ahmad et al. [31, 54]

1. Historical heating consumption
2. Outdoor dry-bulb temperature
3. Relative humidity
4. Time index
5. Number of occupants

In the study of Ivanko et al. [84] the DHW heat use is predicted for a hotel, and input parameters are evaluated. In this study, the most influential input parameters for all nine different data-driven methods testes, including NN and SVR, were related to the occupants' presence in the building. The three most important parameters were "the number of guests on a given day", "the number of guests the day before" and "an artificial variable used to predict the daily variation of the guest presence". Combined, these parameters were able to give a reliable model of the DHW heat use [84].

2.6 Feature extraction methods

The selection of input parameters to prediction models is very important [54]. If there are many input parameters, the prediction algorithm becomes complex, and the risk of over-fitting increases [54]. Feature extraction methods can help reduce over-fitting, computational costs, improve model performance and identify the intrinsic dimensionality of a given problem [54], all without sacrificing the accuracy of the model [13].

In general, there are two different approaches for selecting model inputs. The first one relies on the concept of subset selection. Typical methods of this type are wrapper, filter, and embedded methods. A disadvantage with this type of method regards the redundancy of subset selection. The other approach for selecting model inputs is based on feature reconstruction. An example of a model in this category is principal component analysis (PCA). The method involves projecting onto the first few principal directions. A new set of data with lower dimensions is obtained through linear combinations of the original data. The main disadvantage connected to this method is that none of the original data can be abandoned, and it may therefore be difficult to interpreter the input parameters. [54]

2.6.1 Variable ranking

Variable ranking use a scoring function to find the number of most relevant parameters to the output. The Pearson correlation coefficient, equation 2.1, is a widespread function in terms of energy prediction. In this equation r_{xy} is the Pearson correlation coefficient between input parameter (x), and target output parameter (y).The sample size is n, the individual sample points are x_i and y_i, and the $\overline{x}$ and $\overline{y}$ are the mean value of input and output parameters. [13]

$$r_{xy} = \frac{\Sigma_{i=1}^{n}(x_i\overline{x})(y_i\overline{y})}{\sqrt{\Sigma_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\Sigma_{i=1}^{n}(y_i - \overline{y})^2}} \tag{2.1}$$

The Pearson correlation coefficient is easy and quick to use and determines the strength and direction of the linear relationship between two variables. Challenges related to this method are determining the number of desired parameters. In addition, the method is only able to calculate the relationship between individual variables and output instead of relationships between subsets of input and output parameters. [13] The strengths and weaknesses related to the method is given in Table 2.6.1.

Table 2.10: *Strengths and weaknesses related to variable ranking [13]*

Strength	**Weaknesses**
Fastest and easiest to use	Hard to determine desired number of parameters
Quantitatively calculate the relevance between individual variables and output	Can not consider the effect of inter-relevance between input parameters and outputs
	Can not select the best subset

2.6.2 Wrapper methods

Feature selection processes that focus on the relationships of the parameters to the classification at the end of the machine learning protocol are called wrapper approaches [85]. The wrapper method selects the best subset with the highest prediction performance in a specific learning algorithm [13]. This method is one of the most precise methods since it detects possible interactions between variables and takes the specific characteristics of the prediction algorithm into account [84].

The wrapper analyses are cyclical in iterating over the same data set multiple times to identify a subset of parameters that provide the best classification accuracy, making this method computationally expensive [85]. Ivanko et al. [84] applied the Wrapper algorithm to categorize the best set of influential variables regarding DHW heat used for a hotel. In this study, the method showed high efficiency in determining the variables included in the prediction model. An overview of the method's strengths and weaknesses is given in Table 2.11.

Table 2.11: *Strengths and weaknesses related to wrapper method [13]*

Strength	**Weaknesses**
Subset selection considers inter-relevant of input parameters	Computational expensive
More stable	High risk of over-fitting

2.6.3 Filter method

Both filter and wrapper methods can be utilized to find the best sub-set selection of parameters, meaning they consider the interrelationship between parameters [13]. In contrast to the wrapper method, the filter method is independent of the machine learning algorithms [85]. Filter methods can be sorted into two different categories: Rank Based (i.e. variable ranking, Chapter 2.6.1) and Subset Evaluation Based [13]. This subsection refers to the Evaluation Based filter method.

Filter methods evaluate the importance of individual or subset of parameters through statistical measures [13]. The method exploits the data set's random characteristics and does not try to understand why the particular parameters are relevant [85]. The parameter is related to the end-classification, independent of the classification algorithm [85]. Filter methods are efficient techniques in terms of computational complexity. However, the method is less stable compared to others [13]. An overview of the method's strengths and weaknesses is given in Table 2.12.

Table 2.12: *Strengths and weaknesses related to filter method [13]*

Strength	**Weaknesses**
Fast and easy to use	Less stable
Subset selection	
Robust to over-fitting	

2.6.4 Embedded methods

The embedded method integrates parameter selection into the learning algorithm [13]. For example, adding regularization to data-driven models can be considered as an embedded method [13]. Challenges related to this method regard the selected regularization method and its lack of adapting the optimization procedure and ensuring optimum solutions. [13]

The embedded feature selection method, ridge regression, creates a parsimonious model when the number of predicted variables in a set exceeds the number of observations or when a data set has a high correlation between predicted variables [85]. Embedded methods, such as ridge regression and LASSE, selects parameters during the modeling process and are embedded within the black-box algorithm [85].

Table 2.13: *Strengths and weaknesses related to embedded methods [13]*

Strength	Weaknesses
Easy to use	Unable to quantitatively present the importance of parameters
Unnecessary to eliminate parameters	

2.6.5 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is one of the most popular methods regarding feature extraction [86]. The PCA technique reduces the dimensionality of data and removes redundancy by seeking clusters of data points that can represent the main parameters of the data [76]. Traditional PCA project parameters into a lower-dimensional sub-space with linearly uncorrelated variables [13]. However, kernel PCA utilized a kernel function to map nonlinear related inputs into a new feature space and further perform a linear PCA in this space [13]. An overview of the method's strengths and weaknesses is given in Table 2.14.

Table 2.14: *Strengths and weaknesses related to PCA [13]*

Strength	Weaknesses
Relatively easy to use	Hard to determine number of desired parameters
Adequate when the original feature space dimension is not too large	For kernel PCA, kernel function needs to be properly selected
Unnecessary to eliminate parameters	

2.6.6 Autoencoder (AE)

Autoencoder (AE) is a type of ANN that can learn a compressed nonlinear representation of the input data [13]. An AE usually consists of two networks, an encoder, and a decoder. The encoder maps original input to a low compressed dimension, and the decoder recovers the original inputs from the compressed representation. AE has been utilized in some studies regarding feature extraction in building energy prediction; however, it is still uncommon. The reason for this is partly since the dimension of the original input parameter is usually small; thus, AE would be computing intensively compared to other methods for feature extraction. [13] Table 2.15 hold an overview of the method's strengths and weaknesses.

Table 2.15: *Strengths and weaknesses related to AE [13]*

Strength	Weaknesses
Learn nonlinear representation of original input More powerful for compressing the dimension of features with lower loss of information	Computational expensiveness

2.7 Modelling accuracy

There are multiple possibilities for evaluating the performance of a data-driven model. This section will include the methods utilized in most studies, including this one.

2.7.1 Over-fitting

In ANN models, the number of hidden layer neurons varies from problem to problem, depending on the number and quality of the training pattern. If too few neurons are selected for the hidden layer, under-fitting can occur. Whereas over-fitting can occur when too many neurons are included. [54]

Over-fitting is a modeling error that occurs when a function is too closely fit to a limited set of data points [87]. This concept is illustrated in Figure 2.19. In addition to the number of neurons, choice of input parameters, number of layers [13], and other changes in the model's structure can lead to over-fitting. [54]

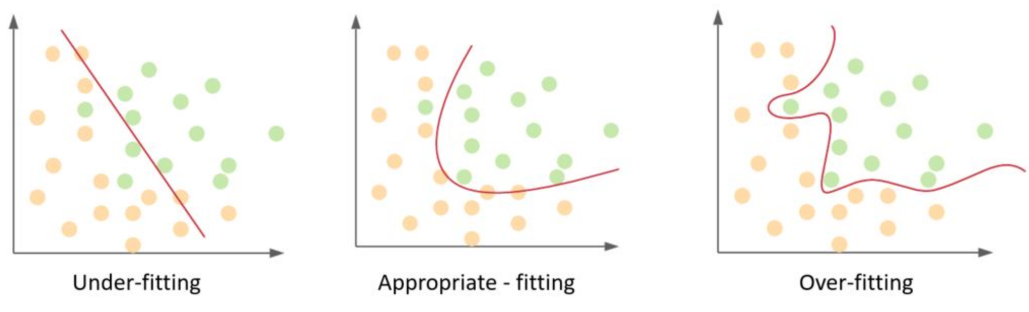


Figure 2.19: *Illustration of over- and under-fitting [88]*

2.7.2 Accuracy matrices

The models' performance can be accessed and examined with the use of different accuracy matrices [54]. The most utilized matrix is MAPE; mean absolute percentage error. This metric calculates the average absolute error as a percentage [54]. RMSE; root mean square error and MAE; mean absolute error are other accuracy matrices widespread in this field of study. All the matrices is presented in equation 2.2–2.4. The different accuracy matrices provide different information regarding the accuracy and forecasting of the model. Error percentage provides a performance evaluation with normalized information, which is good when different models, studies, and building typologies are compared. RMSE equals standard deviation, when the RMSE is calculated based on an average [89]. [49]

$$MAE(^{\circ}C) = \frac{1}{n}\sum_{i=1}^{n}|y_{forecast,i} - y_{actual,i}| \tag{2.2}$$

$$MAPE(\%) = \frac{1}{n}\sum_{i=1}^{n}|\frac{y_{forecast,i} - y_{actual,i}}{y_{actual,i}}| \cdot 100\% \tag{2.3}$$

$$RMSE(^{\circ}C) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{forecast,i} - y_{actual,i})^2} \tag{2.4}$$

2.7.3 Box-plots

A box plot shows the minimum value, upper- and lower quartile, median, and maximum value of a data set [90], and are often utilized in scientific papers. Figure 2.20 holds the meaning related to each component of a box-plot. The square of the figure illustrates the area where 75% of the data-set lies. The whiskers illustrate the minimum and maximum values of the set. The distance between the upper and lower quartile is called the interquartile range (IQR). A data point is considered an outlier if it exceeds a distance of 1.5 times the IQR below the lower quartile or 1.5 times the IQR above the upper quartile [90].

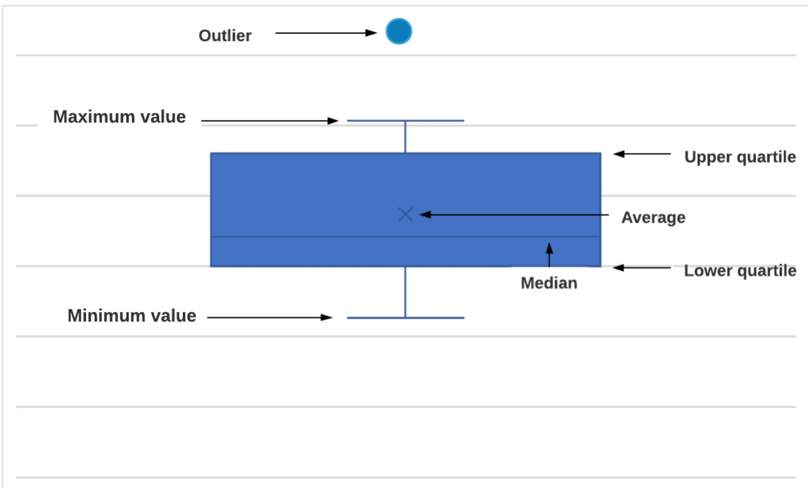


Figure 2.20: *Explanation of box-plots [90]*

3 Methods

This chapter will include the methods used and detailed information on the experiments conducted. First, the literature search will be reviewed, followed by detailed information of the white- and black-box model utilized. The method utilized for the various experiments will also be reviewed and are as followed:

White-box tests

- P-controller and PI-controller
- Different office occupancy schedules
- Residential occupancy and equipment schedule
- One zone split in two
- Building standards: TEK 87, TEK 17, Passive House, and Concrete building
- Change in window location
- Removal of external shutters
- Rotation of building
- Different climate: Trondheim, Oslo, and Malaga

Black-box tests

- Multiple equal predictions
- Different input combinations
- Fewer zones
- Feature elimination
- The wrapper method
- Testing in different seasons
- Time-step accuracy
- Location of error

3.1 Literature search

When finding relevant literature for this study, three search databases were used; Google Scholar, Scopus, and NTNU Open. In each database, articles were searched for based on relevant keywords, usually combined with the word "building". The most used keywords are listed below.

- Data-driven
- Machine-learning
- Parameter
- Black-box

The relevance of the articles where thereby evaluated based on the title. All the information found in the sources has been critically evaluated and compared with multiple studies to determine whether the information is reliable. Information provided by secondary sources has been verified by checking the original source. Secondary sources have also been used to a great extent to find relevant articles and provide a broader range of information. In NTNU Open, professors working in this field of study have been searched for, and meetings were arranged to get more detailed information about the procedure utilized in their study.

When searching for literature, the year of publication has been of great importance. The technology development within data-driven models evolves quickly, and the state-of-art is challenging to capture.

3.2 Development of white-box model

For testing the data-driven model, training data is required. The training data utilized in this study is generated by modeling and simulating a building in the white-box model IDA Indoor

Climate and Energy (IDA ICE), a software developed by EQUA. IDA ICE is a simulation tool with the possibility of detailed simulations of multi-zone models. It was chosen to use a non-residential building for the primary building simulation. This decision was based on the lack of data and research on this building type within our department of study and university. The building modeled is a low-energy building due to the relevance these buildings have in these studies.

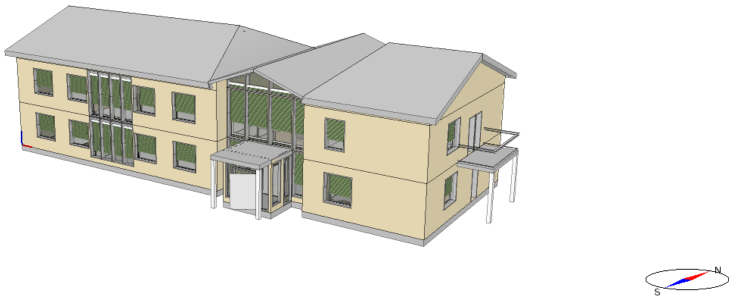


Figure 3.1: *Overview of the IDA ICE modeled building*

It was desired to get a wide variety of results, meaning the building tested needs to be different on multiple levels. A Base Case is therefore made which all the buildings are compared with. All the variations of buildings are based on this particular Base Case. The Base Case is a small office building made after the Norwegian Passive House standard for commercial buildings, NS 3701. The building is located in Trondheim, Norway.

The building design is a two-floor office building with eighteen personal offices, a lobby, three meeting rooms, three corridors, and two bathrooms. The building is made after a template in IDA ICE and adjusted to fit the Norwegian building standards. The simulation of the model is from 01.01.2020 to 31.12.2020, with local weather data. Figure 3.1 gives an overview of the IDA ICE modeled building, and Figure 3.2 holds an overview of the floor plan of the building. The building has the internal dimensions to be 28.1m wide and 12.2m long.

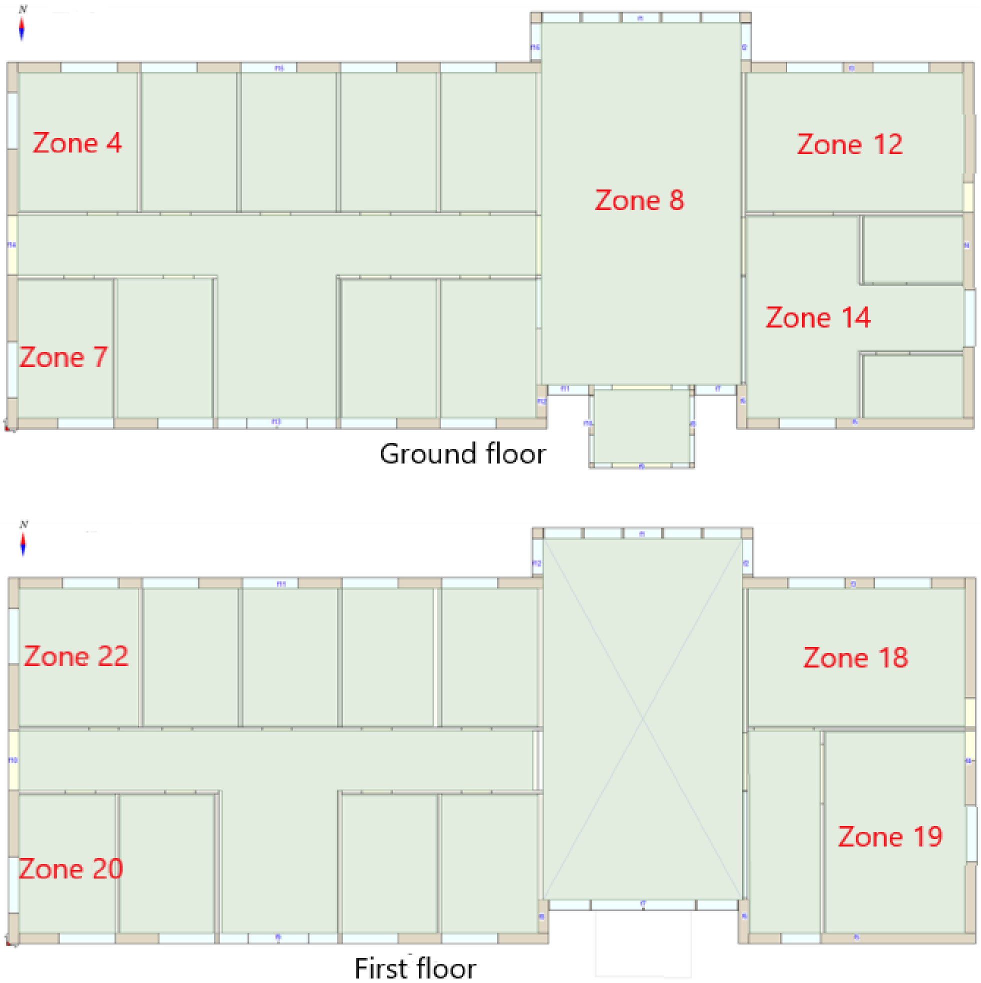


Figure 3.2: *Floor plan of the building with zone names*

3.2.1 HVAC system

For the ventilation, VAV is chosen. The VAV is determined by temperature and CO_2 sensors and uses Proportional Integral (PI) controllers. The set-point for heating is 21°C and 25°C for cooling when the building is occupied. When the building is not occupied, the heating set-point temperature is set to 17°C. A variable set-point is chosen to get a low-energy building. Since a low-energy building is desired, the air handling units' efficiency is set relatively high. Both the supply and extraction fan has an efficiency set to 0,87. The air-to-air heat exchanger has an efficiency set to 0,85, and both the heating and cooling coil has an efficiency set to 1.0. Regarding heating, cooling, and domestic hot water, the energy carrier is set to district heating and cooling, and the COP factor is set to 1 for both. The HVAC system of the modeled building is illustrated in Figure 3.3.

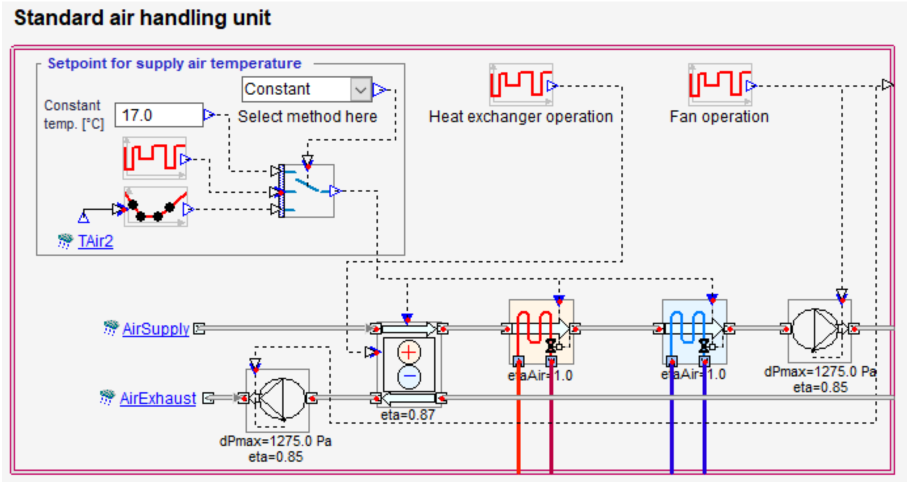


Figure 3.3: *Air handling unit for the Base Case*

A section of the indoor temperature for all the zones of the Base Case is given in Figure 3.4. This indoor temperature will be the output parameter of the black-box model, where the temperatures given in IDA ICE is the "actual" and therefore correct temperatures for the building. From the figure, it is clear that Zone 8 does not reach the desired indoor temperature of minimum 21°C during working hours. The other zones are, however, able to reach this desired temperature.

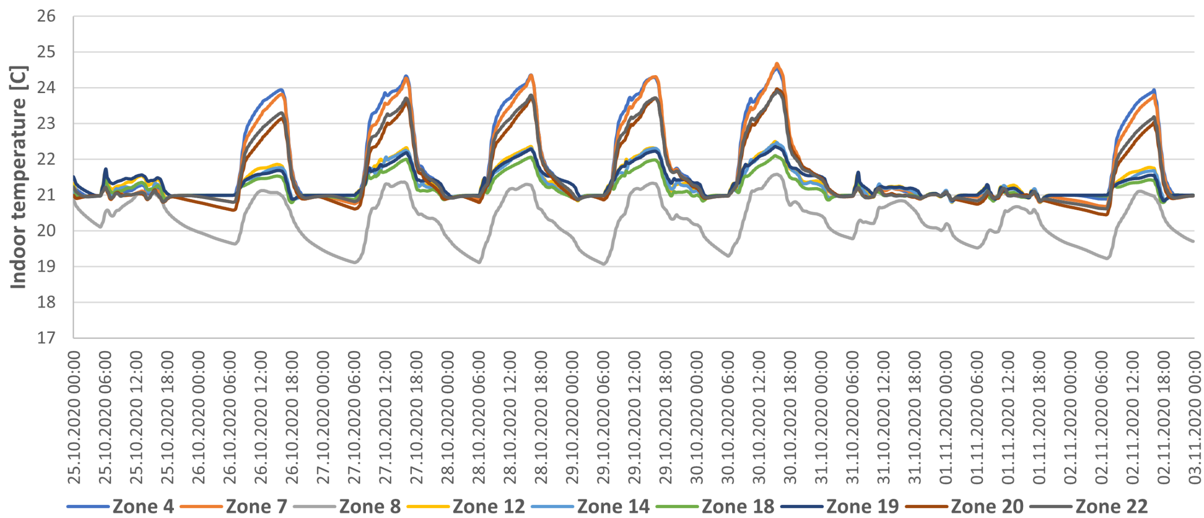


Figure 3.4: *Section of indoor temperature for the Base Case*

Controller

Multiple experiments were conducted with different versions of the Base Case building. The bias of this was to get a wide range of data, covering many different scenarios. Regarding the HVAC system, these experiments were conducted.

- PI-regulator - Bace Case
- P-regulator

The controller used in the Base Case building is a PI-controller. This controller was chosen since it is less sensitive to noise than a Proportional (P) controller. However, for one of the experiments conducted, the controller for the HVAC system is changed to a P-controller. For all other experiments conducted, a PI-controller is utilized. The change of controller was done in the IDA ICE tab "room unite" found under "general". Experiments on the HVAC controllers were only done for P- and PI-controllers, since PID-controller is not a build-in function in IDA ICE.

3.2.2 Internal gains

Different schedules of occupants and equipment are also tested to see how the model act when the internal gain is changed. The experiments conducted are listed below.

- Office schedule for occupants and equipment

    Seven random occupant schedules for offices

- Residential schedule for occupants and equipment
- Zone 12 split in two

Occupancy
When making the data used for the model's occupancy-related information, one week of actual data from a real office is used. The data is stored in an excel file and multiplied by 52, covering a full year. It was desired to test the model for different cases. Multiple random occupancy schedules were therefore made based on the original one. When making multiple cases, excel analyzed the original data for the specific time-stamp and randomized the number if the original value was higher than zero. The excel function used to make random numbers was "RANDBETWEEN". When using this code, the lower value was 0.1, and the upper value was 0.99. The random decimals were further multiplied with a set number of maximum people for each zone, Table 3.1. The set number of occupants is a float, chosen based on the area recommended per person for office buildings [42]. The activity and clothing level for all occupants is set to 1,2 met and one clo, Table 3.2.

Table 3.1: *Detailed information about internal gain for each zone*

Zone	4	7	8	12	14	18	19	20	22
Size [m^2]	14.76	11.86	65.80	27.00	26.60	27.00	25.38	12.05	14.95
No. occupants	2.36	1.90	13.16	8.10	4.04	8.10	7.61	1.93	2.40
No. standard PC	4.43	3.56	6.58	2.70	2.02	2.70	2.54	3.62	4.49
No. light bulbs	0.49	0,40	2.19	0.9	0.89	0.9	0.85	0.40	0.50

Table 3.2: *Energy use related to internal gains*

Occupant activity level	1.2 met (126 W)
Standard PC	125 W
Light bulbs	60 W

Residential occupancy
When making the occupancy schedule for the residential building, the inverse of the office data was used. Meaning when the office was occupied, the residential building was not, and opposite. Each hour of data was further randomized within the same given boundary. To avoid that the buildings were too different, the same internal gain is utilized in the residential

building as in the office building. Normally residential buildings are less occupied than office buildings, but in this test, it was chosen to keep the same ratio for occupancy.

Zone 12 split in two

One zone, Zone 12, was split into two new ones to find how different room sizes affect the model. The splitting was done by right-clicking on the zone and choosing the option "split zone with wall" in IDA ICE. The wall was placed between the two windows of the zones and a door was placed in the middle to make the new zone accessible. The two different layouts of the zone is illustrated in Figure 3.5 and 3.6. The internal gains related to the two new zones are listed in Table 3.3. There are more equipment and fewer occupants in the new split zones compared to the original zone. This is to make the zone more similar to an office than a meeting room and give the rooms a natural area of use.

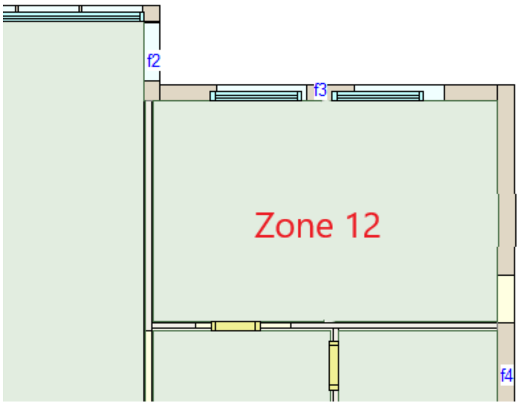


Figure 3.5: *The original layout of Zone 12*

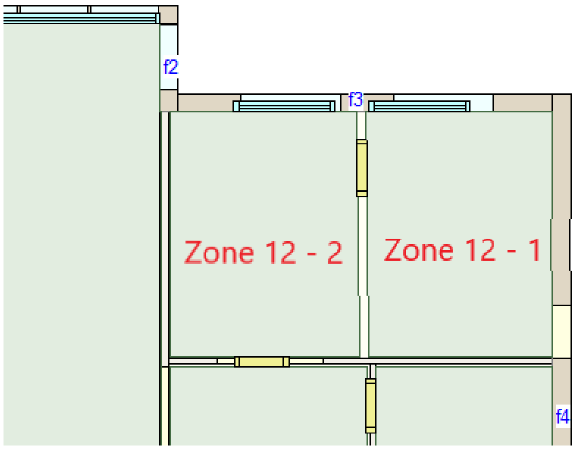


Figure 3.6: *Layout of Zone 12 when split in two*

Table 3.3: *Detailed information about internal gains for Zone 12 when split*

Zone	**12 - 1**	**12 - 2**
Size [m^2]	13.09	13.33
No. occupants	2.09	2.13
No. standard PC	3.93	3.99
No. light bulbs	1.31	1.33

Equipment

The use of equipment varies for most rooms, where larger rooms have less and smaller more. This deviation is based on the building's design as an office building, whereas small rooms are designed as small offices for one to two occupants, while larger rooms are designed as meeting rooms, lobby, or break area. Table 3.1 holds information about the amount of equipment and light bulbs set for each zone, and Table 3.2 the energy use for each component.

A "standard PC" is chosen as the equipment variable to get a variable with relatable energy use. During the simulation, the PC represents the energy use of all technical equipment in offices, for example, printers, chargers, and coffeemakers. Most of the time, the building is set up as an office building. During these times, the equipment schedule is set to on during office hours, Figure 3.7. This schedule is chosen based on when the building is occupied.

One of the experiments analyzes how the building behaves when it is used as a residential building. During this case, the equipment schedule is set to almost the opposite of the office schedule. This schedule is visible in Figure 3.8. This schedule is made based on Figure 2.6.

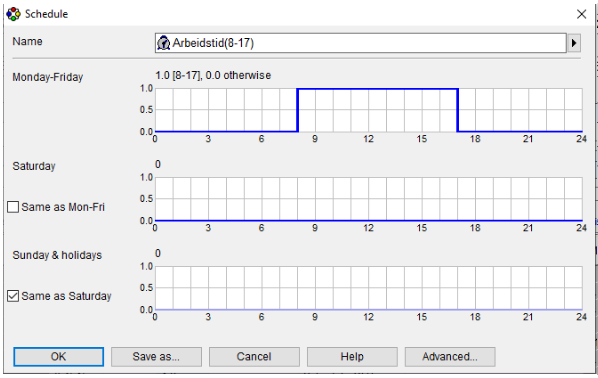


Figure 3.7: *Equipment schedule for office building*

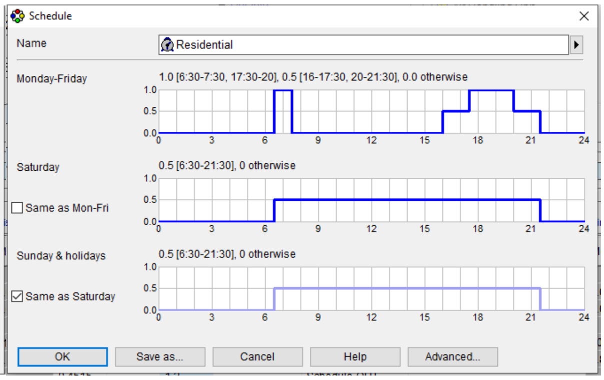


Figure 3.8: *Equipment schedule for residential building*

3.2.3 Building envelope

Regarding the building envelope, there have been conducted several experiments where changes have been made. The envelope of the Base Case is made after the Norwegian Passive House standard. For all the simulations and experiments regarding the building envelope, the building is located in Trondheim, Norway. This subsection will give detailed information about the building envelope set for the Base Case, and the other cases. The experiments conducted in this category are listed below.

- Building envelope

  Passive House - Base Case

  Concrete Building

  TEK 17 building

  TEK 87 building

- Change in window location
- Removal of external shutters
- Building orientation

Building standards

The building standard used in the Base Case is the Norwegian Passive House standard for commercial buildings, NS 3701. Other building standards tested are TEK 17, TEK 87, and NS 3701 with high thermal mass, further called the Concrete Building. The requirements for the different building standards are given in Appendix B.

The u-values for all the buildings made in IDA ICE and their components are listed in Table 3.4. As seen in Table 3.5 the internal walls and internal floors are equal for both the Passive House, TEK 17, and TEK 87. This decision was made to have as equal buildings as possible without affecting the heat flow out of the building's boundary to a large degree.

Table 3.4: *U-value for all the building elements in all building types utilized in the experiment [W/m^{2}K]*

	I. wall	E. wall	I. floor	E. floor	Roof	Window	Door
TEK 87 building	0.619	0.288	0.773	0.291	0.192	0.826	1.980
TEK 17 building	0.619	0.206	0.773	0.173	0.174	0.826	0.943
Passive House	0.619	0.096	0.773	0.087	0.079	0.826	0.333
Concrete Building	1.148	0.115	2.091	0.087	0.099	0.826	0.333

Note: I. = Internal, E. = External

Table 3.5 holds information about the building construction utilized for the Passive House, TEK 17 and TEK 87 buildings. The Concrete Building was included to see how the thermal mass of the envelope changes the performance of the black-box model. Table 3.6 holds the layers and dimensions of all the materials used in the Concrete Building envelope. According to Direktoratet for byggkvalitet [91] these are specific layers external walls, floors, and roofs must contain to be safe against natural stresses. Some of these layers include material that is water- or windproof. In this study, the wall layers have been simplified, where a good u-value and thermal mass are the construction aims.

Table 3.5: *Materials in the construction, from inside to outside, for Passive House, TEK 17 and TEK 87 building*

	Interial wall	External wall	Internal floor	Ground floor	Roof
			Inside		
	Gypsum(0.026m)	Render(0.01m)	Coating(0.005m)	Coating(0.005m)	LI(X)
	Air gap(0.03m)	Wood(0.07m)	Render(0.02m)	Concrete(0.2m)	Wood(0.2m)
	LI(0.03m)	LI(X)	Wood(0.15m)	LI(X)	
	Air gap(0.03m)	Render(0.01m)			
	Gypsum(0.026m)				
			Outside		
TEK 87		X = 0.1m		X = 0.1m	X = 0.13m
TEK 17		X = 0.15m		X = 0.15m	X = 0.15m
PH		X = 0.35m		X = 0.4m	X = 0.4m

Note: Coating = Floor coating, LI = Light insulation, PH = Passive House

Table 3.6: *Detailed information about the building materials in IDA ICA for the Concrete Building*

Internal wall	External wall	Internal floor	Ground floor	Roof
		Inside		
Gypsum(0.02m)	Render(0.01m)	Coating(0.005m)	Coating(0.005m)	Concrete(0.3m)
Air gap(0.03m)	Concrete(0.3m)	L/W concrete(0.02m)	Concrete(0.2m)	LI(0.35m)
Concrete(0.1m)	LI(0.3m)	Concrete(0.25m)	LI(0.4m)	
Air gap(003m)	Render(0.01m)			
Gypsum(0.02m)				
		Outside		

Note: Coating = Floor coating, LI = Light insulation

The Passive House standard is specifically chosen for the Base Case due to the large probability that a building with such advanced technology as a black-box probably also have a good building envelope. The thermal mass of buildings often varies from building to building, based on the materials used. To learn more about how the model performs with a different thermal mass, the Concrete Building was included as an experiment. TEK 17 is the newest, and therefore most relevant building standard in Norway and was chosen based on this. TEK 87 is an older building standard and is chosen to get information about the older buildings.

Figure 2.2 illustrates that the total energy use is relatively equal for buildings with the building standards TEK 87 and older. An outdated building standard (TEK 87) is therefore chosen to include protected and similar buildings. In these buildings, it is possible to upgrade the HVAC system, but upgrades on the building structure are more limited [92]. Therefore the HVAC system and windows of all the buildings are however the same. This decision was made to make sure the buildings did not deviate largely from each other. In the building envelope used for the Passive House, the insulation in the external walls and roof is 350mm and 400mm thick. These values are realistic for buildings located in northern countries, where Passive Houses often use 300 - 400 mm insulation [93].

The annual energy use for the different building structures are given in Table 3.7, and 3.8 for the Base Case/Passive House. As expected, the building with the most insulation has the lowest energy use and the least the most.

Table 3.7: *The energy use of the different building standards given in kWh for total,* kWh/m^2 *for per* m^2, *and kW for the peak demand (PD)*

	TEK 87			**TEK 17**			**Concrete**		
	Total	Per m^2	PD	Total	Per m^2	PD	Total	Per m^2	PD
Lighiting	1948	3.81	0.58	1948	3.81	0.58	1948	3.81	0.58
HVAC aux	2794	5.46	5.87	2456	4.80	6.12	1243	2.43	3.84
D. cooling	514	1.00	15.04	728	1.42	18.44	513	1.00	13.97
D. heating	22530	44.05	54.72	8508	16.63	20.41	8203	16.04	14.72
Equipment, tenant	16041	31.36	6.80	16043	31.36	6.80	16040	31.36	6.80
Total	43827	85.69	83.01	29683	58.03	52.36	27947	54.64	39.91

Note: PD = Peak demand, D. = District

Change in window location

One experiment is conducted to see the effect of windows location. In this experiment, the windows on the west side of the building are removed in Zone 7, 20, and 22. In addition, there is added another window on the southern side of Zone 4. For Zone 12, one of the windows on the southern side is removed, and one is added one the east wall. Figure 3.9 illustrated the new locations for the windows on the ground floor.

This experiment is also conducted where the windows are located on the opposite wall. For this experiment, both windows in Zone 4 are located on the western wall, and both windows in Zone 12 are located on the eastern wall. The locations of the windows for this experiment are illustrated in Figure 3.10.

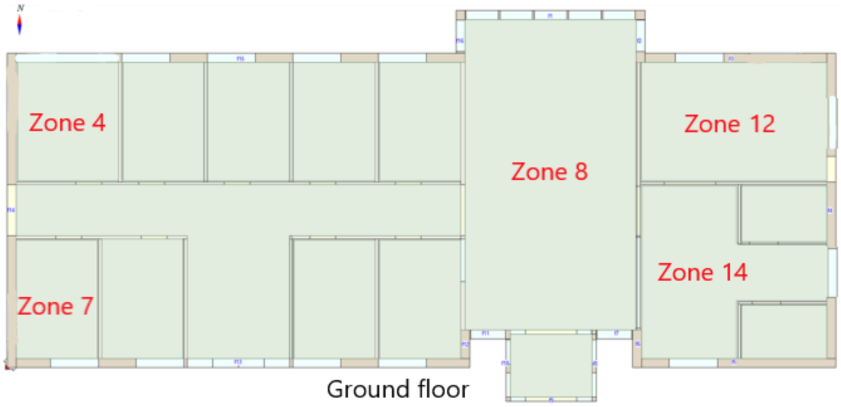


Figure 3.9: *Overview of one of the new locations for windows in the experiment "location of windows"*

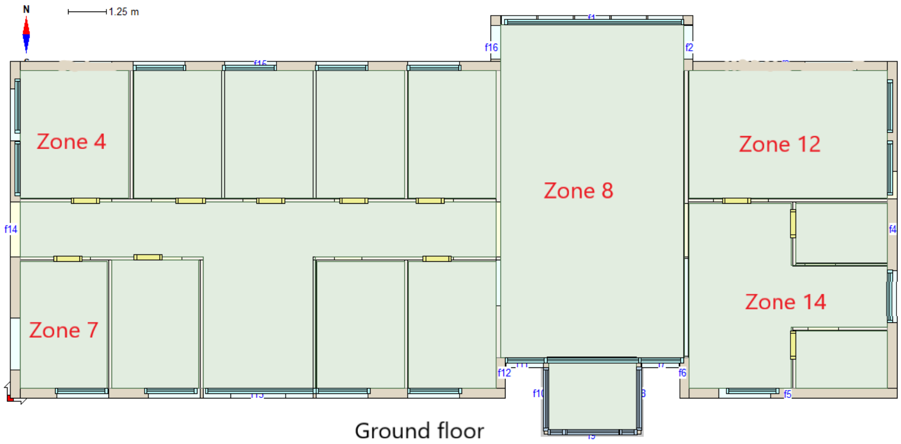


Figure 3.10: *Overview of the second locations for windows in the experiment "location of windows"*

Shutters

The simulated IDA ICE building has external shutters on all the windows. The shutters used are *generic shutter shade* and are connected to a sun controller. More detailed information about the settings for the shutter is given in Figure 3.11 and 3.12. In one experiment, these shutters are removed from all the windows in the IDA ICE model to see how this affects the black-box model.

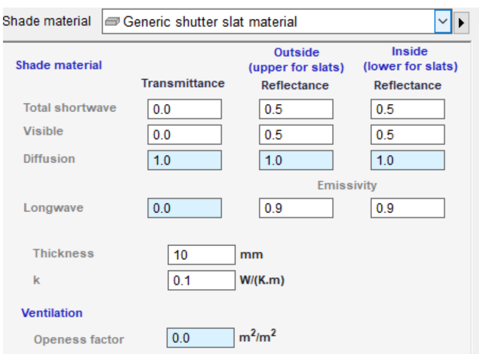


Figure 3.11: *Detailed information about the shutter material*

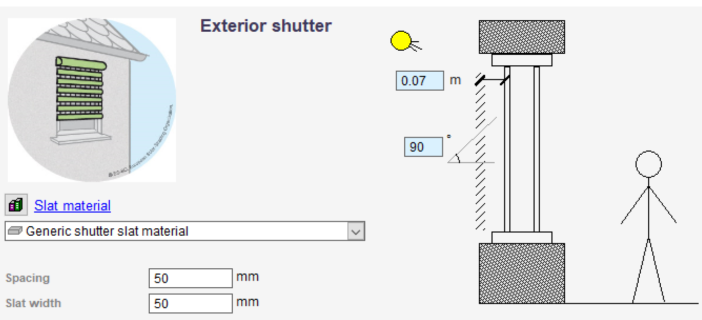


Figure 3.12: *Detailed information about the exterior shutters used in the IDA ICE model*

Rotated building
The orientation of the building may have some effect on the different zones. An experiment where the building is rotated 180°was therefore conducted to see the impact of the orientation. After the rotation, the northern side was facing south, and the west side was facing east. The rotation was done in the "site" function to IDA ICE.

3.2.4 Different climate

To investigate the climate's effect on the building, different locations for the building are tested. In these experiments, the same building, the Base Case, is simulated in different locations. The locations were chosen based on the desire to get a considerable variation in climate and more reduced differences to see the effect. The utilized locations are listed below.

- Trondheim, Norway - Base Case
- Oslo, Norway
- Malaga, Spain

Oslo was specifically chosen to see the difference between small climate changes and distances. Malaga was chosen due to its "temperate" classification in the Köeppen climate classification [21]. The location of the utilized cities is illustrated in Figure 3.13.

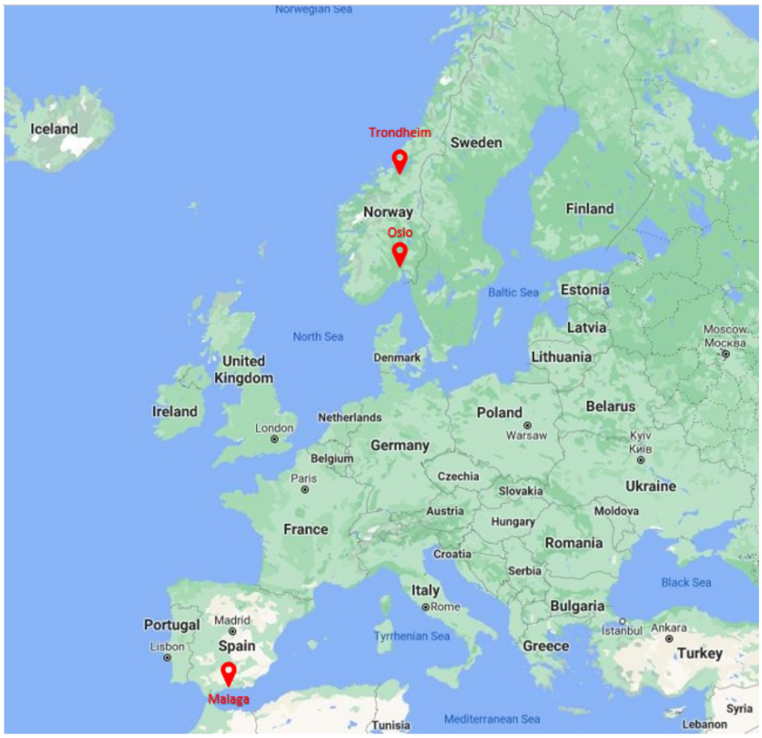


Figure 3.13: *Map over Europe marking the relevant cities used in this experiment*

The climate is quite similar in Malaga, Spain, and Hong Kong [21]. The case where the Passive House is located in Malaga may be similar to the case of Wang et al. [31] where a high-class office building is simulated, giving a bias of comparison. Table 3.8 holds the annual energy use for the building when it is located in the three different locations.

Table 3.8: *The buildings energy use at different location, given in kWh for total,* kWh/m^2 *for per* m^2, *and kW for the peak demand (PD)*

	Trondheim			Oslo			Malaga		
	Total	Per m^2	PD	Total	Per m^2	PD	Total	Per m^2	PD
Lighting	1948	3.81	0.58	1948	3.81	0.58	1948	3.81	0.58
HVAC aux	1320	2.58	4.81	1633	3.19	4.82	4777	9.34	7.16
D. cooling	594	1.16	15.92	691	1.35	15.77	18959	37.06	44.09
D. heating	7283	14.24	15.74	13764	26.91	21.29	5.61	0.01	0.51
Equipment	16040	31.36	6.80	16040	31.36	6.80	16041	31.36	6.80
Total	27185	53.15	43.85	34076	66.62	49.27	41730	81.58	59.14

Note: PD = Peak demand, D. = District

According to the Köeppen climate classification [21], Figure 2.3, Oslo is located in a mild climate, and Trondheim in a cold. Therefore, the values used for district heating for these locations are a bit odd, Table 3.8, since the building located in Oslo uses more energy on heating than the Trondheim building. These values can be explained by Figure 3.14, which illustrates the outdoor dry-bulb temperature used in the IDA ICE simulation for the two locations. The figure illustrates that for the specific year simulated, the weather was cooler in Oslo than in Trondheim.

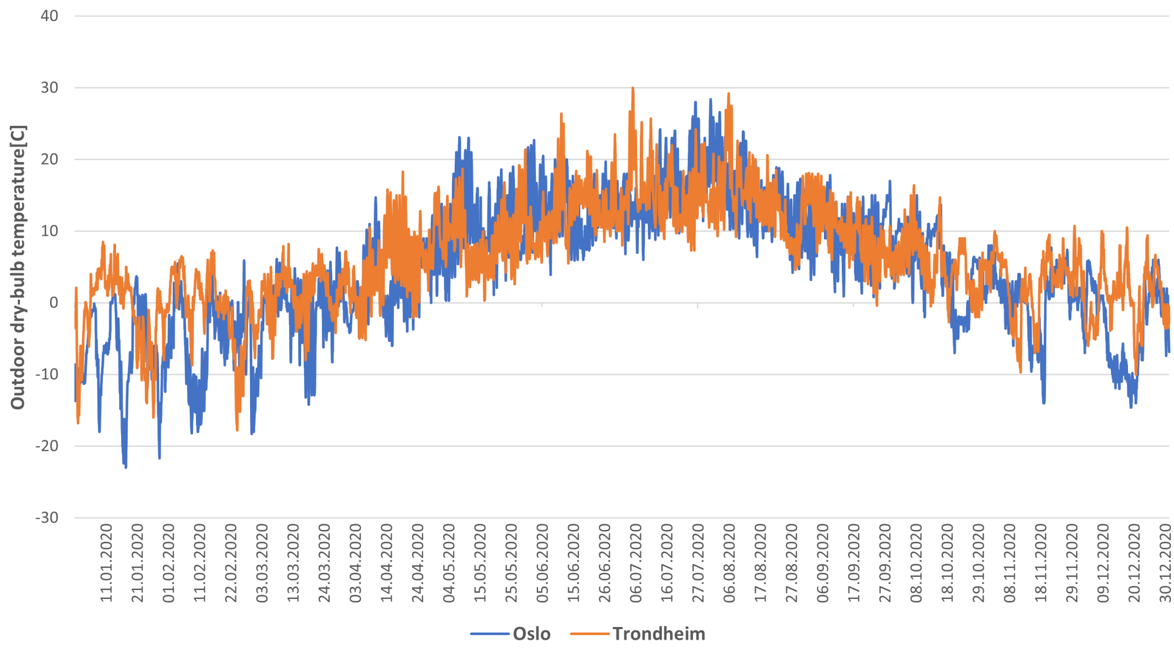


Figure 3.14: *Outdoor dry-bulb temperature for Oslo and Trondheim used in IDA ICE simulation*

3.3 Black-box model

The black-box model utilized in this study is a hybrid of a multiple-input multiple-output (MIMO). The model utilized only use input and outputs from nine of the buildings twenty-six zones, making the model a hybrid and not a pure MIMO [53]. A hybrid MIMO was chosen to reduce the complexity of the model while still getting more information about the whole building. [66].

The black-box algorithm used is the Long short-term memory (LSTM) model, an artificial recurrent neural network (RNN). RNN models are the most utilized model among the machine learning methods [8]. This popularity is due to the model's flexibility and strong ability to model the intricate patterns hidden in data. A schematic overview of the architecture of RNN models is illustrated in Figure 2.12.

LSTM was first proposed by Hochreiter and Schmidhuber [94] in 1997 as a solution to the vanishing and exploding gradient problem of the RNN. The main advantage of this model is the use of gates to manage memory by choosing to upgrade the information or not [66]. LSTM Network models can deal with non-linear HVAC systems and learn long-term dependencies when processing time-series compared to traditional machine learning methods, such as SVM and ordinary Neural networks (NN) [53, 66]. This advantage is due to the internal memory cells of the LSTM model[66].

3.3.1 LSTM - hybrid - model

The model utilized was made in Keras, an open-source library for Python 3.4 version. *Keras* is a high-level NN API made for Python and can run on TensorFlow. *TensorFlow* is an open-source library made by Google for numerical computation and large-scale machine learning [53]. The black-box model utilized in this study was designed by Gaurav Chaudhary, PhD. candidate at NTNU, and is attached in Appendix C.

The model is a multi-time-step and multi-zone black-box model for multi-step predictions of indoor air temperature. The model is an encoder-decoder network with a sequence-to-sequence-based approach. This method utilizes multi-layered LSTM to map the input time series sequence to a vector of fixed dimension. Further, another LSTM decodes the target time series sequence from the vector. The LSTM model utilizes input data from the past four days and predicts the indoor air temperature for the next 24 hours. [53]

NN is often characterized by a large set of hyperparameters, which defines the network's topology, computational power, and more. The hyperparameters value are used to control the learning processes, making the proportion of the hyperparameters essential and the need for them to be adequately configured important. This is to harness the functionality of the network. Hyperparameters can not be learned in the training process but need to be initialized manually. For LSTM models, hyperparameters include batch size, numbers of NN layers, size of the input layers, size of output layers, number of epochs, and others. Table 3.9 holds detailed information about the configuration of the LSTM model utilized in this study. The batch number of the code was chosen to be 64. However, when the LSTM model had problems running, the batch number was reduced to 32. This modification usually fixed the issue related to running the model. [53]

Table 3.9: *Detailed information about the configuration of the hyperparameters utilized in the LSTM model*

Hyperparameters	
Batch size	64
Number of NN layers	100
Number of epochs	50
Dropout factor	0.3
Number of past time-steps utilized	384
Number of future time-steps	96
Number of input layers	54
Number of output layers	9

Preventing over-fitting of the predicted output parameters is important during the training of the model. A dropout mechanism was therefore put forward to prevent this. During the training process, some units are randomly discarded from a network at a certain probability. The dropout rate was set to 0.3, Table 3.9. [53]

The time-step utilized is 15 minutes, meaning that the interval between the input data collected and the output data predicted is 15 minutes. The number of past time-step utilized is 384, Table 3.9. This number is utilized since it is the number of time-steps for four days, which is the amount of training data needed for prediction. The future time-step of 96 represents the number of time-steps predicted in each prediction and is the number of time-steps in a 24-hour prediction with a 15-minute interval.

The number of input layers, 54, is the number of input parameters utilized, including the output parameters, which are used as an input in the form of historical information about the indoor air temperature. The nine output layers represent the nine zones where the temperature is predicted. The theory related to choosing and analyzing good values for the other hyperparameters is not included in this study and hence not discussed.

3.3.2 Training, validation and testing of LSTM model

As mention in Chapter 2.4.5 artificial models need to be trained, validated, and tested to complete the model. This study is chosen to distribute the available data set with a distribution rate of 60% for training, 20% for validation, and 20% for testing. This ratio was chosen since it is the most utilized ratio in other studies [49], even though the Project work[1] concluded that a large amount of data for testing and validation is of importance. Since the simulated year, 2020, was a leap year, the assigned days for training equals 220, and the assigned days for validation and testing are 73 days each. But as seen in Table F.1 in Appendix F.1 the error related to both cases are fairly low. An illustration of the data distribution with a 60-20-20 ratio is given in Figure 3.15.

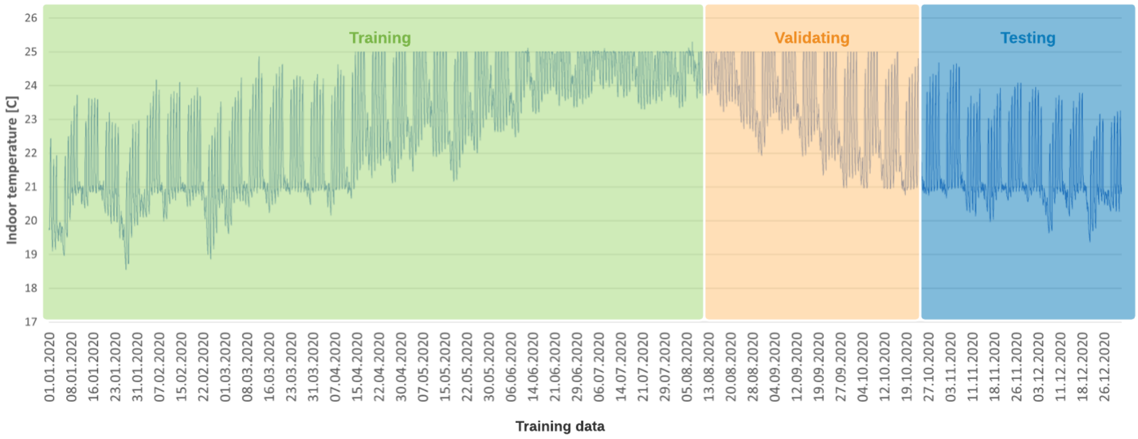


Figure 3.15: *Distribution of data for training, validation and testing. The indoor temperature illustrated is for the Base Case Zone 7*

3.3.3 Input parameters utilized

The LSTM model is used to predict the indoor air temperature of each zone, which is one of the output parameters this particular model is well suited to predict [66]. The input parameters for the model are generated in IDA ICE for each case building, Section 3.2. All the IDA ICE files are saved as "unpacked", and the values used are found within the energy folder. The desired values are extracted from each file and saved in a combined *csv* file.

The time-step utilized was 15 minutes, and building information available in IDA ICE is given in 10 minutes time-stamps. The values are therefore interpolated to fit the desired case. A 15 minute time-step was chosen as a compromise since 10 minutes time-step is very computationally expensive. In the project work [1], the accuracy-related to each time-step was investigated, and little difference of accuracy was found for all the time-steps examined (10min, 30min, 60min). Therefore, a 15-minute time-step is considered a good choice, which will give good and representative results. The input and output parameters used in this experiment are given in Table 3.10.

The input parameters found most relevant and most utilized, based on the information found in the literature study, are extracted from the generated white-box model and used to train the black-box model. However, some of the parameters included are not as widespread and assumed not essential to capture the energy behavior of the building, for example, wind speed, sky cover, and lighting. These parameters are included to ensure their lack of importance. In the parameter equipment, the parameter lighting is included as one of the equipment, strengthening the assumed lack of importance related to this parameter. An overview of the utilized input parameters is given in Table 3.10. The zone-related parameters, equipment, heat demand, lighting, occupancy, and indoor temperature, include parameters for each zone predicted. I.e., the parameter includes information about each specific zone.

Table 3.10: *Parameter variables used in the experiments*

	Input parameter	Abbreviation	Unit
Input 0	Outdoor dry-bulb temperature	OT	°C
Input 1	Relative humidity	RH	%
Input 2	Wind speed - East to west	Wx	m/s
Input 3	Wind speed - North to South	Wy	m/s
Input 4	Direct normal radiation	SR_{Nor}	W/m^2
Input 5	Diffuse radiation on horizontal surface	SR_{Hor}	W/m^2
Input 6	Sky cloud cover	SC	%
Input 7	Hour of the day	h	Integer
Input 8	Day of the week	d	Integer
Input 9	Equipment load in zone i	Eq,i	W/m^2
Input 10	Heating demand in zone i	Hd,i	W/m^2
Input 11	Lighting load in zone i	Li,i	W/m^2
Input 12	Occupancy in zone i	Occu,i	Float
Input 13	Indoor temperature in zone i	IT,i	°C
	Output parameter		
	Indoor temperature in zone i	IT,i	°C

3.3.4 Zones utilized

The black-box model utilized is a hybrid MIMO since more than one zone is incorporated, while not all building zones are. During most of the experiments utilized, nine of the total twenty-six zones are incorporated in the model. In all the nine zones, specific zone information is used as input, and a corresponding output parameter is extracted. The specific zones utilized in the model are chosen due to their location, with a desire to get as varied zoned as possible. An overview of the building with zone names is given in Figure 3.2. All the zones are designed after different areas of use. An overview of each zone's area of use, orientation, and the floor is given in Table 3.11.

Table 3.11: *Information about the zones used in the study*

Zone	Floor	Type	Number of E.walls	Direction of E.wall
4	1.	Office	2	N + W
7	1.	Office	2	S + W
8	1. + 2.	Lobby	2	N + S
12	1.	Meetingroom	2	S + E
14	1.	Meetingroom	2	S + E
18	2.	Meetingroom	2.	N + E
19	2.	Meetingroom	2	S + E
20	2.	Office	2	S + W
22	2.	Office	2	N + W

Note: E. = External

3.3.5 Delimitation's when presenting the results

When the tests were conducted a large amount of data is generated. To limit the results some delimitations were taken.

Zones
It has been chosen to highlight specific zones when comparing the parameter relevance of models. The highlighted zones are Zone 7, 8, 12, and 22. These specific zones were chosen to get a broad representation of the zones, with a mix of large and small zones with different orientations, floors and area of use.

MAPE of 24h prediction
For determining the accuracy related to each case, MAPE is used. To limit the results, it is chosen only to compare MAPE for 24h prediction, meaning the prediction accuracy of time-step number 96. MAPE is chosen due to its ability to evaluate with normalized information, making it suitable for comparing different cases. More information about MAPE is given in Chapter 2.7.2.

Average and box plot
Due to the time-step of data and method used for parameter evaluation, each case holds a set of data with 96 * 73 values for each zone for each parameter tested. To present the data in a comparable way, it is chosen to use average values and box plots when representing the results. For the cases where many results are being compared, average values for prediction accuracy are chosen, while when less data are compared, box plots are utilized.

3.3.6 Evaluating the model and parameter importance

Different experiments were conducted to evaluate the model and get more knowledge of its performance during different situations. The experiments conducted regarding the model's behavior are listed below.

- Multiple equal simulations
- Fewer inputs, and different input combinations
- Fewer zones
- Feature elimination
- Feature extraction - Wrapper method
- Training, validating and testing in different seasons
- Locating the errors

Multiple equal simulations
The reliability of the black-box model was tested to see the variation between each simulation. This was done by re-staring the model and running the black-box model with the same input data. This was done when generating the results for Figure 4.2 and Section 4.1.2.

Standard deviation of feature elimination
When calculating the standard deviation (STD) the excel function "STDEV.S" was utilized. The STDEV.S function calculates the STD in a sample set of data [95]. In this thesis, the values inserted are related to when multiple equal simulations are conducted, such as in Section

4.1. Since the same simulation only is conducted three to five times, the data used to find the STD is limited and was only based on three to five values.

In Section 4.2.2 all the MAPE's in Section 4.1, illustrated in Figure 4.6 - 4.8 is compared to the STD in Appendix A. The MAPE's utilized in the comparison is the average of the three similar values related to each parameter. The difference between the MAPE's, and when excluding one parameter, is then calculated for each zone and parameter. Appendix A holds the STD for each feature elimination, for each zone. The value generated when calculating the difference between the MAPEs is then compared to the corresponding STD.

Few inputs
A simulation was done with fewer input parameters to investigate how the model is affected by changes in inputs. An overview of the input parameters used is given in Table 3.12. This procedure was utilized when creating part of the results in Figure 4.2.

The method was also used when testing different input combinations and how well the model works on fewer inputs in Chapter 4.2.1. During this experiment all the input combinations listed in Table 3.12 are tested. Experiments where meteorological data, time-index, and zone-related information were removed, were also tested. During these experiments, all the inputs in the relevant category were removed from the input file before training the model, and the input combination is named after the missing parameters.

Table 3.12: *Parameters used in experiment with few inputs*

Input parameters	Combination 1	Combination 2	Combination 3
Outdoor temperature	Used	Used	
Relative humidity	Used		
Wind speed East to West			Used
Wind speed North to South			Used
Direct normal radiation		Used	
Diffuse radiation on horizontal surface		Used	
Sky cloud cover	Used		
Hour of the day			Used
Day of the week	Used	Used	
Equipment load in zone i	Used	Used	
Heat demand in zone i	Used		Used
Lighting demand in zone i	Used		
Occupancy in zone i			Used
Indoor temperature in zone i	Used	Used	Used

Fewer zones
Experiments where zones were removed was conducted to see how the model's accuracy changes when fewer zones are included. In these experiments, only data from the relevant zones were included in the input of the black-box model. The desired output of the model was also modified to only include the relevant zones. This procedure was done when making parts of results in Figure 4.2, and in Section 4.1.3. In Figure 4.2 the relevant zones are Zone 7, 8, 12, and 22. In Chapter 4.1.3 all zones are included except Zone 8.

Feature elimination
This technique involves eliminating one and one input parameter individually, and training,

validating, and testing the model without the missing parameter. The model's accuracy without the relevant parameter is then compared to the model's accuracy with all parameters and the cases where other parameters are missing. When illustrating these results, the name of the missing parameter is the name of the tested case. In these experiments, the simulation with high error signifies an input parameter of importance.

The new input file with the missing parameter is made by deleting the relevant parameter(s) in the original csv file. In the LSTM model, the code is modified by changing the number of input layers. The new number of input layers is 53-52 when a meteorological or time-related parameter is removed and 45 when a zone-related parameter is removed, for example, equipment or lighting. To limit the amount of prediction, feature elimination with solar radiation and wind includes both perimeters in these categories. For zone-related information, the parameter is removed for all zones.

The wrapper method

Both PCA and the Wrapper method have been considered for this study to evaluate the parameter importance and find a good subset of inputs for the model. The PCA method was desired to use due to its considerable popularity and ease of use. The Wrapper method was chosen due to its ability to find subsets. In addition, the method has already been utilized at this university, making the process of development more accessible.

These models are based on placing the data-driven model inside a "for loop". More information about the PCA and wrapper method is given in section 2.6. Unfortunately, the model utilized in this study was not modified and suited for loops before the end of the timeline due to errors accruing when the model was run multiple times. These experiments were therefore limited due to the limited amount of time. Out of the possible experiments, only the wrapper method was conducted.

The wrapper method aims to find the best possible input combinations for one specific model. The model finds this input combination by running the model for every possible combination of the inputs and printing the accuracy of the simulation. The input combinations tested are for all possible combinations, with all possible amounts of inputs. All these possible combinations were in this experiment set up in an excel sheet with a assigned name. When the predictions of the wrapper method combined with the LSTM model is completed, the accuracy related to each case is compared, where the best accuracy assigned the best input combination. In this thesis, the wrapper method is tested for the Base Case, the Malaga building, and the TEK 87 building. For all of the cases tested, the output is indoor temperature; this parameter is an additional input parameter for all cases. The model for the wrapper method utilized in this thesis was developed in collaboration with PhD candidate Gaurav Chaudhary, and is attached in Appendix D. The input file utilized to give all possible input combinations is attached in Appendix E.

Testing in different seasons

An experiment where the training, validation, and testing phase is shifted was conducted to see how the model act during different testing conditions. An overview of the three different cases tested is given in Table 3.13 and illustrated in Figure 3.16. In the Base Case and all other experiments, "Test = Season 3" is utilized.

Table 3.13: *Dates used for training, testing and validation*

	Test = Season 3	**Test = Season 2**	**Test = Season 1**
Training	01.01 - 07.08	26.05 - 31.12	14.03 - 19.10
Validation	13.08 - 24.10	01.01 - 13.03	20.10 - 31.12
Testing	20.10 - 31.12	14.03 - 25.05	01.01 - 13.03

During the Project Work[1], an similar experiment was done. The experiment concluded that the accuracy for the model is lowest when the training and testing conditions are most similar. Therefore, it is assumed that the model performs best during “Test = Season 3”.

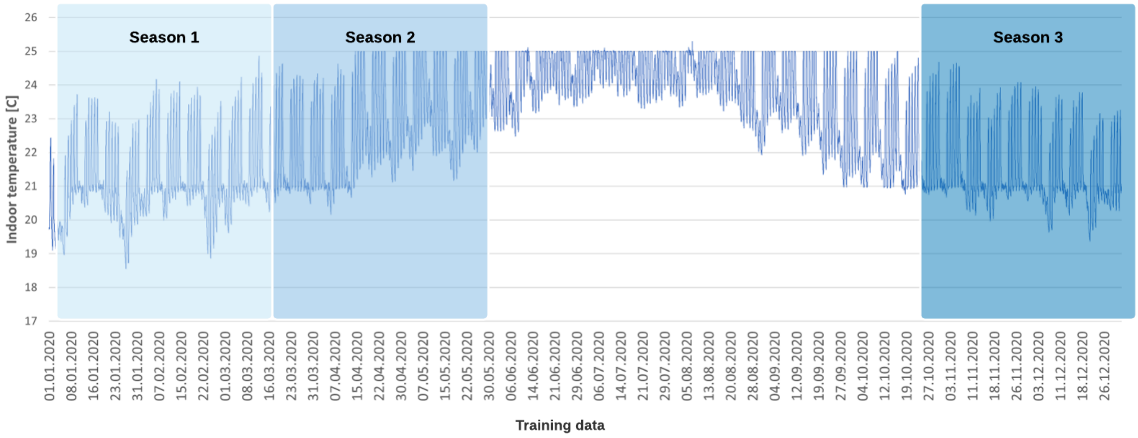


Figure 3.16: *Illustration of the different seasons for testing. The indoor temperature utilized in figure is form Base Case, Zone 7*

Time-step accuracy

The accuracy of each time-step is found by taking the average MAPE for each time-step for all the different zones separately. This analysis was only conducted for the Base Case, but similar results for the other cases are assumed.

Location of error

The location of errors was found by placing the plot of the indoor temperature above the MAPE. The x-axis is equal for the two different plots. Further vertical lines are placed on top of the two plots where the MAPE peaks. The MAPE utilized in this experiment is for 24-hour prediction. Therefore, the x-axis represents the time when the prediction was conducted and not the time of the predicted temperature.

4 Results

In the experiments, a hybrid MIMO LSTM black-box model is utilized and evaluated to predict indoor temperature for a building during various conditions. A Base Case with variation in occupation schedules, building standards, and climates will be used as input for the model. The Base Case is a small office building located in Trondheim, Norway, and build after the Norwegian Passive House standard for commercial buildings, NS 3701. More detailed information about the Base Case and the other variations is given in Section 3.2. Information about the black-box utilized is given in Section 3.3.

The results start with evaluating the data-driven model utilized, followed by evaluating input parameters, changes in the internal gains, different building envelopes, and different climates. Finally, the time-step of the model is evaluated.

4.1 Evaluating the model

The tree accuracy matrices MAE, MAPE, and RMSE, are utilized to evaluate the model. These are used to give a reasonable basis for comparison for other studies since utilized accuracy matrices vary in other scientific papers. More information about the matrices is given in Chapter 2.7.2.

RMSE equals standard deviation when RMSE is calculated based on average values [89]. The STD of the indoor temperature generated from the IDA ICE Base Case is given in Table 4.1, which indicated the variation of the actual indoor temperature. The RMSE, Figure 4.1, is lower than the standard deviation of the input, meaning the accuracy is reasonable based on the challenging output parameters.

Table 4.1: *Standard deviation of the Base Case's indoor temperature*

Zone 4	**Zone 7**	**Zone 8**	**Zone 12**	**Zone 14**	**Zone 18**	**Zone 19**	**Zone 20**	**Zone 22**
1.605°C	1.649°C	2.450°C	1.518°C	1.466°C	1.621°C	1.521°C	1.749°C	1.686°C

Figure 4.1 shows the prediction accuracy related to each zone. Zone 8 has a higher error related to it, followed by zone 22, 20, 4, and 7. Figure 3.2 illustrates the location of each zone, and from this figure, it can be seen that Zone 8 is the two-story lobby with a glazed envelope, and the other zones with a higher error are all smaller zones located west.

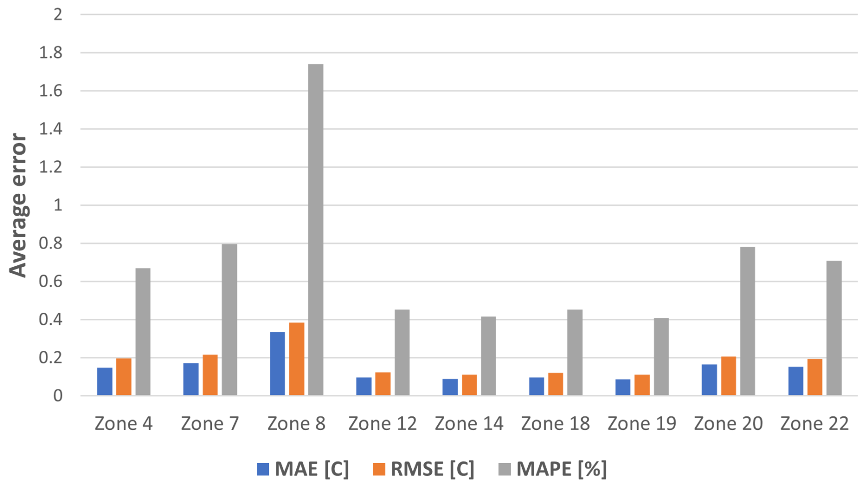


Figure 4.1: *Average MAE, MAPE and RMSE for the Base Case*

The accuracy of the following results will be presented as the MAPE of the output. MAPE provides a performance evaluation with normalized information, giving a basis for comparison between the different cases [49], which is of importance in this study to compare the outcome of all the experiments.

The reliability of the black-box model is tested by conducting multiple predictions with the same input data. The average results related to this experiment are given in Figure 4.2, named prediction one to five. The first prediction illustrated is the case illustrated in the previous results. Table 4.2 holds the standard deviation related to each zone, based on the multiple predictions executed. The average STD for all the zones is 0.028 %. The deviation given is very low, which indicated that the model performs well and is stable.

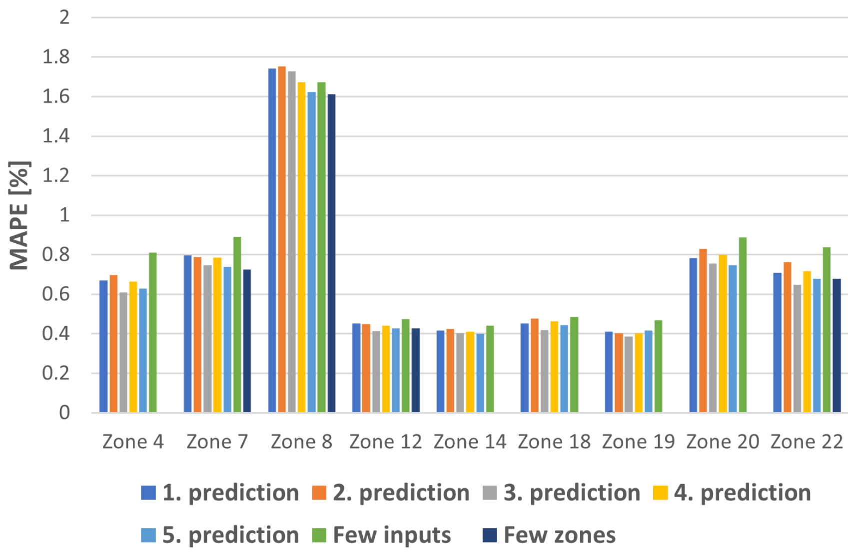


Figure 4.2: *Average MAPE for different predictions with equal input data, and experiments with less inputs and fewer zones tested*

Table 4.2: *The STD of the MAPE related to multiple predictions [%]*

Zone 4	Zone 7	Zone 8	Zone 12	Zone 14	Zone 18	Zone 19	Zone 20	Zone 22
0.035	0.026	0.054	0.016	0.010	0.022	0.012	0.034	0.043

Tests with fewer zones and fewer input parameters were also conducted. These tests were done to learn more about the behavior and stability of the model. During the test with fewer zones, only Zone 7, 8, 12, and 22 were included. For the tests with less inputs, the input combination "Combination 1" in Table 3.12 was used. The results of these two experiments are similar to the original model, which strengthens the model's credibility.

4.1.1 Testing in different seasons

In locations north of the equator, the sun is generally affecting the southern facade of buildings. However, the sun angles are different for different seasons. Therefore, an experiment was conducted where the testing occurs in different seasons. This experiment aimed to see whether the more extensive error in Zone 4, Zone 7, Zone 20, and Zone 22, Figure 4.1, was related to solar radiation and changed during different testing seasons.

Figure 4.3 illustrates the results for testing the Base Case in Season 1 (01.01 - 13.03), Season 2 (14.03 - 25.05) and Season 3 (20.10 - 31.12). As suspected, the testing in Season 3 gives the best results, followed by Season 2. For Season 3 and Season 1, the MAPE is quite equal, only with different magnitudes. For Season 2, the error is quite similar for all zones but slightly higher for Zone 8 and Zone 14. Detailed information of the experiment is given in Section 3.3.6, where Figure 3.16 illustrates the indoor temperature for the different seasons tested.

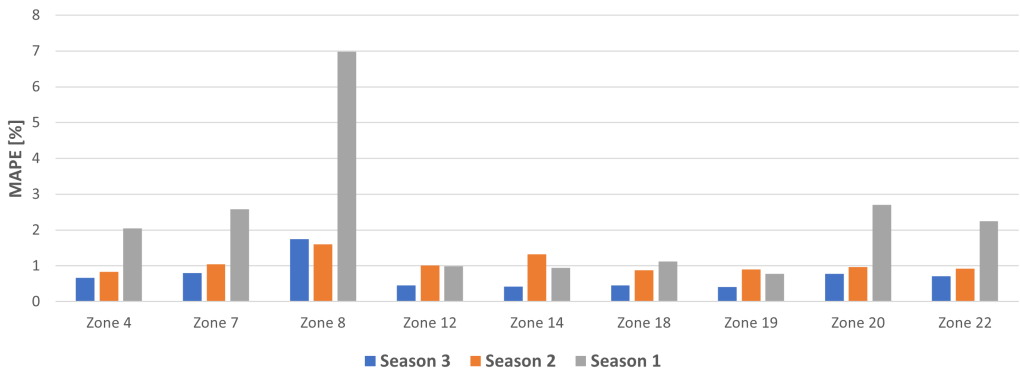


Figure 4.3: *MAPE for training, validation and testing in different seasons*

Zone 8, testing in season 1

For testing in Season 1, the error related to Zone 8 is remarkably high. When the MAPE is plotted together with indoor temperature, it is difficult to find a clear pattern for when the error occurs, but it seems to be a trend that the MAPE is low when the temperature is high and opposite, Figure 4.4. When the MAPE is plotted with the outdoor temperature, some small patterns occur, Figure 4.5. This pattern involves a higher MAPE when the outdoor temperature is low. However, this pattern is not very clear, and there are only slight hints of this. Overall the trend is that the MAPE is low when the temperature is high. This trend occurs both for small peaks and for more prominent areas, both for indoor and outdoor temperatures.

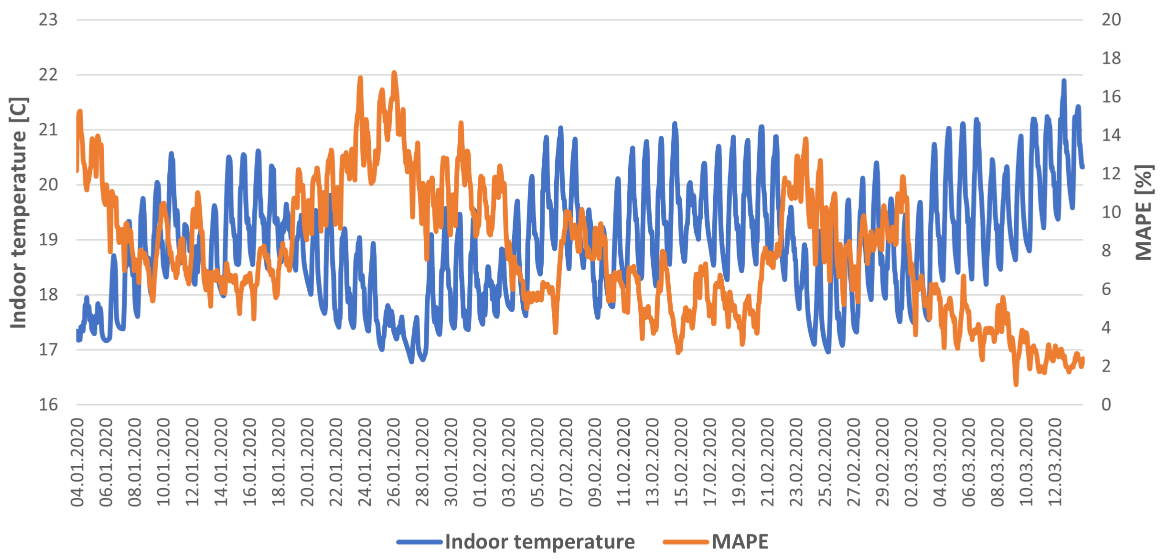


Figure 4.4: *MAPE and indoor temperature for the testing phase of Zone 8, when testing in Season 1*

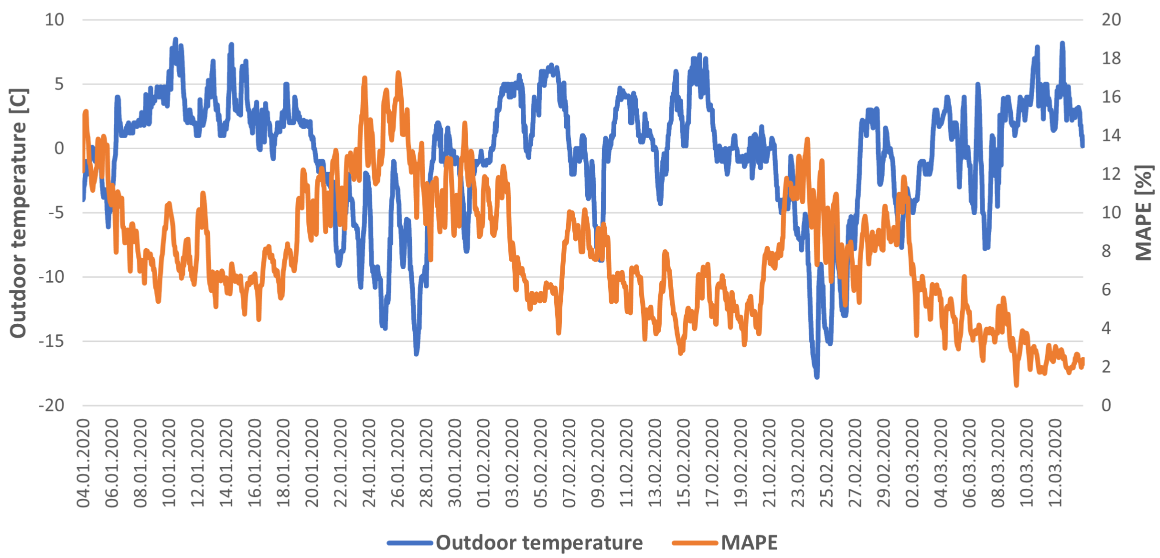


Figure 4.5: *MAPE and outdoor temperature for the testing phase of Zone 8, when testing in Season 1*

4.1.2 Randomness of variable evaluation

A feature elimination method was adopted to learn more about the importance of each input parameter. However, since the model is based on random numbers, the method is conducted several times for the same input parameters. Figure 4.6 - 4.8 holds three different predictions where the feature elimination is applied to the Base Case.

When comparing the three different cases, it is clear that the 1. and 2. perdition is most different and that the 3. prediction is something in between the two first cases. The most significant difference between the two cases is the input parameter daily time-index, which is very sensitive and varies significantly. In addition, there is some difference regarding the error related to Zone 8. The STD for all these predictions is given in Appendix A. The average STD when feature elimination is conducted is 0.030 %.

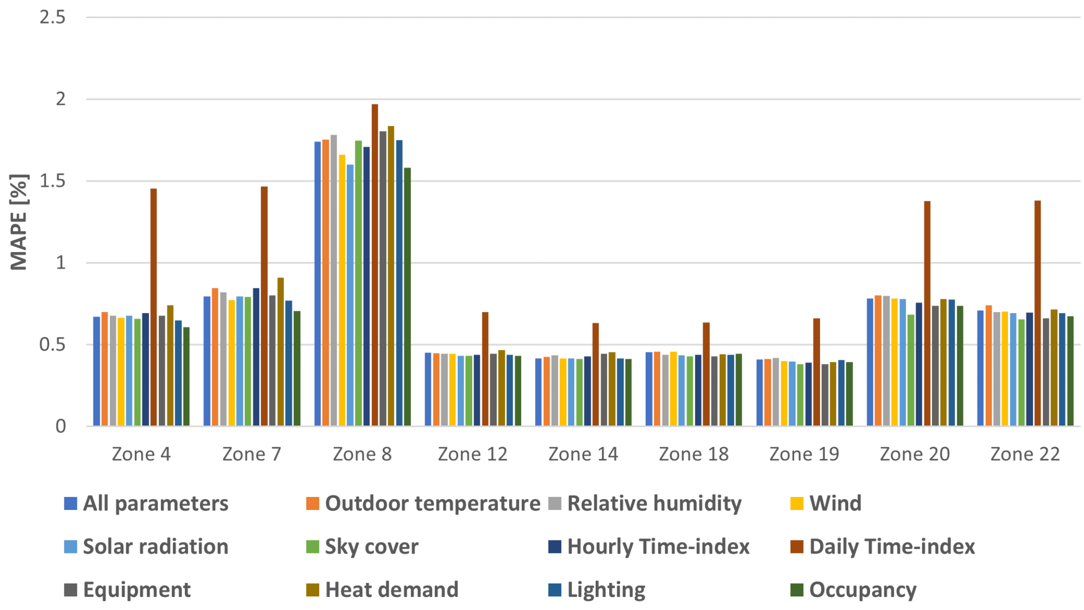


Figure 4.6: *1. prediction of feature elimination on the Base Case*

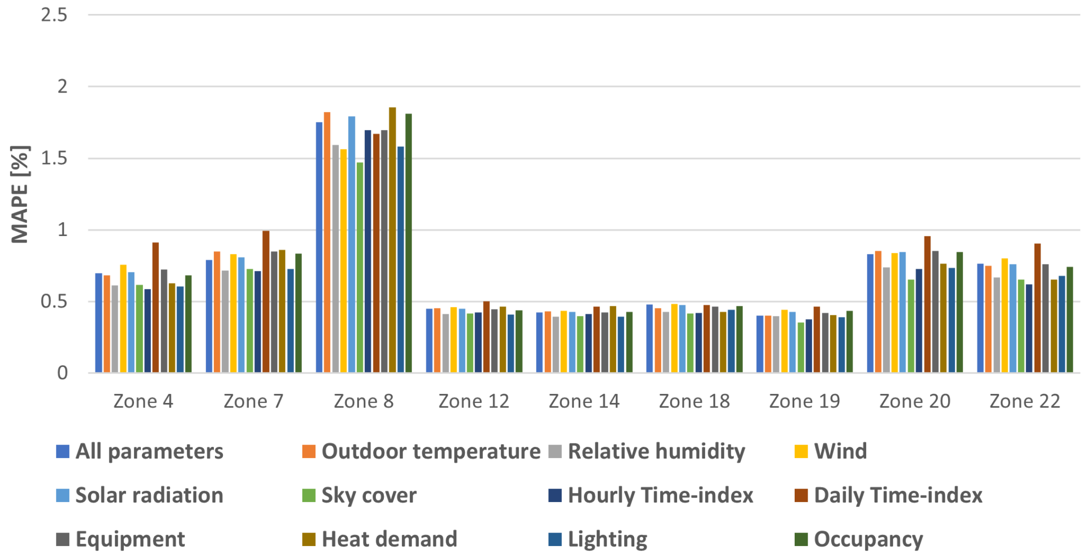


Figure 4.7: *2. prediction of feature elimination on the Base Case*

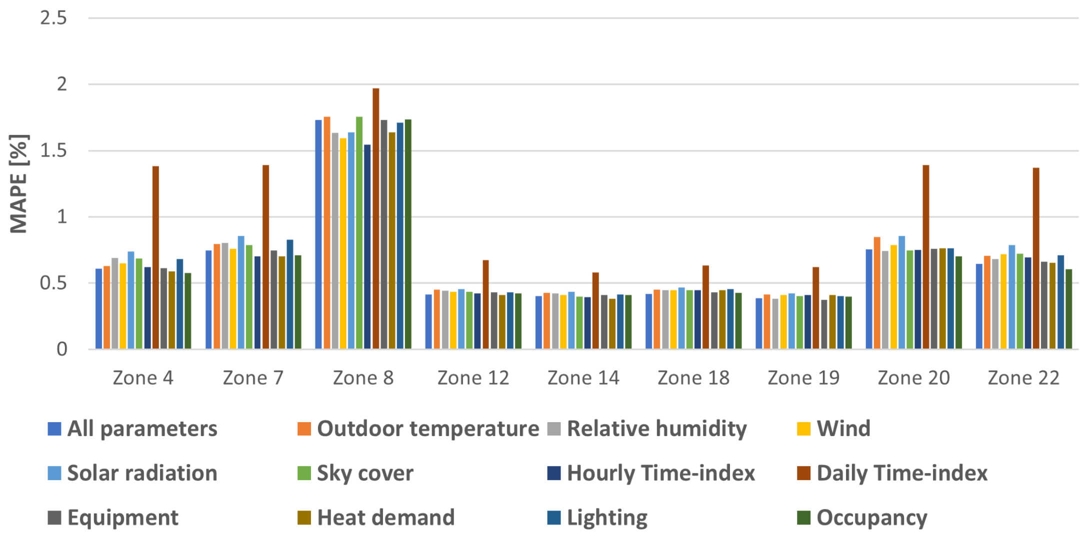


Figure 4.8: *3. prediction of feature elimination on the Base Case*

Deeper investigation of the daily time-index

Figure 4.9 illustrates a box plot of the daily time-index for the three different predictions. In this figure, the first three boxes represent the same zone during different predictions, and the next three another zone, and so on. When analyzing the figure, it is clear that all of the cases have a similar median for all the different zones, while the average and 75% confidence interval vary to a larger extend. In addition, all the cases consist of many upper outliers. These outliers affect the average of each case and are the reason for the significant variations in average. The MAPE for the case without the daily time-index has similar changes for each prediction, which can be seen when comparing the MAPE for the different zones. Here the changes in average, box size, whiskers, and outliers are quite identical for the different zones related to each prediction.

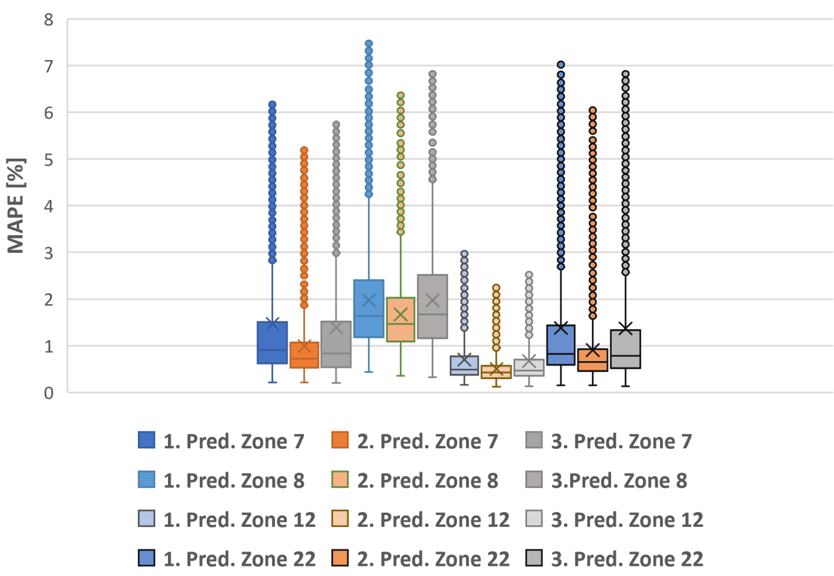


Figure 4.9: *Box plot of the daily time-index related to the three different predictions*

Figure 4.10 holds a box plot of six different predictions for Zone 8 where the daily time-index is removed. The results of the following predictions lay between the first and second predictions conducted, indicating that the results are more stable than first assumed based on Figure 4.9. The figure illustrates that the first and second predictions are "extreme" cases in different directions.

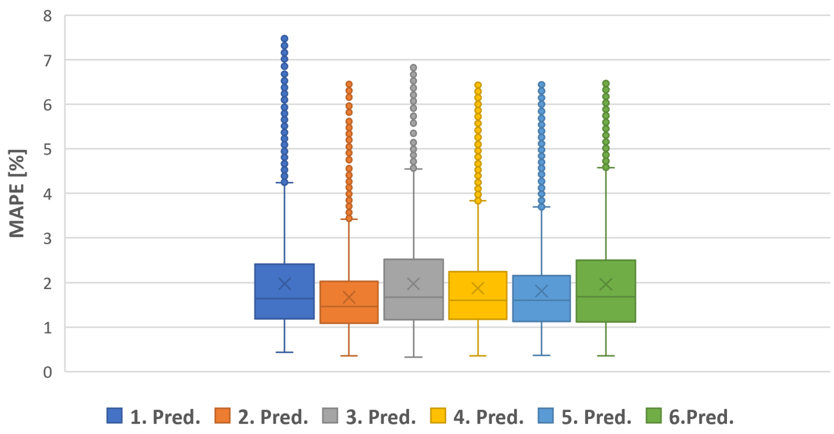


Figure 4.10: *Box plot of the Base Case when daily time-index is removed for six different predictions, Zone 8*

4.1.3 Accuracy when one zone i removed

When analysing Figure 4.1 - Figure 4.8 Zone 4, 7, 20 and 22 have a higher error related to the prediction compared to Zone 12, 14, 18 and 19. All the zones with the lower error share a minimum of one wall to another zone where the indoor temperature is predicted. An experiment was conducted where Zone 8 was removed to see if this is the reason for the more accurate results. The results from this experiment are illustrated in Figure 4.11.

When analyzing the results, it is clear that the changes in error related to each zone in this test are negligible and that the zones affect each other to a small degree. This can be stated based on the small changes in these results compared to the Base Case in Figure 4.6, primarily when the STD related to each prediction is considered.

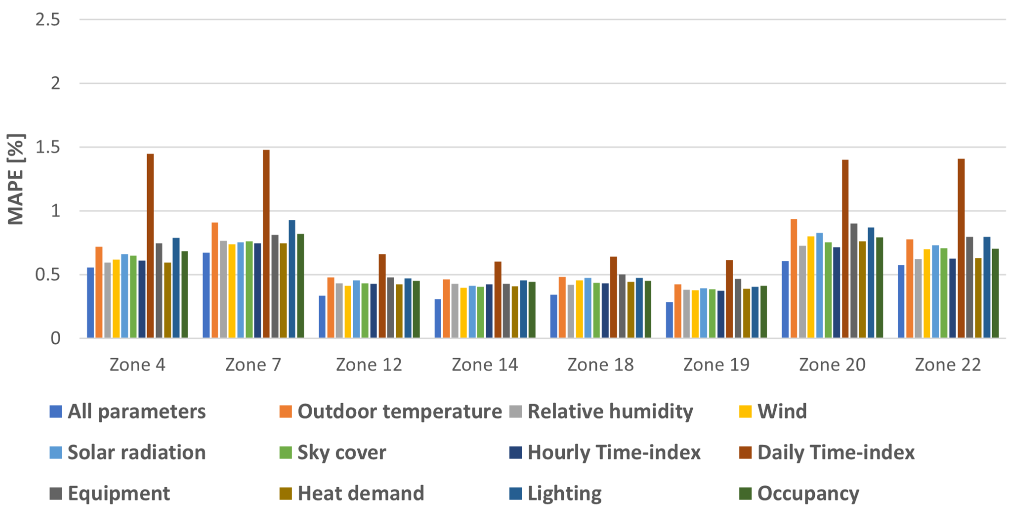


Figure 4.11: *Prediction of feature elimination where Zone 8 is removed*

4.1.4 Variation in indoor temperature and internal gains

The variation in error related to each zone may have a context with the variations in indoor temperature in each zone. Figure 4.12 represents the indoor temperature for all the zones during the whole simulated year. Here Zone 4, 7, 8, 20, and 22 have a higher variation in indoor temperature, seen from both the 75% confidence interval and the maximum and minimum whiskers. These are the same zones that have a higher MAPE in Figure 4.1.

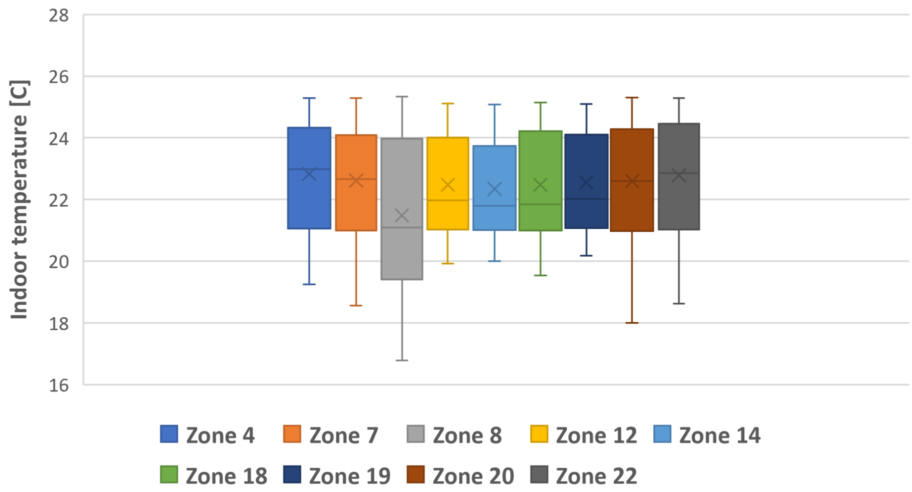


Figure 4.12: *Box plot of indoor temperature for each zone in the Base Case*

The heat demand for space heating is investigated to map the amount of external and internal heat gain for each zone, Figure 4.13. The heat demand is higher for Zone 8, which can be explained by the zones glazed envelope. Zone 4, 7, 19, 20, and 22 have a lower heat demand than the other. These zones may have a more considerable amount of internal and external heat gain than the others, which would be a reasonable explanation of the low heat demand, especially when considering the high median indoor temperature for Zone 4, 7, 20, and 22.

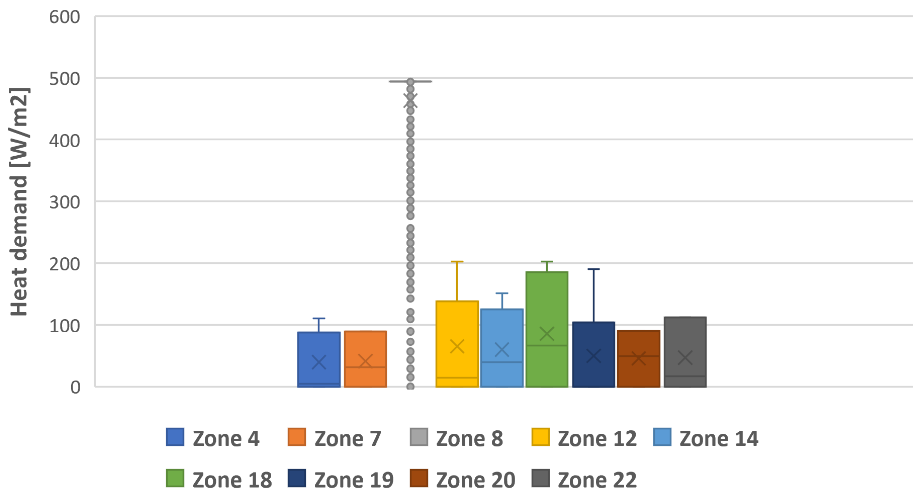


Figure 4.13: *Box plot of heat demand for each zone in the Base Case*

4.2 Parameter evaluation

This subsection includes the primary results regarding input parameters. Here are both feature elimination and the wrapper method included.

4.2.1 Fewer parameters

Multiple experiments were conducted with different parameter combinations to see how the model acts with less parameter input. Information about the method used for this experiment, as well as the parameters included in the different cases are given in Chapter 3.3.6 and Table 3.12. For the input combinations "Meteorological", "Time-index" and "Zone data" all input in the named category is removed. Meaning that in "Zone data" the inputs related to information in each zone are removed, in this case, equipment load, heat demand, lighting demand, and the number of occupants.

When analyzing the results, it is clear that some combinations are similar to the Base Case in error and others are not, Figure 4.14. "Combination 2", "Meteorological" and "Zone data" have equal or lower MAPE as the Base Case for all of the different zones, and maybe good options for input combinations. The parameters missing in these cases may therefore be unnecessary.

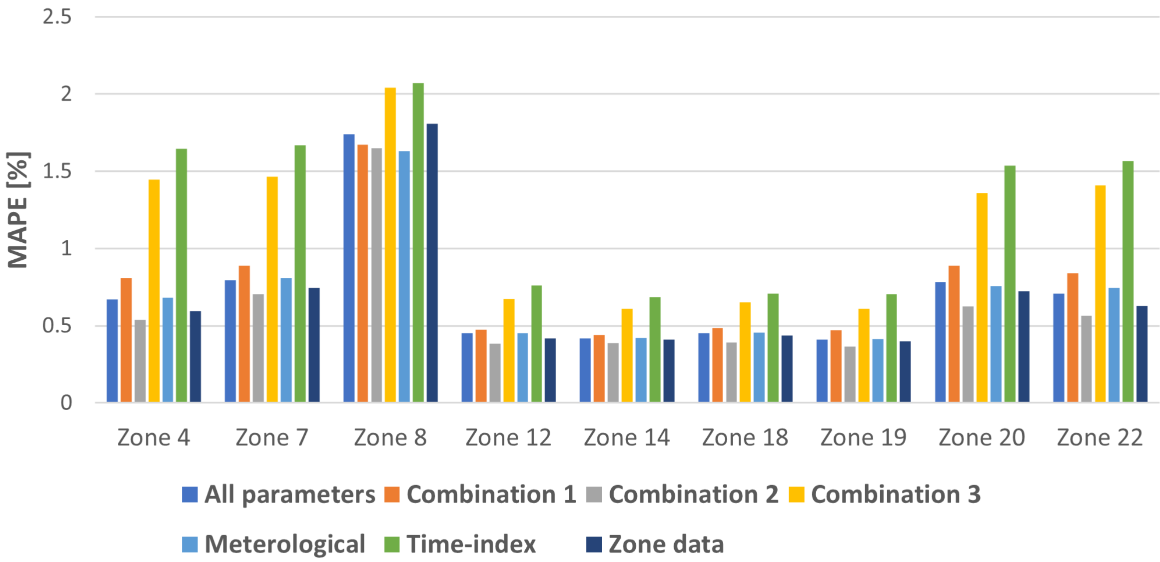


Figure 4.14: *Average MAPE for different input combinations*

When analysing the highlighted zones the trend continues, Figure 4.15 - 4.18. The case where time-indexes are removed give the most error, followed by "Combination 3" and "Combination 1". The high error related to time-indexes may indicate that one or both of these parameters are of high importance. As seen from the figures, the lower whisker and the median are quite similar for all the cases, which means that the lower values are quite similar. There are, however, outliers for all cases. These data points may be the reason for the bigger variation between the cases.

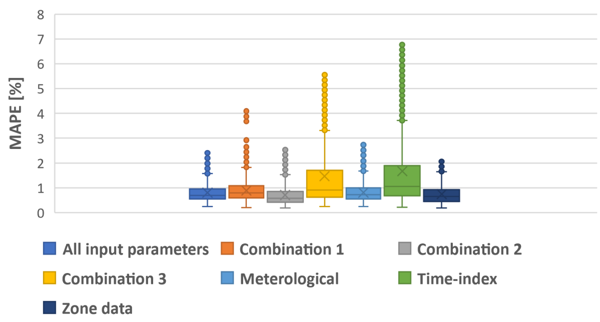


Figure 4.15: *MAPE for Zone 7 when testing for different parameter combinations*

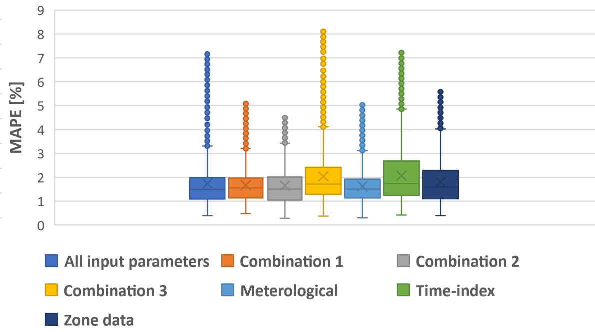


Figure 4.16: *MAPE for Zone 8 when testing for different parameter combinations*

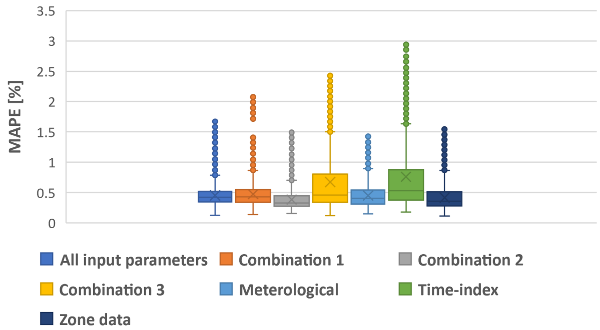


Figure 4.17: *MAPE for Zone 12 when testing for different parameter combinations*

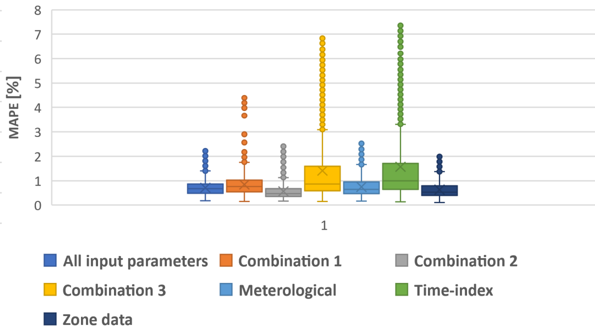


Figure 4.18: *MAPE for Zone 22 when testing for different parameter combinations*

4.2.2 Feature elimination

The results in Figure 4.6 give a good overview of the average MAPE when feature elimination is conducted. This subsection will include more values related to the feature elimination of the Base Case. Based on Figure 4.6, it seems like all the parameters are of equal importance, except the input parameter daily time-index, which is of great importance. Box plots are made for some zones to get a better insight into the effect of the input parameters. These results are presented in Figure 4.19 - 4.22.

The box plots illustrated that the amplitude of error varies for the different zones and that some parameters can have good results for some zones and bad for others. For Zone 7 and 22, many parameters get a higher MAPE when missing than the case with all parameters. This indicates that the parameters with a high error are of importance for the prediction of this zone. For Zone 8 and 12, most parameters get a lower MAPE when missing, indicating that these parameters are redundant.

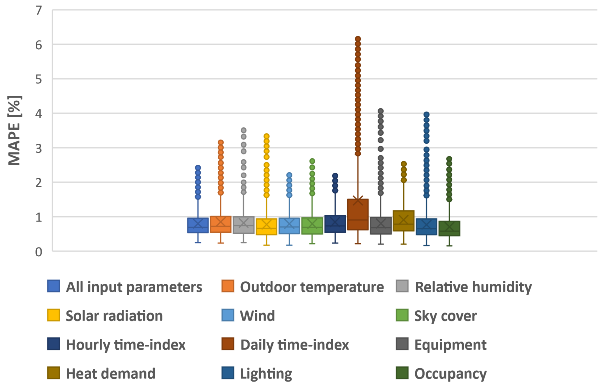


Figure 4.19: *Feature elimination for Zone 7, Base Case*

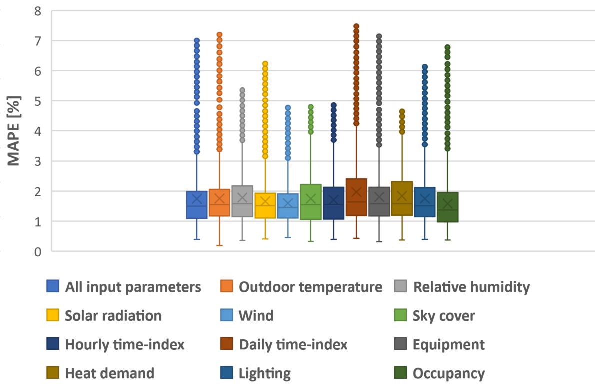


Figure 4.20: *Feature elimination for Zone 8, Base Case*

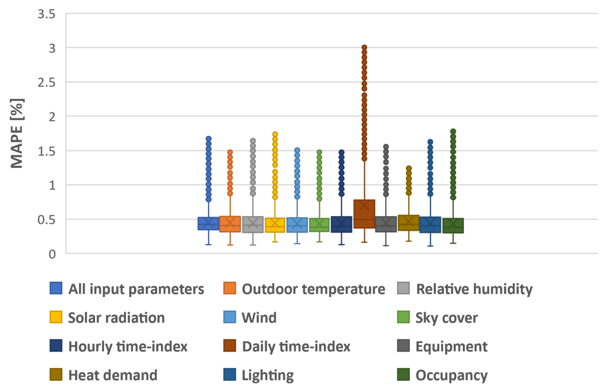


Figure 4.21: *Feature elimination for Zone 12, Base Case*

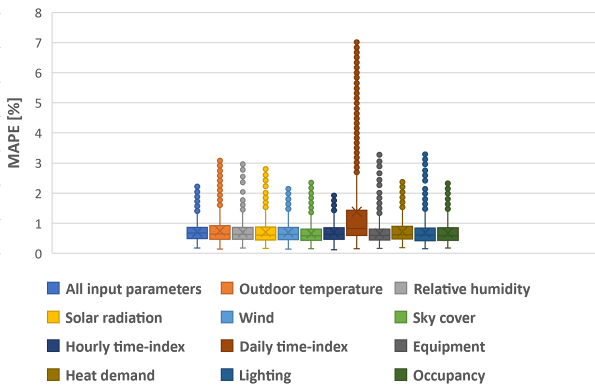


Figure 4.22: *Feature elimination for Zone 22, Base Case*

Average result of feature elimination

This experiment is conducted by calculating the STD of the average MAPE when all parameters are included and the average MAPE of the feature elimination for one specific parameter in one specific zone. The difference is then compared with the STD of that specific parameter in that specific zone, Appendix A. If the difference is ± the STD, the importance of the value is classified as uncertain. If the MAPE is higher than the STD, the parameter is classified as essential and given the color green in the table. Parameters with lower values than the STD are classified as damaging for the model and are given the color red.

Table 4.3 holds the difference of the average MAPE values for each parameter for all the office zones predicted. The results show that the daily time-index is essential for all the zones. In addition, the outdoor temperature has proven to be crucial for Zone 7, 20, and 22, while solar radiation is essential for Zone 4 and 7. For Zone 20, several parameters are badly affecting the model. These parameters have a neutral effect on the other zones.

Table 4.3: *The average difference between the MAPE with and without a feature, for the office zones [%]*

	Zone 4	Zone 7	Zone 20	Zone 22
Outdoor temperature	0.011	0.054	0.045	0.026
Relative humidity	-0.001	0.003	-0.030	-0.023
Wind	0.031	0.011	0.013	0.035
Solar radiation	0.046	0.042	0.038	0.040
Sky cover	-0.007	-0.009	-0.096	-0.030
Hourly Time-index	-0.026	-0.023	-0.043	-0.036
Daily Time-index	0.589	0.506	0.452	0.513
Equipment	0.013	0.022	-0.006	-0.012
Heat demand	-0.008	0.047	-0.020	-0.031
Lighting	-0.015	-0.002	-0.031	-0.012
Occupancy	-0.037	-0.027	-0.027	-0.032

When analyzing the results for the meeting rooms and lobby, Table 4.4, the daily time-index also here stands out as essential, except for Zone 8. It seems like the outdoor temperature is an essential parameter for Zone 12, 14, 18, and 19. For the parameters affecting the model badly, sky cover negatively affects three of the zones.

Table 4.4: *The average difference between the MAPE with and without a feature, for the meeting rooms and lobby [%]*

	Zone 8	Zone 12	Zone 14	Zone 18	Zone 19
Outdoor temperature	0.036	0.013	0.013	0.004	0.010
Relative humidity	-0.071	-0.005	0.002	-0.012	0.000
Wind	-0.136	0.007	0.007	0.013	0.018
Solar radiation	-0.063	0.007	0.012	0.009	0.017
Sky cover	-0.084	-0.011	-0.012	-0.019	-0.020
Hourly Time-index	-0.090	-0.011	-0.002	-0.015	-0.007
Daily Time-index	0.129	0.186	0.145	0.131	0.184
Equipment	0.004	0.001	0.011	-0.008	-0.007
Heat demand	0.035	0.009	0.022	-0.012	0.004
Lighting	-0.060	-0.013	-0.006	-0.005	0.000
Occupancy	-0.032	-0.008	0.003	-0.004	0.009

4.2.3 Wrapper method

The wrapper method was conducted of three different input files; The Base Case, The TEK 87 building, and the building located in Malaga. These cases were chosen to get a variety in both building structure and climate. The results are divided into three different categories based on the zones are of use, listed in Table 3.11. The principle of the wrapper method is to test the model for all possible combinations. When this was conducted, each combination was assigned a combination number (comb. nr.) to make it easier to extract combinations of interest. The combination with best results is presented with their combination number, where the inputs included in the combination if further explained in the following tables, based on the information given in Table 3.10. Appendix E includes all combinations tested with their assigned combination number.

Small private offices

The zones classified as private offices are Zone 4, 7, 20, and 22 and are located on the west side of the building. The results of the wrapper method for these zones are given in Table 4.5. The table illustrated a small change in MAPE from best to the third-best case, and the difference is between the STD for all zones, which means that the best result may be due to coincidence.

Many combination numbers from 82-98 are classified as good combinations for the Base Case, where the combinations 82 and 85 occur twice each. For the TEK 87 building, combination number 42 and 84 occur three times each, while combination number 82 occurs twice. For the Malaga building, it is combination number 83 and 539, which are repeated. When similar combinations get good scores multiple times across predictions, the credibility of the combinations strengthens.

Table 4.5: *Results of the wrapper method for small private offices. The minimum values represents the MAPE [%], anf the comb.nr. represents the input combination of the wrapper*

	Base Case				TEK 87				Malaga			
Zone	**4**	**7**	**20**	**22**	**4**	**7**	**20**	**22**	**4**	**7**	**20**	**22**
Min.	0.570	0.644	0.666	0.611	0.963	1.194	1.187	1.080	0.443	0.498	0.491	0.576
Comb.nr	768	21	59	85	82	82	21	91	83	355	359	819
2. min.	0.593	0.703	0.685	0.621	1.015	1.227	1.226	1.101	0.450	0.502	0.492	0.590
Comb.nr	820	768	82	89	42	86	32	84	819	806	778	83
3. min.	0.593	0.703	0.685	0.621	1.025	1.230	1.235	1.105	0.462	0.503	0.510	0.602
Comb.nr	82	775	85	88	84	42	84	42	804	359	83	804

The parameters included in the various input combinations mentions in Table 4.5 is given in Table 4.6. In the table, only combinations resulting in the two best MAPE are included. A similarity with all the combinations is that almost all include the daily time-index. For combinations 82-91, all meteorological and time-indexes are included, and the only variation is the zone-related parameters. Due to these combinations' good results, one can assume that these parameters are valuable for small office zones.

Table 4.6: *Parameters included in input combinations with best results for office zones*

Comb. nr.	**21**	**32**	**82**	**84**	**85**	**86**	**89**	**91**	**355**	**359**	**768**	**778**	**806**	**819**
Input 0 - OT	X	X	X	X	X	X	X	X						
Input 1 - RH			X	X	X	X	X	X						
Input 2 - W_x		X	X	X	X	X	X	X						
Input 3 - W_y			X	X	X	X	X	X						
Input 4 - SR_{Nor}			X	X	X	X	X	X			X	X		
Input 5 - SR_{Hor}			X	X	X	X	X	X					X	X
Input 6 - SC			X	X	X	X	X	X						
Input 7 - h			X	X	X	X	X	X	X		X	X	X	
Input 8 - d	X	X	X	X	X	X	X	X	X	X	X	X		X
Input 9 - Eq,i			X			X	X	X	X			X		
Input 10 - Hd,i						X	X	X	X	X				X
Input 11 - Li,i				X			X	X	X			X	X	
Input 12 - Occu,i					X			X						

Glazed lobby

For the lobby, Zone 8, none of the combinations repeat itself, Table 4.7. However, the difference from best to second best MAPE varies significantly, 0.061, 0.046, and 0.033 %. These values are higher than the average STD for parameter elimination of 0.030 %, which strengthens the results to some degree. For the Base Case, the difference in MAPE is higher than the STD of the zone, 0.054 %. Combination number 82 and 83 proved to be suitable for the office zones and are included among the best combinations for the lobby.

Table 4.7: *Results of the wrapper method for the lobby. The minimum values represents the MAPE [%], anf the comb.nr. represents the input combination of the wrapper*

	Base Case	**TEK 87**	**Malaga**
Zone	**8**	**8**	**8**
Min.	1.410	1.800	0.810
Comb.nr	59	20	83
2. min	1.471	1.846	0.843
Comb.nr	760	82	270
3. min	1.471	1.848	0.844
Comb.nr	794	1	6

The combinations with the best results are combination number 20, 59, and 83. The inputs included in these combinations are given in Table 4.8. The only parameter these two combinations have in common is the outdoor temperature. Therefore, this parameter must be essential for this zone, especially since combination number 1 is listed as one of the best combinations and only includes this parameter. The Malaga and TEK 87 building has a good score on a combination only including one parameter, comb. nr. 1 and 6. These single parameters must therefore be of high importance for these specific buildings.

Table 4.8: *Parameters included in input combinations with best results for the lobby*

Comb. nr.	**1**	**6**	**20**	**59**	**83**	**270**	**760**
Input 0 - OT	X		X	X	X		
Input 1 - RH				X	X		
Input 2 - W_x				X	X		
Input 3 - W_y				X	X		
Input 4 - SR_{Nor}				X	X	X	X
Input 5 - SR_{Hor}		X			X	X	
Input 6 - SC					X		X
Input 7 - h			X		X		X
Input 8 - d				X	X		X
Input 9 - Eq,i							
Input 10 - Hd,i					X	X	
Input 11 - Li,i							X
Input 12 - Occu,i							

Medium sized meeting rooms

The results for the medium-sized zones are listed in Table 4.9. For the Base Case, the number repeating itself is combination number 82, which occurs twice for this case. For the TEK 87 building, the combination number 82 also occurs multiple times, where combination number 20 and 618 also are popular. For the Malaga building, Zone 14 and 18 have the exact same MAPE for the three best combinations. For the other predictions conducted, the MAPE varied between the zones.

Table 4.9: *Results of the wrapper method for meeting rooms. The minimum values represents the MAPE [%], anf the comb.nr. represents the input combination of the wrapper*

	Base Case				**TEK 87**				**Malaga**			
Zone	**12**	**14**	**18**	**19**	**12**	**14**	**18**	**19**	**12**	**14**	**18**	**19**
Min.	0.408	0.381	0.413	0.365	0.443	0.506	0.506	0.549	0.450	0.521	0.521	0.415
Comb.nr	82	288	597	774	82	82	82	20	880	362	362	89
2. min	0.415	0.387	0.415	0.372	0.471	0.520	0.520	0.576	0.455	0.522	0.522	0.419
Comb.nr	21	768	599	809	42	618	618	82	874	841	841	353
3. min	0.415	0.387	0.415	0.372	0.474	0.524	0.524	0.590	0.456	0.526	0.526	0.422
Comb.nr	812	349	82	356	618	20	20	87	599	342	342	513

The parameters combination number 20 and 82 have in common are the outdoor temperature and hourly time-index, which are the only parameters included in combination number 20. Table 4.10 holds an overview of the input parameters included in the other combinations. A similarity for most of the combinations is that at least one time-index is included, both for most cases. Besides the time-indexes, wind from east to west, sky cover, and equipment are often included.

Table 4.10: *Parameters included in input combinations with best results for meeting rooms*

Comb. nr.	**42**	**288**	**353**	**362**	**597**	**599**	**618**	**774**	**809**	**841**	**874**	**880**
Input 0 - OT	X											
Input 1 - RH	X								X			
Input 2 - W_x	X				X	X	X					
Input 3 - W_y												
Input 4 - SR_{Nor}		X						X				
Input 5 - SR_{Hor}		X			X	X						
Input 6 - SC		X			X	X	X			X		
Input 7 - h		X	X		X	X	X	X	X			
Input 8 - d	X	X	X	X	X	X	X	X		X	X	X
Input 9 - Eq,i		X	X	X	X		X		X		X	
Input 10 - Hd,i				X				X				X
Input 11 - Li,i			X			X						X
Input 12 - Occu,i										X	X	X

4.3 Internal variation in the Base Case

Several experiments are carried out to learn more about how the data-driven model is affected by internal changes. These experiments contain changes in occupancy schedules and HVAC regulators.

4.3.1 HVAC controller

In the Base Case, a PI-controller is applied for controlling the HVAC system. In this part experiment thus controller is replaced with a P-controller, Figure 4.23. Comparing the results with the results where the PI-controller is applied, Figure 4.6 - 4.8, there is hardly any difference in prediction accuracy.

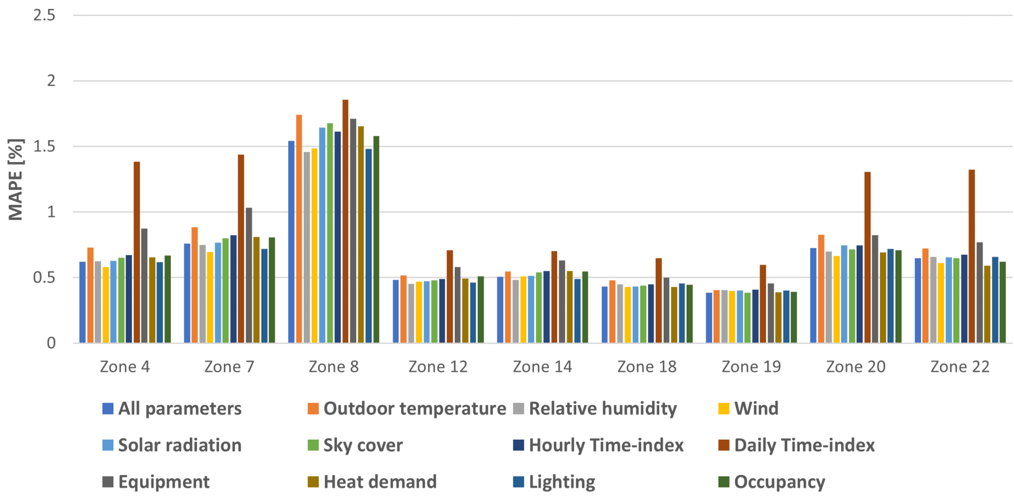


Figure 4.23: *Feature elimination with P-controller*

A section of the indoor temperature when the two different HVAC controllers are utilized is illustrated in Figure 4.24 - 4.27. The indoor temperature for the different zones is pretty equal independent of the controller utilized. These results explain why the controller has such a small impact on the model's accuracy.

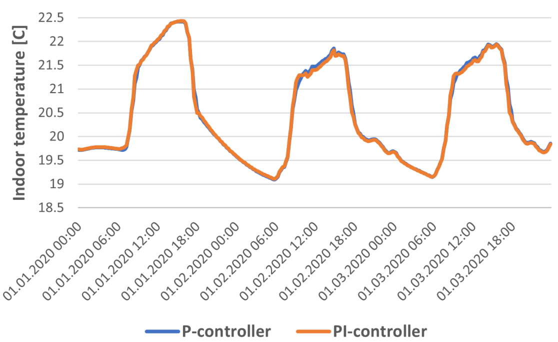


Figure 4.24: *Indoor temperature for Zone 7 with two different HVAC controllers*

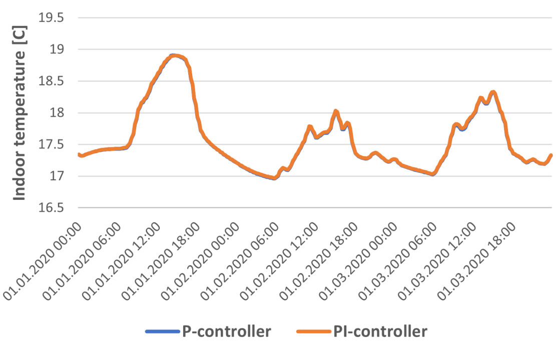


Figure 4.25: *Indoor temperature for Zone 8 with two different HVAC controllers*

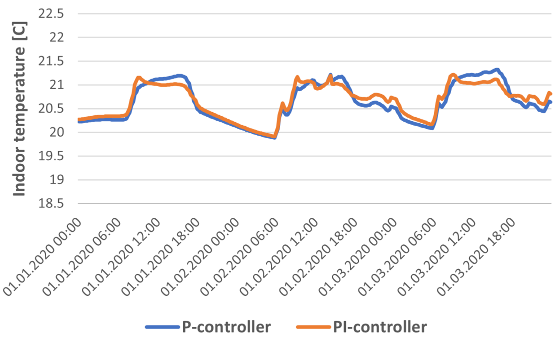


Figure 4.26: *Indoor temperature for Zone 12 with two different HVAC controllers*

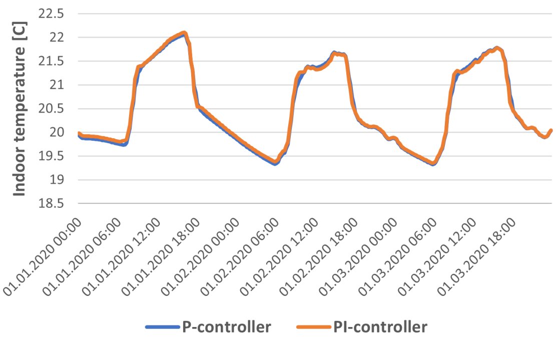


Figure 4.27: *Indoor temperature for Zone 22 with two different HVAC controllers*

4.3.2 Sensitivity to schedule changes

The schedule used in the predictions is random and based on an actual office schedule, making them random for each hour but similar in occupancy time. The model is tested for several similar office schedules to ensure that the building works similarly for similar schedules and that these promising results are not by coincidence. These schedules have the same arrival and departure time, but the amount of occupants varies at all times. Figure 4.28 holds the average MAPE for the seven different schedules tested. The figure shows that the prediction accuracy is quite similar for all cases. The small difference in MAPE can be due to variation in prediction or the different schedules.

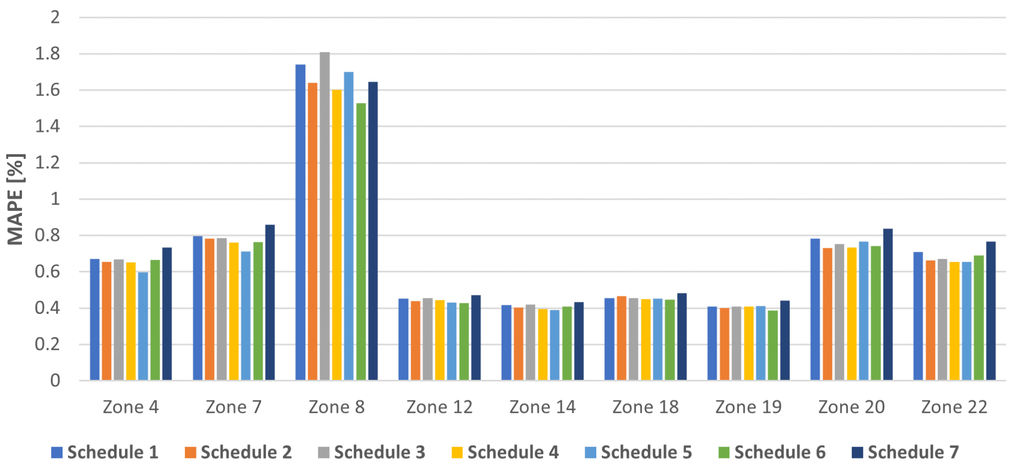


Figure 4.28: *The average MAPE for different office schedules for the Base Case*

Figure 4.29 - 4.32 illustrate the MAPE for the different schedules in each zone. Both the median and average are quite similar for all the different schedules, for all zones. The confidence interval is also of similar size and area for all the different schedules. As for the whiskers, both minimum and maximum are quite equal. However, all the cases have a large number of upper outliers. These outliers are the biggest variation between the different cases. From all of the zones, Zone 8 has the most extensive variations in MAPE.

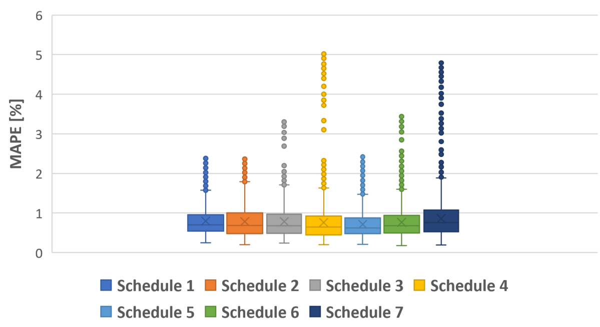


Figure 4.29: *Box plot of MAPE with different schedules for Zone 7*

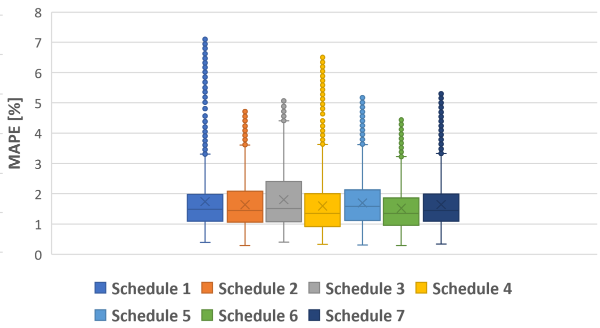


Figure 4.30: *Box plot of MAPE with different schedules for Zone 8*

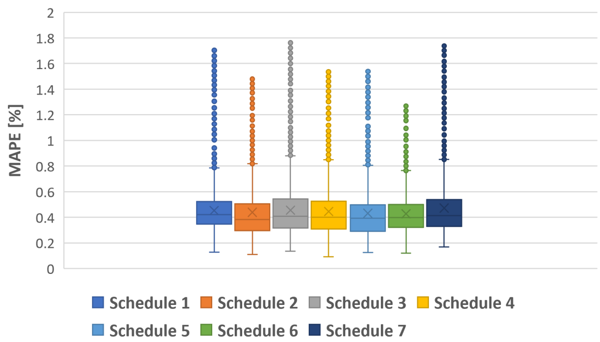


Figure 4.31: *Box plot of MAPE with different schedules for Zone 12*

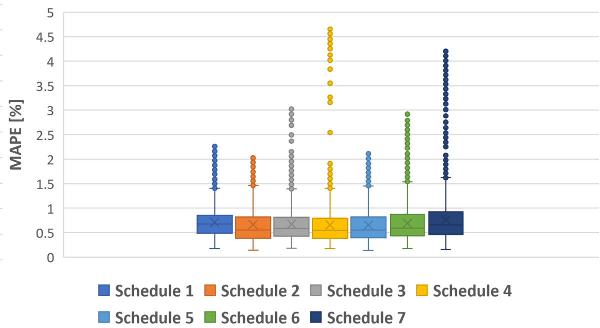


Figure 4.32: *Box plot of MAPE with different schedules for Zone 22*

4.3.3 Residential schedule

As for now, all the experiments conducted have been on an office building. To get a broader understanding of the black-box model, the Base Case was transformed into a residential building by changing the schedule of the occupants and equipment. These changes can be read more about in Chapter 3.2.2. Figure 4.33 illustrated the MAPE for the residential building when feature elimination is conducted.

The figure is quite similar to the corresponding figures for office buildings. The main difference between the figures is the lack of importance for the input parameter daily time-index. The lack of importance for this parameter may be coincidental or due to the changes in the building.

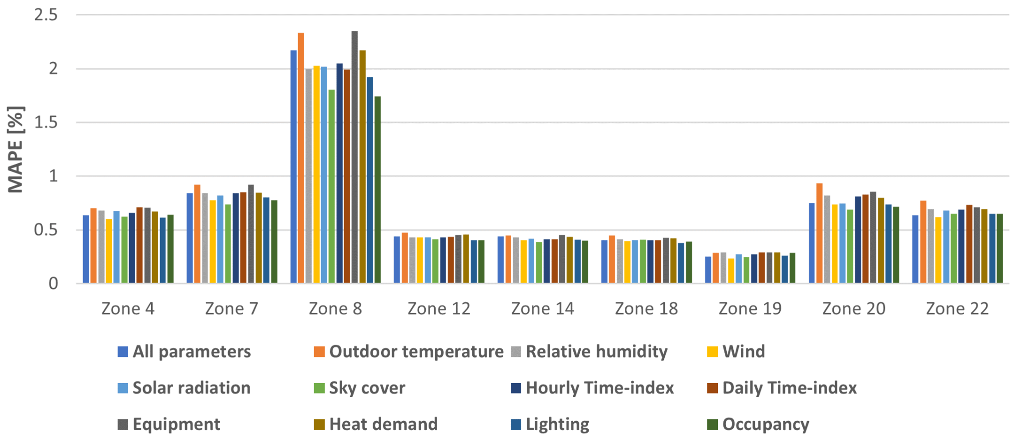


Figure 4.33: *MAPE for feature elimination for residential building*

Residential - Solar radiation

The solar radiation may have some impact on the lack of importance for the input parameter daily time-index. Figure 4.34 and 4.35 are combined plots with solar radiation and indoor temperature. When comparing the figures, it is clear that the solar radiation coincides with the occupation of the building and therefore amplifies the temperature difference between occupied and not occupied conditions for the office building. For the residential building, solar radiation occurs when the building is not occupied and, therefore, helps even out the temperature difference between occupied and not occupied conditions.

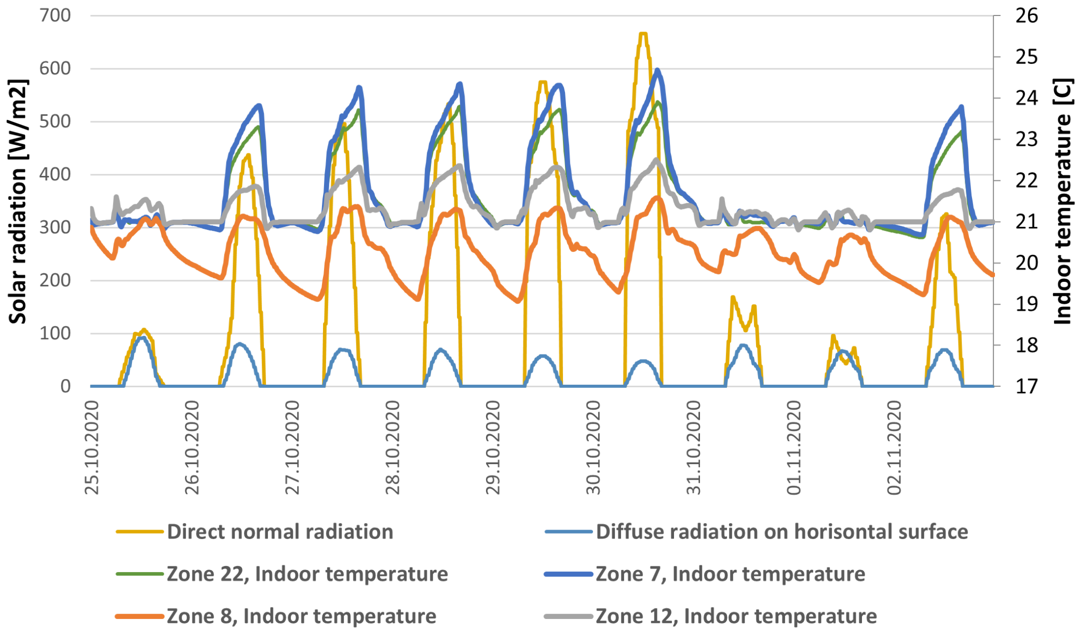


Figure 4.34: *Indoor temperature and solar radiation for the office building*

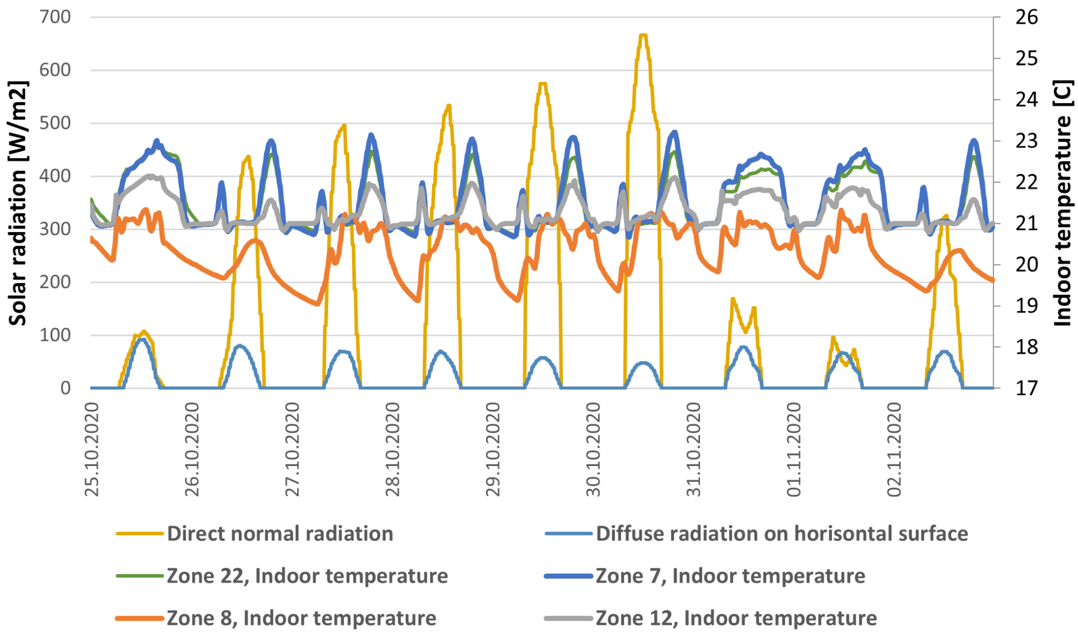


Figure 4.35: *Indoor temperature and solar radiation for the residential building*

Residential - Daily time-index

Figure 4.36 - 4.39 holds scatter plots of the daily time-index and indoor temperature for both the residential and office building. In the figures, it is clear that there is a larger variation in temperature throughout the day for the office zones. When analyzing the whole week, it is visible that the indoor temperature is similar for all days for all the residential buildings, while some office zones are a lower indoor temperature during weekends. This temperature difference may be why the daily time-index is more important for an office building, which is not occupied during weekends.

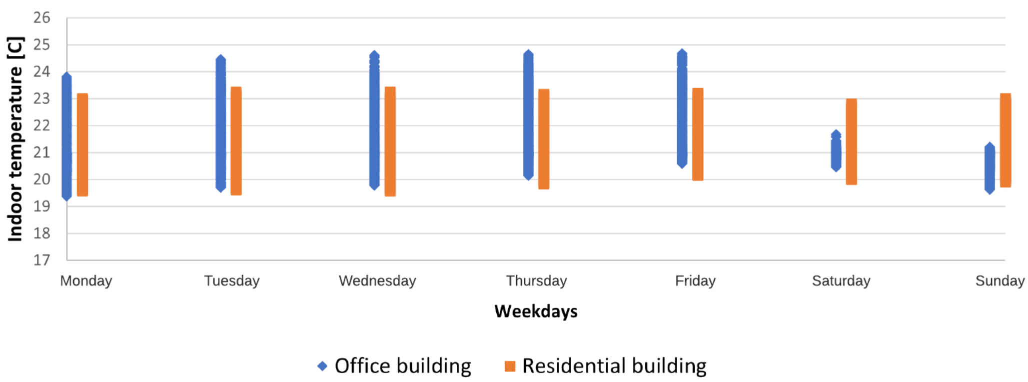


Figure 4.36: *Scatter plot of daily time-index and indoor temperature for Zone 7 in office and residential building*

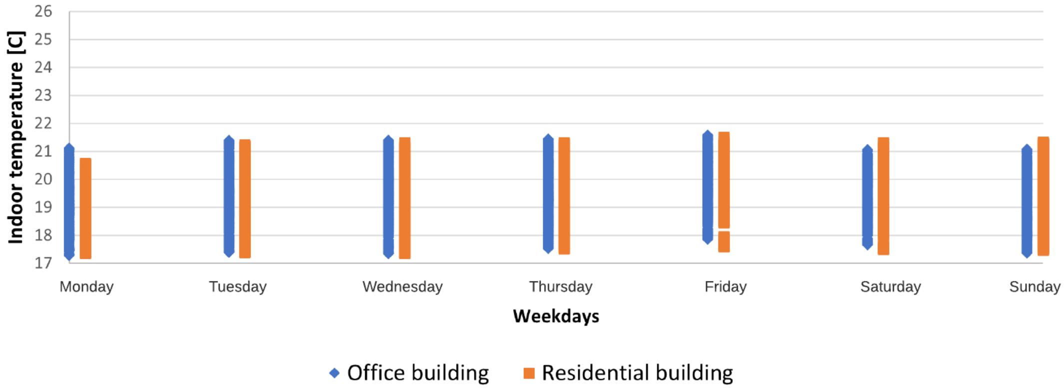


Figure 4.37: *Scatter plot of daily time-index and indoor temperature for Zone 8 in office and residential building*

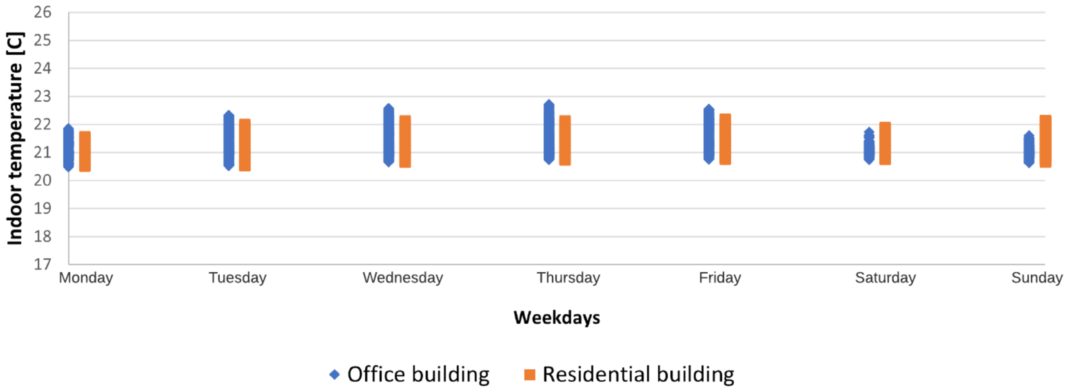


Figure 4.38: *Scatter plot of daily time-index and indoor temperature for Zone 12 in office and residential building*

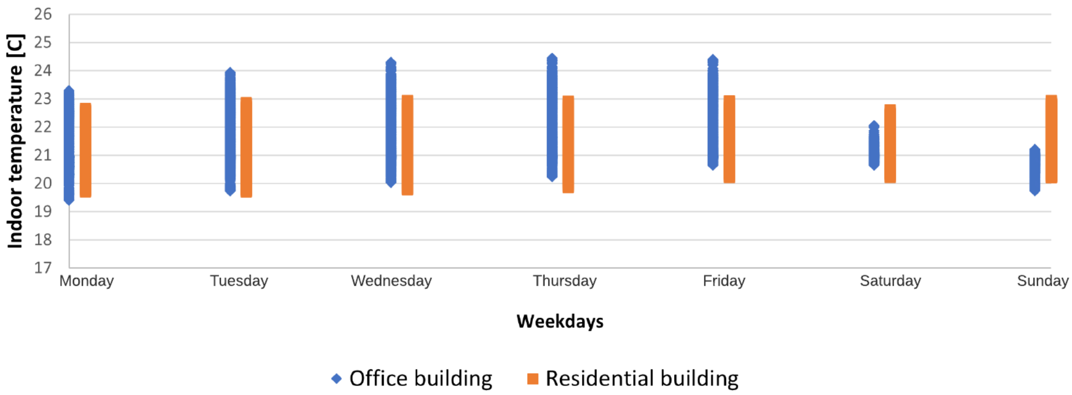


Figure 4.39: *Scatter plot of daily time-index and indoor temperature for Zone 22 in office and residential building*

4.4 Building envelope

The building envelope used in the Base Case is based on the Norwegian Passive House standard for commercial buildings, NS 3701. This building envelope is chosen based on the likelihood that a building with this advanced technology for temperature regulation would probably have a good building envelope. However, to see how the black-box model behaves with a different building envelope, different building envelopes are tested. All the different envelopes in this section have the same occupants' schedule, HVAC regulation, internal loads, and location.

4.4.1 Building standard

Four different building envelopes are tested to get a good range of data. These building envelopes were based on different building standards: Passive House, TEK 17, and TEK 87. In addition, a concrete building, similar to the Passive House except with a higher thermal mass, is also tested. The concrete building is chosen to see how the model acts with a higher thermal mass. The TEK 17 building standard is chosen since it is the newest standard for "ordinary" buildings. TEK 87 was chosen to get information related to older buildings.

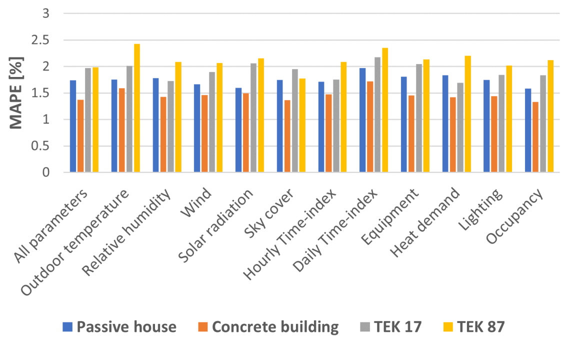


Figure 4.40: *MAPE of feature elimination for all building envelopes for Zone 7*

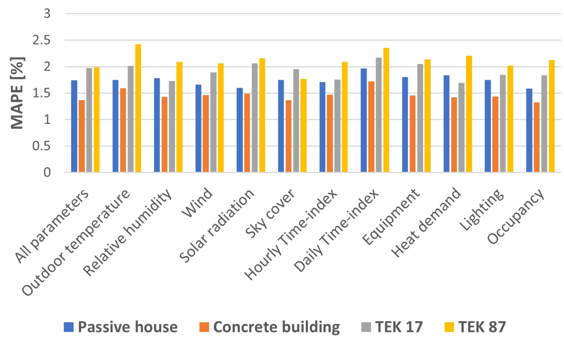


Figure 4.41: *MAPE of feature elimination for all building envelopes for Zone 8*

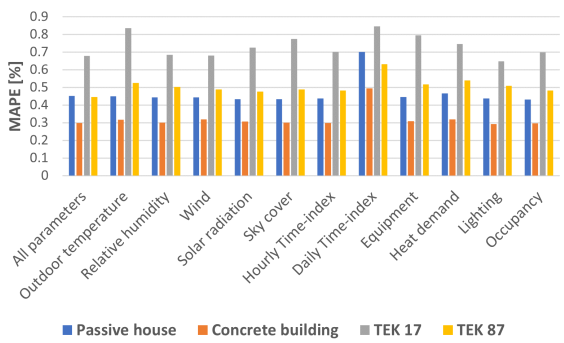


Figure 4.42: *MAPE of feature elimination for all building envelopes for Zone 12*

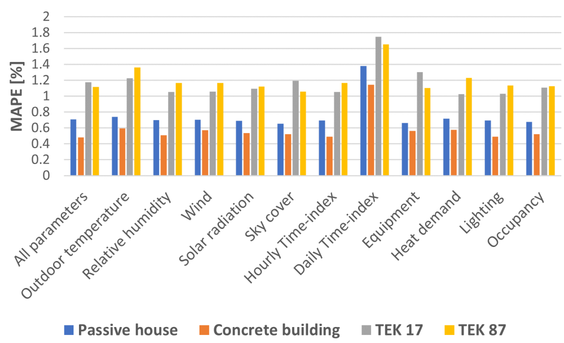


Figure 4.43: *MAPE of feature elimination for all building envelopes for Zone 22*

The results illustrated in Figure 4.40 - 4.43 all show that the Concrete building has the lowest MAPE and is, therefore, the building envelope most suitable for predictions. The accuracy of the other building envelopes varies to some degree, but all over the Passive House have following lowest MAPE, followed by the TEK 17 building. Regarding the parameter importance, all envelopes had a higher error when the daily time-index was missing. The TEK 17 and TEK 87 buildings also had some increase in error when the outdoor temperature was missing.

4.4.2 Location of windows

As seen in Figure 4.6 -4.8 Zone 19 have the lowest MAPE for all cases. Zone 12, 14, and 18 also have significantly lower MAPE compared to the other zones. An experiment related to changing the location of the windows was conducted to see if the variation in MAPE was related to windows. An overview of the windows' original and new position is given in Figure 3.2, 3.9, and 3.10.

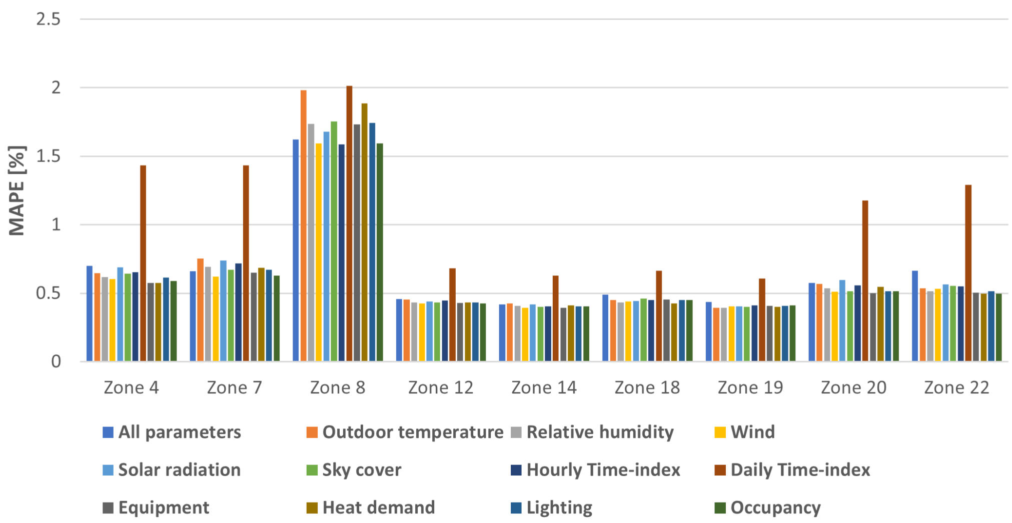


Figure 4.44: *Average MAPE of feature elimination when the location of windows are changed*

When analyzing Figure 4.44 it seems like the results are equal to the Base Case. A deeper investigation of the results is therefore included, Figure 4.45. This investigation includes all possible window locations for the two zones. Here, it is clear that there are many more outliers for the case with two windows on the northern wall for Zone 4. However, when examining the indoor temperature for all the cases, Figure 4.46, the confidence interval for the indoor temperature is quite similar for the three cases. However, the median for indoor temperature is remarkably higher for the cases with two windows on the northern or western wall.

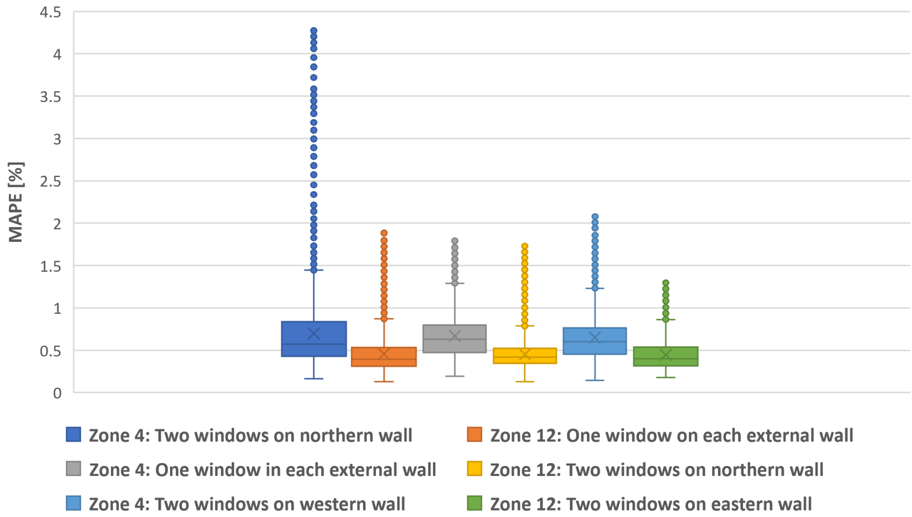


Figure 4.45: *MAPE for change in window location*

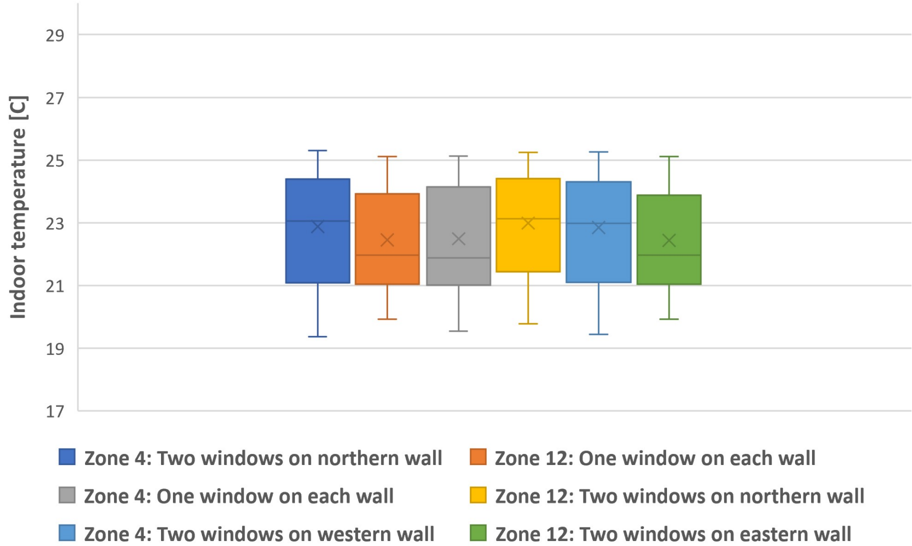


Figure 4.46: *Box plot of indoor temperature for different locations of windows*

4.4.3 Removal of external shutter

An experiment where the external shutters on the building were removed was also conducted. The results of this experiment are illustrated in Figure 4.47. Here the average error related to temperature prediction increases when the shutters are removed. The increase in MAPE is more significant for Zone 7, 14, and 20 than other zones. These are all zones facing south.

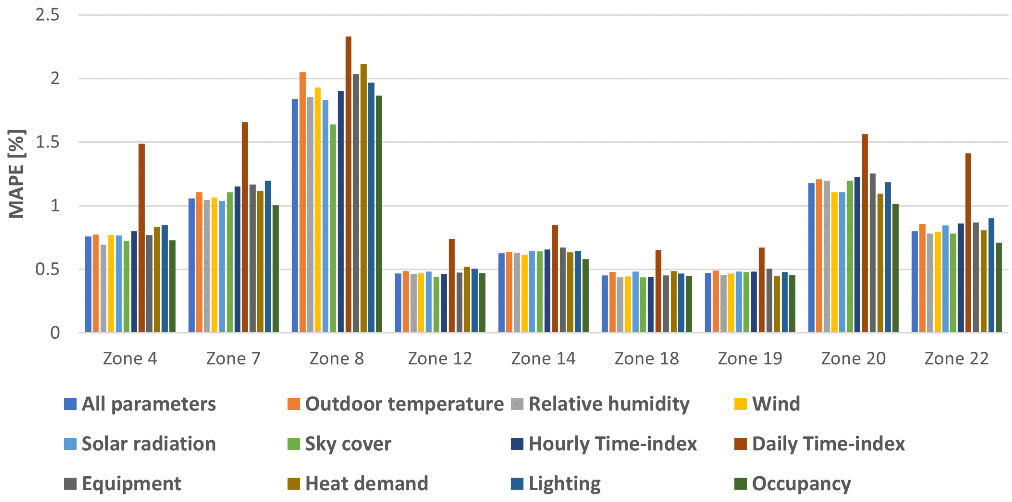


Figure 4.47: *Average MAPE with feature elimination for the building when external shutters are removed*

4.4.4 Rotating the building

When rotating the building 180°the effect the building orientation has on each zone would be revealed. Figure 4.48 illustrates the average MAPE for the rotated building with feature elimination. When comparing the figure to Figure 4.6 - 4.8 there is no apparent difference, and it is, therefore, reasonable to assume that the orientation has little importance on the building for this particular case.

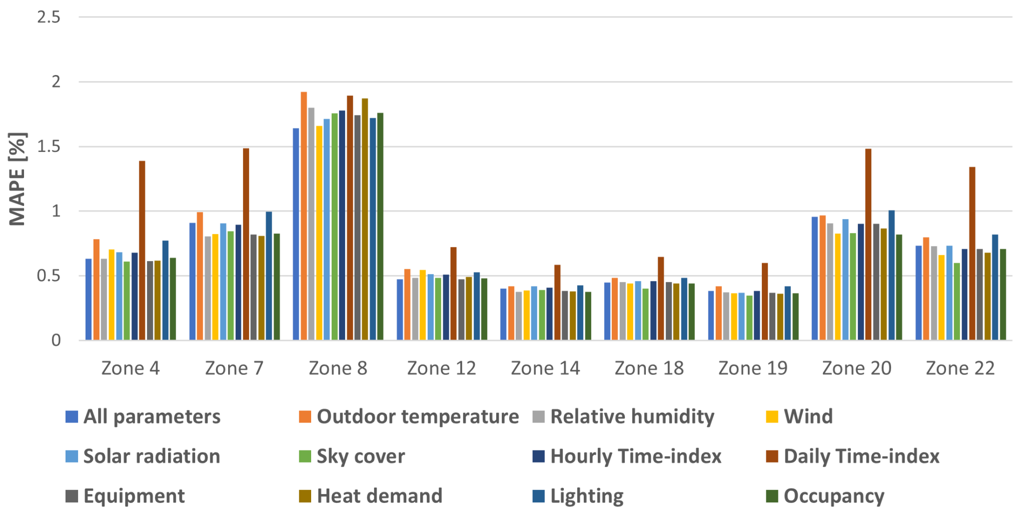


Figure 4.48: *Average MAPE with feature elimination for the building when rotated 180°*

A box plot of the indoor temperature is included, Figure 4.49, to ensure that the orientation of the building does not affect the building to a large extent. The figure is identical to the Figure 4.12, which holds is the indoor temperature with the original building orientation. For sure, one can say that the orientation is insignificant for temperature predictions for this particular building.

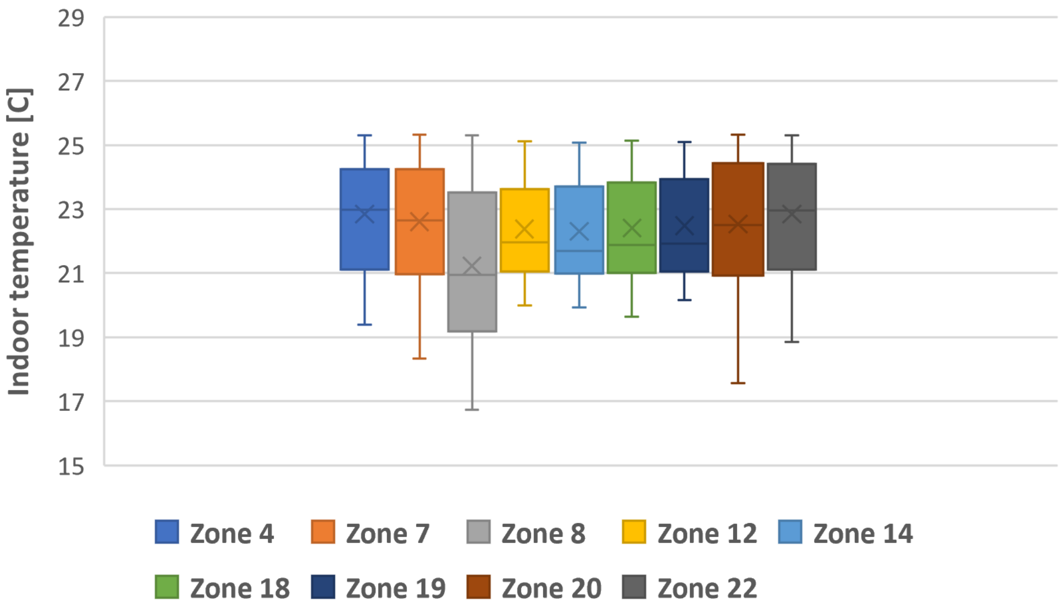


Figure 4.49: *Box plot of indoor temperature for rotated building*

4.4.5 Splitting one zone into two

The impact the size of the zone have on the model has also been examined, Figure 4.50 - 4.51. This was done by splitting Zone 12 in two, as this originally was one large zone. The results show that the original large zone has a more stable MAPE; however, the case has more outliers than the smaller zones. The indoor temperature of the original Zone 12 has a lower and more stable temperature compared to the others. For the two split zones, the results are almost identical. As for the smaller zones, the results are quite equal, but Zone 12-2 has a slightly higher MAPE regarding whiskers and outliers.

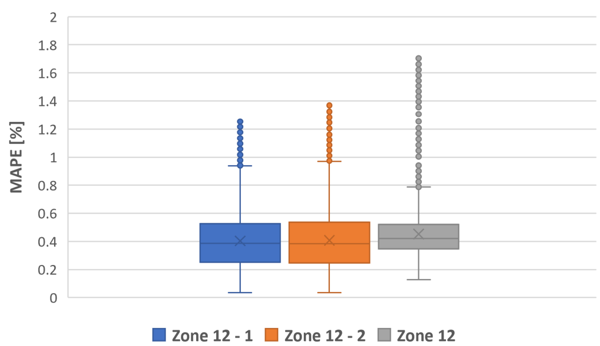


Figure 4.50: *Comparison of MAPE for Zone 12, when zone is split in two*

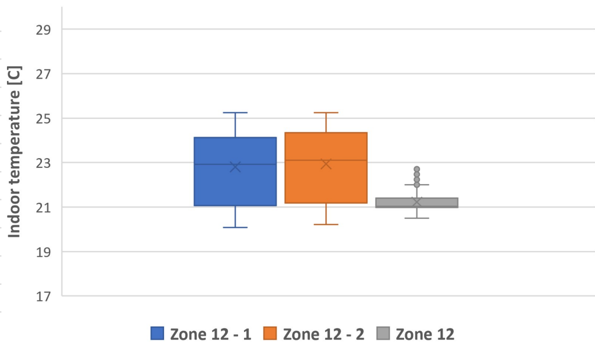


Figure 4.51: *Comparison of indoor temperature for Zone 12, when zone is split in two*

4.4.6 Comparing different cases of envelope

When comparing the results of the different experiments, the case with no exterior shutters has the highest average error and the case where Zone 8 is removed the lowest. For Zone 7 and 20, the error is lower for the "change in window location". In this case, one window was removed for Zone 7, 20 and 22, and relocated for Zone 4 and 12, as seen in Figure 3.9. The lower error for Zone 7 and 20 may indicate that the number and location of windows are essential in some cases.

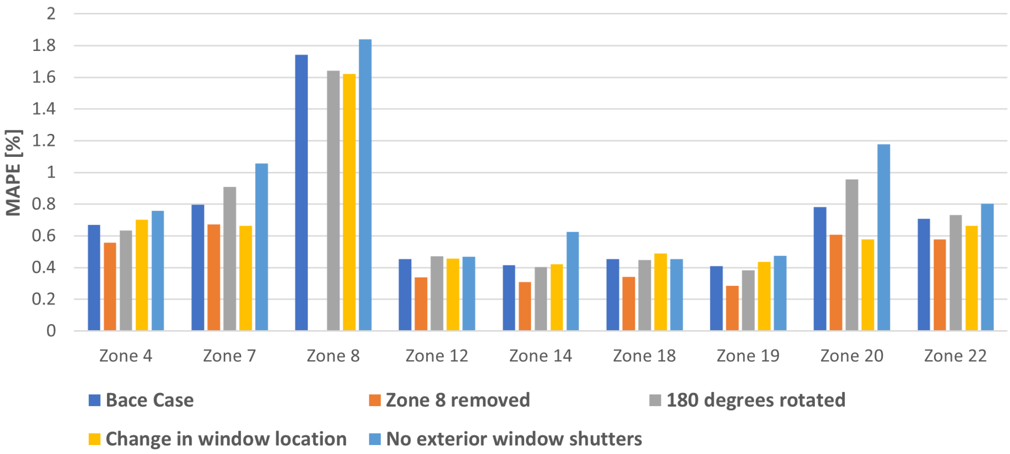


Figure 4.52: *Average MAPE for all zones for different building cases*

4.5 Testing for different climates

The Base Case building is simulated in three different locations, Trondheim, Oslo, and Malaga, to see how the climate affects the building. The different locations are chosen to get a good representation of the different climates in the Koepper climate classification[21], as well as see the effect of minor climate differences. The results show that the accuracy is best for Malaga, and worst for Oslo, Figure 4.53 - 4.56. As seen throughout the results, the Oslo building is more dependent on the outdoor temperature and daily time index.

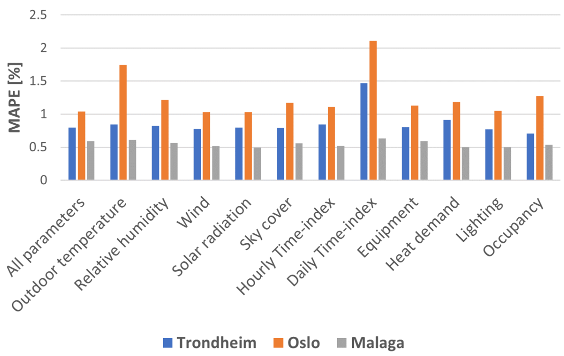


Figure 4.53: *Average MAPE for feature elimination for Zone 7 in different locations*

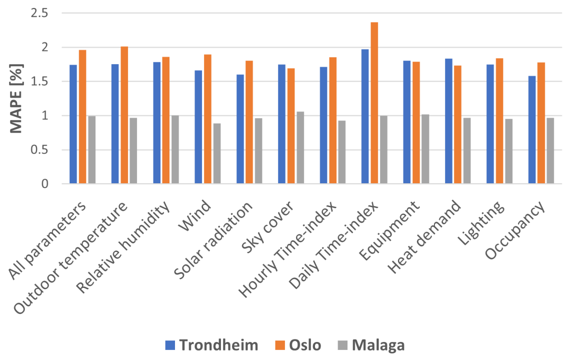


Figure 4.54: *Average MAPE for feature elimination for Zone 8 in different locations*

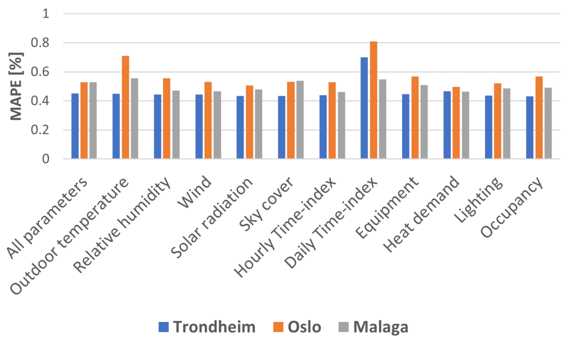


Figure 4.55: *Average MAPE for feature elimination for Zone 12 in different locations*

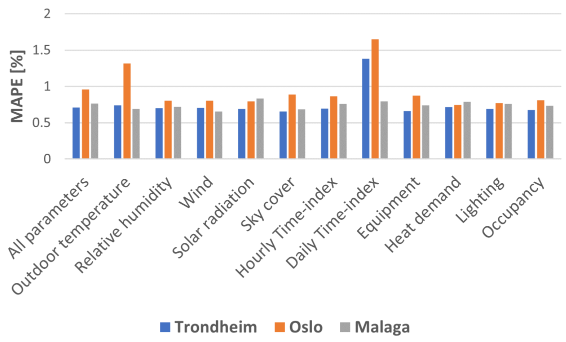


Figure 4.56: *Average MAPE for feature elimination for Zone 22 in different locations*

4.5.1 Indoor temperature for different climates

The indoor temperature of the testing period varies for all three different locations. The Malaga building has a high indoor temperature compared to the others, and it can seem like the temperature is mostly between 24 - 25°C for all the highlighted zones. As for the other buildings, the temperature varies to a more considerable extent between the zones, and more outliers can be found, Figure 4.57. Comparing the Trondheim and Oslo building, the most significant difference between the two cases is more outliers for the Oslo case.

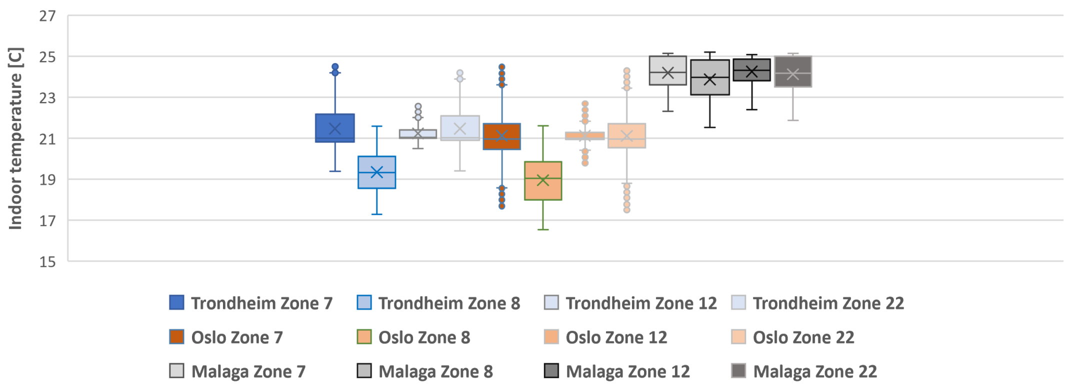


Figure 4.57: *Box plot of indoor temperature for four four zones in three different climates*

4.5.2 Space heating for different climates

When comparing the heat demand for the testing season for all the different locations, it is clear that the Malaga building hardly has any, Figure 4.58. Zone 8 has a high heat demand for the other buildings, and it seems like that capacity is maximized. For Zone 7, 12, and 22, the median is higher for the Oslo building, while the confidence interval is more extensive for Zone 12 and 22 in Oslo compared to Trondheim.

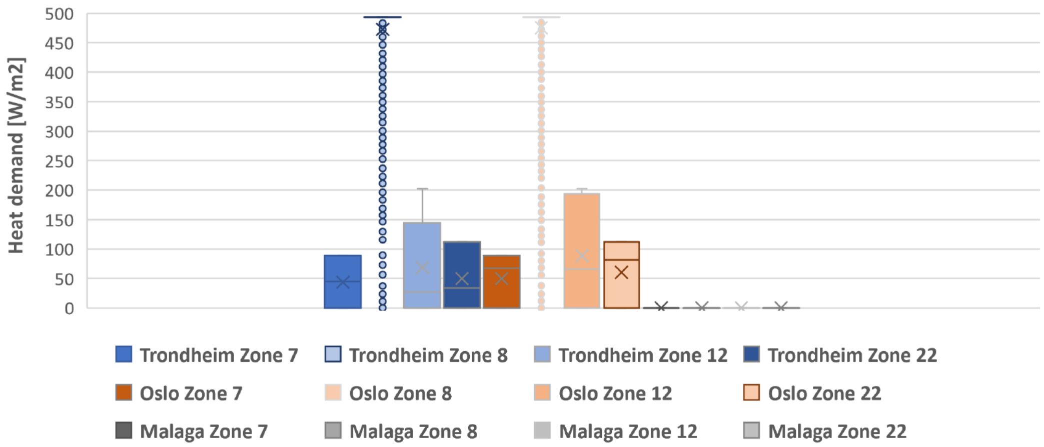


Figure 4.58: *Box plot of heat demand for four zones in three different locations*

4.6 Modeling accuracy

The model utilized makes predictions for each 15min for the following 24h, at each time-step. The results presented earlier only contain information about 24h prediction. This section will give information about the prediction accuracy of the other time-steps and localize the peaks of error.

4.6.1 Time-step accuracy

The accuracy-related to each time-step varies, Figure 4.59. A clear trend is that the accuracy decreases with the time-step. However, the first few time-steps also have a higher MAPE. The results presented indicate that the prediction accuracy is best for time-step 2-7, i.e., 0.5-1.45h predictions.

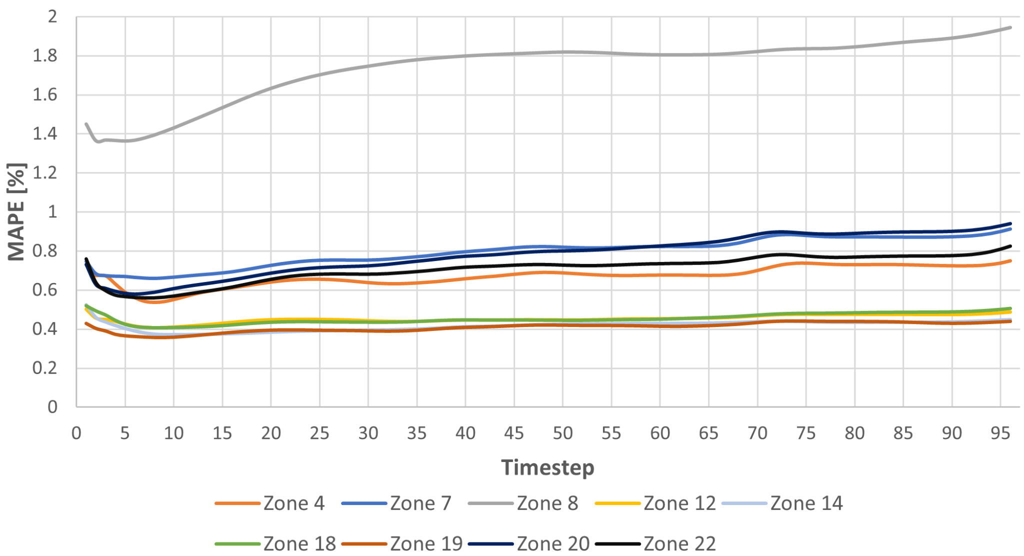


Figure 4.59: *MAPE for different time-steps of prediction*

When comparing the predicted temperature to the actual temperature, Figure 4.60 - 4.63, it is clear that the predicted temperature is quite similar to the actual one. For all the cases, it is the 15minute ahead prediction that is the most off regarding indoor temperature. For the other predictions, it is challenging to separate the prediction accuracy.

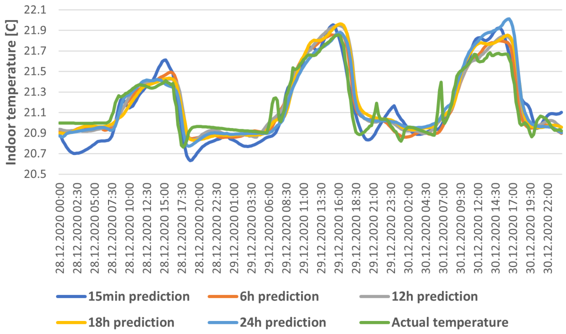


Figure 4.60: *Predicted temperature versus actual temperature for different time-steps of prediction, Zone 7*

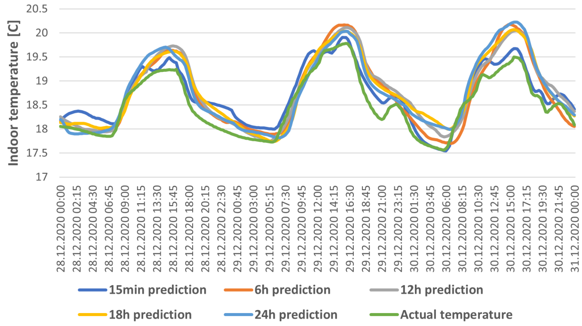


Figure 4.61: *Predicted temperature versus actual temperature for different time-steps of prediction, Zone 8*

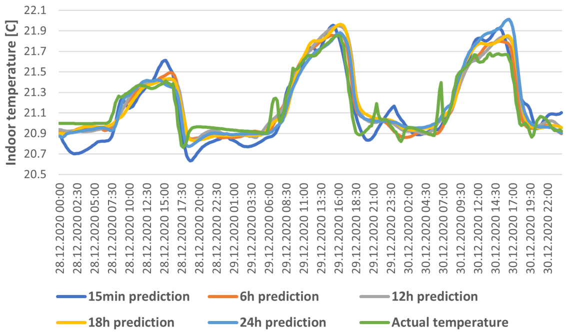


Figure 4.62: *Predicted temperature versus actual temperature for different time-steps of prediction, Zone 12*

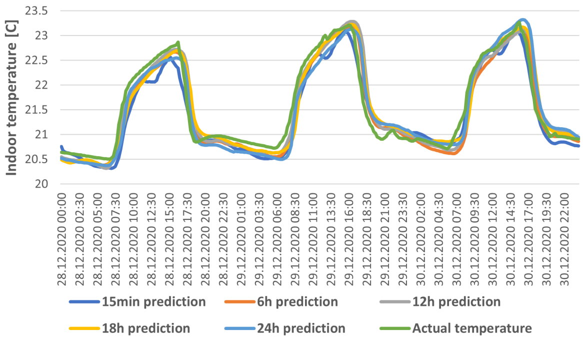


Figure 4.63: *Predicted temperature versus actual temperature for different time-steps of prediction, Zone 22*

4.6.2 Location of error

To better understand how the model works, Figure 4.64, the MAPE is plotted with the indoor temperature. As seen in the results, Zone 8 has immense changes in temperature and the highest peaks in MAPE. When following the vertical lines placed over the MAPE peaks, one can see that the peak often occurs then a change in the temperature pattern occurs. These changes are both minimum values and the transition to the weekend.

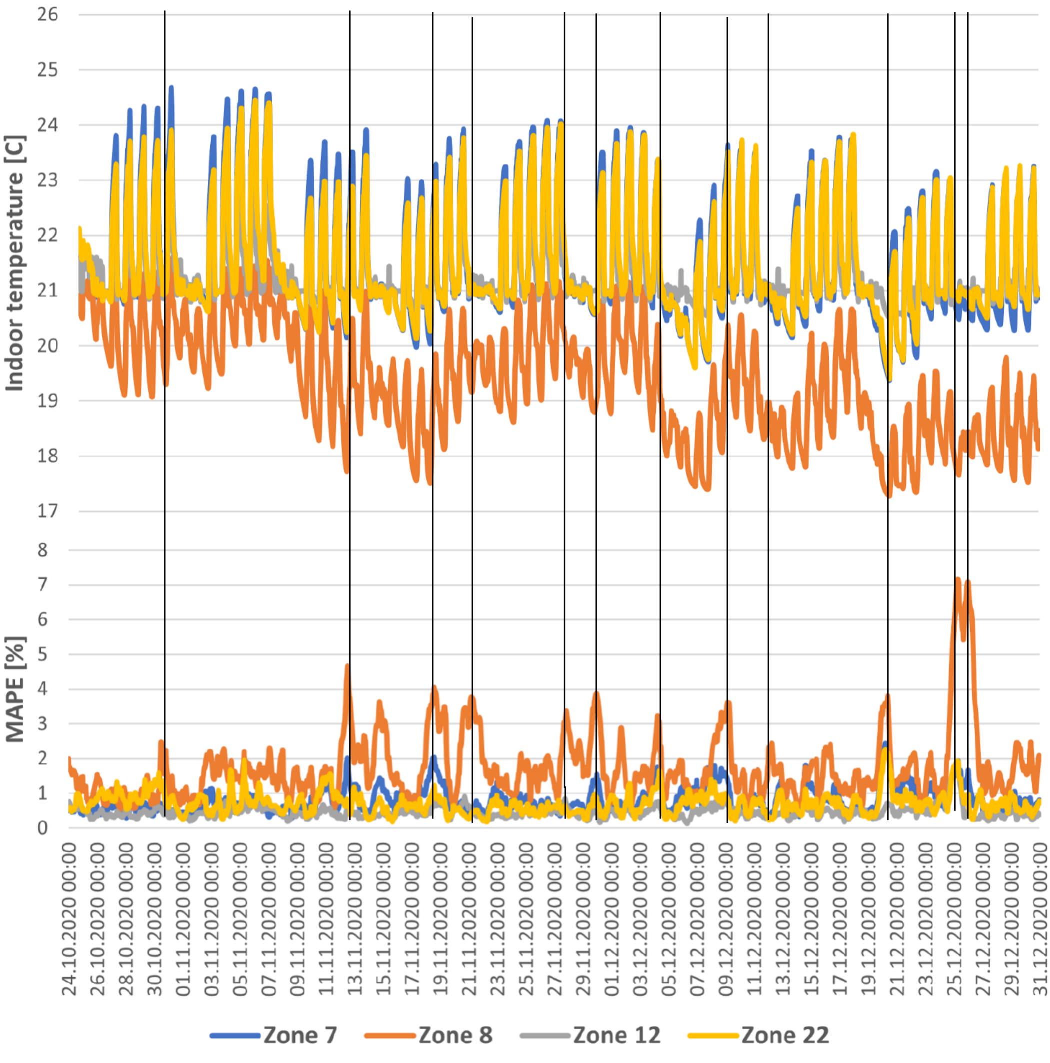


Figure 4.64: *Combined plot of the MAPE and indoor temperature for the Base Case/Passive house*

5 Discussion

The discussion will mainly focus on the results and try to explain and find connections between them. All experiments are compared to the Base Case, Figure 4.6 - 4.8, if else is not stated.

5.1 Reliability of the black-box model

In this subsection, the reliability of the black-box model will be discussed. This includes insecurities related to the white-box model utilized as input, the accuracy of the predictions, time-steps, and the locations of errors.

5.1.1 Reliability of the white-box models

The results of the black-box model are generated based on the simulation of the white-box model. Therefore, realistic values generated in the white-box model are crucial for the reliability and realism of the black-box model. Therefore, simplification in the white-box models needs to be confirmed not to affect the results in the black-box model.

One of the simplifications made in the white-box model is the schedule of occupants and equipment. The schedule utilized is based on an actual office building regarding the hours occupied. The number of occupants in each hour is, however, random. The randomizing of the number of occupants can lead to more variations for each hour than realistically. A set range of occupants is chosen, so the variation is within reasonable limits, but the values may still be unrealistic. Another downside of setting the variation for each hour is that one may miss out on the variation of occupancy within each hour. However, as assumed by Sun et al. [13], short leave of occupants and minor deviations from the simplifications may not affect the consumption to a large extent.

The schedule for the actual office building is only one week. Therefore, this schedule is multiplied to cover a whole year, while the randomizing still occurs for each hour occupied, meaning the occupied hours are equal for each weekday. The similarity in occupancy that occurs every week may negatively impact the model and classify the time-indexes as more valuable than they are for most cases. The importance of the daily time-index will probably be most affected since every weekday is similar, in contrast to every hour, which varies. On the other hand, the occupied hours for an office building will probably be similar for each weekday due to set schedules by the employer, but variation may occur. The variation in set schedule probably varies between buildings and may be more widespread after COVID-19 and the normalization of home-office.

The same goes for the equipment schedule, which has the same time for turning on and off each week. Realistic data would probably include some variation in the use of equipment for each zone, based on the occupant's habits, and for each day based on the fact that the occupants' work is varied. However, office appliances are most often turned on during office hours [46], but deviations can occur based on the occupant's habits. How much this affects the model and the parameter importance is hard to state since the variations can be immense due to different turn-off ratios for each building. On-site measures of the buildings where this technology is being utilized are therefore of great importance.

Another deviation in the white-box models is the layers of the envelope. According to Byggteknisk Forskrift [42] there are specific layers an external envelope must include, which has been excluded in this study. These layers are included to make the building more resistant to moisture damage. This simplification will not affect the results of the building [53], since IDA ICE is a program for energy simulations and mainly calculates heat loss and not moisture damages.

In cases where the Base Case is compared to other cases, the first prediction is utilized. This is both when building standards and climate are compared. This particular prediction has a significantly higher MAPE than the other similar predictions, Figure 4.6 - 4.10. However, the increase of MAPE can be seen as small compared to the scale of error but still needs to be kept in mind when comparing the results of the various tests. Therefore, the main source of error for this thesis is the use of unrealistic schedules for occupants and equipment.

5.1.2 RMSE and STD

Comparing Figure 4.1 with Table 4.1 it is clear that all the RMSE values for the model are lower than the STD from each particular zone. This indicated that the model is good, and the results are valid [53]. The high STD for the input data indicates the degree of variation in the output of the black-box model. The prediction data have a lower RMSE than the variation of the actual data, indicating that the model can capture the behavior of the building and the natural temperature variations.

These promising results may be due to an extensive training period that covers multiple seasons. As seen in Figure 3.15 the training period covers Winter, Spring, and Summer, while the validation season takes place during Autumn. The climate in November and December is often similar to January and February, making these months suitable for testing since training has been conducted in a similar season.

The ratio of data distribution for training, validation, and testing (60% - 20% - 20%) may also play an essential part in the accurate prediction results. Dedicating this large share of data for training will give the model insight into many different scenarios. However, the model is only tested for the end of autumn/winter, meaning that the prediction accuracy given in the model only accounts for these seasons. During summer or other seasons, the prediction accuracy may be different. On the other hand, there is reason to believe that the model will have similar or better performance for the following seasons since it already has experienced it. This accusation accounts for all the different cases' tested.

5.1.3 Randomness in the model

The black-box model utilized is based on random numbers. A goal, which is also a confirmation that the model works and is accurate, is that the accumulated answers are equal for each similar prediction. This similarity of results occurred when multiple predictions were done for the utilized model, Figure 4.2. The small variations occurring in the results are assumed acceptable, based on the larger variations in the STD of the input parameter. The STD calculated for the multiple predictions are on average 0.028% when all parameters are included. Based on this low value, one can assume that the model has a good performance and accuracy.

When conducting multiple similar predictions, Figure 4.2, predictions with fewer input parameters and fewer zones were also conducted. Compared to the identical predictions with all inputs and all zones, the prediction with few inputs has a slightly higher error. This error may be due to a bad combination of inputs or a lack of necessary information. The inputs used are listed as “Combination 1” in Table 3.12. Either way, it strengthens the Base Case of the model and that the inputs utilized are mostly good. The results are quite equal for the case with fewer zones and when all are included, if not better.

When removing Zone 8 from the model’s input and output side, an increase of error was expected for Zone 12, 14 and 18, since all of these have one shared wall with Zone 8. However, no significant changes occur. This lack of change indicates that there is small communication between the internal walls.

The model utilized is a hybrid MIMO model. One of the advantages of MIMO is that communications between zones nearby occur in the form of possible heat flow through internal walls. The results presented in Figure 4.11, shows that the assumed advantage is not present, which Figure 4.2 also confirms. A similar accuracy indicates a small amount of communication between the zones. Therefore, the accuracy was not sacrificed by utilizing a hybrid MIMO model instead of a pure MIMO model for this exact case.

The lack of communication between the zones can be a drawback for the building generated in IDA ICE or the LSTM model utilized. Maybe the LSTM model struggles to capture the relation between zones since most zones are perfectly heated, and there is a minor temperature difference and, therefore heat flow, between the zones. Zone 8 has the most varying indoor temperature out of all the zones. This zone may therefore be perceived as noise for the other zones instead of help. For another building or another model, these results may be different. Testing this building with another data-driven model or a building with less insulation and varying temperatures may give other results. Therefore, the experiment should be conducted on the TEK 87 building or lower insulation in the internal walls.

5.1.4 Testing in different seasons

As expected, this experiment gave the best results for “Season 3”, and worst for “Season 1”. This outcome may be due to less experience with cold temperature for “Season 1”. As seen in the Project Work [1] the best accuracy occurs when the testing and training occur in periods with similar temperatures. Moreover, as seen in Figure 3.15 the indoor temperature is similar at the end and beginning of the year. If both the testing and training occurs in a temperate season, the results may have been different.

The large MAPE may also be due to extreme values. The prediction was only conducted once for both of the other cases, and since the model is based on random numbers, this may explain the large values compared to the other cases. The likeliness of this is, however, small. During the experiment where the same case was predicted multiple times, the results were quite similar for all cases, and the STD was found to be 0.028 %. Based on this insecurity range, the values are still remarkably high compared to “Season 3”. Therefore, it is assumed that the model is entirely accurate, and extreme values for these cases seem unlikely.

When analyzing Zone 8 for "Season 1" the MAPE tends to increase when the temperature decreases; this is especially clear for the outdoor temperature, Figure 4.5. This may be since a decrease of temperature, both indoor and outdoor, is equivalent to an increase of temperature difference between set-point temperature and occupied temperature conditions. A more considerable variation in temperature means more extensive temperature variation throughout the day, which is naturally more challenging to predict than a stable indoor temperature.

5.1.5 Time-step accuracy

The results show that the time-step accuracy decreased when the number of time-step predicted ahead increases. This increase of error may be related to the insecurity that increases the further away the prediction is, since the conditions can deviate more from the current conditions. The large deviations for the first time-steps may be because the model emphasizes the small changes occurring at the current time too much. If the temperature starts to rise, the model thinks it will continue to, and opposite. For longer predictions, the current changes are probably emphasized to a minor degree due to a long time until the prediction.

The downside of the longest prediction being the most incorrect is that long-term prediction is the most valuable. Long-term predictions can be used for finding the optimal conditions based on a long-term scenario. Short-term predictions may have resulted in other conditions based on what seems like the best option from a short-term perspective. In addition, there may be a time restriction for short-term predictions, which may lead to unfinished calculations for the model.

5.1.6 Location of error

When the figure of the MAPE and indoor temperature for several zones are compared, a vague pattern of the peaks in error occurs, Figure 4.64. The MAPE increases when a change in indoor temperature patterns occurs, which often happens at the beginning or end of a weekend. The figure also illustrates that the peaks are significantly higher for Zone 8. This is natural since this zone has the most variation in indoor temperature.

The peak occurring in these moments may be due to a change of pattern in indoor temperature. The indoor temperature is set to a set-point temperature of 17°C when not in use, while a desired indoor temperature of 21-25°C is used otherwise. Then the building is set to a set-point temperature; no energy is used for heating until the set-point temperature is reached. During these conditions, the change in indoor temperature depends entirely on the external environment. Hence the internal thermal loads are not existing at this time.

The significant peaks near weekends help explain why the input parameter daily time-index is essential for the model and possible measures to minimize the peaks. Naturally, this sudden change in building behavior is hard to predict. However, this change happens at the same time every afternoon on weekdays. An improvement of the input variables related to time-index may improve these errors. Combining the hourly and daily time-index may be a good measure to better capture the transition.

When the building is set to a lower set-point temperature, it is natural that Zone 8 is more sensitive to the external environment. The sensitivity is due to the glazed envelope, which has a higher u-value than the envelope used for the other rooms. Therefore, a higher outbreak in terms of the error is expected for these envelopes.

The results show that the concrete building has a more stable indoor temperature compared to the Base Case. The stable temperature is due to the building's high thermal mass, making the building less affected by external changes. The Malaga building does also have a stable indoor temperature. The stability in terms of indoor temperature may result in lower peaks in error for these buildings.

5.2 Affect of HVAC system and internal gains

This subsection will discuss the test conducted with different controllers and the effect occupants and equipment has on the model.

5.2.1 HVAC controllers affect

When testing for different HVAC controllers, there was no difference found regarding the performance of the black-box model. This lack of difference may be due to similar indoor temperatures for the two different controllers. Similar conditions for indoor temperature are expected with a PID-controller, which is better at adapting to challenging conditions. Therefore, similar results are also expected regarding prediction accuracy with this controller.

The conditions given by the controller are suitable for all zones, except for Zone 8. Zone 8 does not reach the desired indoor temperature and should have started the zone's heating earlier. If the settings of the HVAC system were better for Zone 8, the prediction accuracy might have been better for the zone. This due to more stable temperature conditions.

5.2.2 Occupancy affect on the model

Different office schedules

When testing the model for sensitivity of different office schedules, Figure 4.28 - 4.32, the model performs quite well. The average, median, confidence interval, and wishers are all located in the same area for all the zones, except Zone 8, which has variations for all the different schedules. These similarities indicate that the model is robust for different schedules and that the schedule utilized is not good due to coincidence. Regardless, the results do not strengthen the schedule's degree of realism.

As for Zone 8, the variation was more prominent than for the others. As seen in the past test, the variation for equal predictions for Zone 8 has an STD of 0.054 %. The more significant variations occurring in Zone 8 regarding change of schedule may be due to the high STD. The false assumption may very well be the case since the insecurity margin is only based on five predictions. If this is the case, the models' effect of different schedules is negligible. On the other hand, there is a possibility that the glazed envelope has affected the MAPE, by making the zone much more sensitive to internal gain and changes.

Residential occupancy

When analyzing the feature elimination for residential building, Figure 4.33, the first thing noticeable is the daily time-index which have a similar result as the other parameters. This similarity has rarely occurred in other predictions but does to some degree in the second prediction for the Base Case, Figure 4.7. The results of this may, therefore, be both random or due to the schedule.

In contrast to the office building, the solar radiation helps keep a more constant indoor temperature for the residential building, Figure 4.35. The stable temperature is possible due to a good overlap of solar radiation when the building is not occupied, i.e., when the building is not affected by internal gains or heat supply. Since the building is occupied during weekends, the HVAC setting is equal most of the time, and when not, the solar radiation helps to keep a stable indoor temperature. The constant HVAC settings combined with the overlap of solar radiation may be why the daily time-index is not as crucial for this schedule.

When analyzing the scatter plot of the daily time-index for residential and office buildings, it is here clearly illustrated that the indoor temperature is more stable for the residential building throughout the week compared to the office building, Figure 4.36 - 4.39. This stability is probably due to a more constant occupation all days of the week, resulting in a more constant internal heat flow and HVAC settings.

The scatter plots, Figure 4.36 - 4.39, show that the indoor temperature vary to a much larger extent for Zone 7, 8, and 22, compared to Zone 12. The small variations in temperature regarding Zone 12 are probably since the room is quite large and has good insulation. These are the main building characteristic differences between the zones. Besides, zone 12 only has windows facing north, resulting in less heat gain from solar radiation. Unlike the others, this zones is designed as a meeting room. The zones, therefore, have little equipment and can be heavily occupied. These internal gains may positively affect the zone, resulting in a more stable indoor temperature. The good modeling results for residential buildings also occur in the study of Zeng et al. [29] where hotels had a lower MAPE than shopping centers and offices.

5.2.3 Equipment's affect of the model

The use of equipment in all experiments is based on set schedules similar for all weekdays and weeks. This simplification will probably weaken the importance of this parameter in the tests conducted. For an actual building, this parameter will, therefore, probably be of more importance.

In section 4.4.5 one zone is split into two smaller ones, resulting in a more varying MAPE and increased and varying indoor temperature for the two new zones. The two new zones were designed as offices and had more equipment and fewer occupants than the original zone. Due to the more varying MAPE and increase of indoor temperature, there are reasons to believe that the equipment greatly affects the indoor temperature. The results also indicate that equipment information is a more valuable parameter than the number of occupants.

In the study of Zeng et al. [29] the results indicated that office buildings were the most challenging building type to predict. The challenges may be due to the heavy use of equipment, which contributes to internal heat gain challenging to predict. The use of energy-efficient equipment will reduce the internal heat from these appliances and probably result in better prediction accuracy of these zones.

5.3 Building envelopes affect

This subsection will discuss the building envelopes effect on the data-driven model. It includes an evaluation of insulation, thermal mass, the use of windows, and room size.

5.3.1 Affect of thermal mass and insulation

When analyzing the results of the building standard, the MAPE is lowest for the Concrete building, followed by Passive house, TEK 17, and TEK 87, Figure 4.40 - 4.43 for Zone 7, 8, and 22. Meaning TEK 87 has the highest MAPE for these zones. These results are as expected, and based on it, it can seem like high insulation and thermal mass is suitable for modeling accuracy. This may be because high insulation prevents variation in temperature, something that can be assumed is suitable for temperature prediction. The Concrete building has almost the same u-value as the Passive House and still has a clear lower MAPE for the three different zones. The low MAPE is probably due to the high thermal mass of the building, which can store both heat and cold and be an excellent tool to achieve a more stable temperature. The more stable temperature is probably the effect that is responsible for the lower MAPE.

As for Zone 12, the ranking of prediction accuracy is slightly different. The new ranking from best to worst is Concrete building, Passive house, TEK 87, and TEK 17. This result is also the case for some of the parameters in the other zones. This result is difficult to explain from an energy modeling perspective since the structure of TEK 17 is more similar to the Passive House and the Concrete building structure, which have better accuracy. The results may therefore be due to variation in prediction accuracy.

Regarding parameter importance, the MAPE is relatively stable for all Concrete building and Passive house cases, except for the parameter daily time-index. These similar results for other parameters may be due to the stable temperatures of the building, making it easy to predict no matter input parameters.

As for the TEK 17 and TEK 87 buildings, the MAPE related to each parameter elimination varies more. The input parameters heat demand, outdoor temperature, and equipment stand out as essential parameters for all the zones. These parameters are strongly related to the indoor temperature regarding internal gain, space heating, and exfiltration of heat. Both the buildings have reduced insulation and thermal mass compared to the other, which may be why the MAPE is larger when these particular parameters are missing. Due to the buildings' lack of ability to store and keep heat, the parameters strongly related to heat gain and loss are more important.

In Subsection 4.1, all rooms have the same external envelope, meaning the windows and materials for the walls, floors, and roofs are equal. This envelope is the case for all zones, besides Zone 8, which consists of mostly a glass envelope. The tests resulted in lower accuracy for this zone compared to the others, which the significant temperature variation can explain, Figure 4.12. The temperature variations are a consequence of the construction's low thermal mass and insulation, making the zone more sensitive to the external environment.

The desired indoor temperature for all the zones is 21°C - 25°C when occupied. As seen in Figure 3.4 Zone 8 is the only zone not able to stay within these desired values. This flaw may be of huge influence when predicting the indoor temperature and is one of the main reasons the error is larger for this zone. The temperature never reaches the desired ones and therefore never stabilized around a value. This temperature flaw is most lightly a consequence of a glazed envelope, which has a high u-value and isolates the heat badly. This envelope are most lightly also the reason for the large variations in both indoor temperature and heat demand, Figure 4.12 - 4.13. These results correspond and strengthen the finding of insulation being an excellent characteristic for buildings suited for temperature predictions.

5.3.2 Affect of windows

In the experiment where the locations of some windows are changed, there are minor differences in the MAPE related to parameter elimination, Figure 4.45. The main difference is related to Zone 20 and 22, where the overall MAPE is reduced for both zones. This difference is probably due to less external heat gain from solar radiation, which came from the second window. Based on these results, it may seem like the prediction accuracy is better for zones with fewer windows.

As seen in the results, only the MAPE for Zone 20 and 22 is reduced, not for Zone 4 and 7. Zone 4 still contains two windows, only in one different location. The results of moving the window to the same facade had little impact on the prediction accuracy. For Zone 7, the same changes have been made, as for Zone 20 and 22, even tho the impact is remarkably more minor. This lack of impact can indicate that the window's location significantly impacts the higher the window is located since Zone 20 and 22 are on the first floor, while Zone 7 is on the ground floor. This may be because windows located on a higher floor are more exposed to radiation and convection.

When analyzing the MAPE for Zone 4 and 12 before and after the window's location is changed, remarkably more outliers can be found for Zone 4 "Two windows on the northern wall". These outliers may be because the wall utilized was tiny, and with two windows, it will almost be like a glazed envelope on that particular facade. Moreover, as seen in Figure 4.12, the indoor temperature varies more for glazed envelopes. As for Zone 12, the MAPE is quite similar for all cases.

Regarding indoor temperature, a clear trend can be seen. For zones with two windows on the northern or western wall, both the median and average indoor temperature are higher than those with one window on other walls. The high temperature may be due to more intense solar radiation. The more intense radiation may lead to a higher indoor temperature over a short time; in contrast, when the windows are located on different walls, the external heat gain is lower over a more extended period. From an energy engineering perspective, the more intense radiation leading to a short period of temperature changes seems more challenging to predict than a more even temperature increase over time. However, based on the results, it seems like the window position does not affect the MAPE of the temperature prediction.

Shutters
When removing the external shutters of the building, the MAPE increased for Zone 7, 14, and 20, which all are zones facing south. For buildings north of the equator, the southern facade is mainly exposed. Therefore, the location of the zones is probably the reason for the increase of MAPE, due to the increase of external heat gain. The shutters used in this study are probably of high quality and work well since both the MAPE and indoor temperature for the southern zones are similar to the others when the shutters are utilized.

5.3.3 Affect of room orientation and size

Orientation
When changing the orientating of the building, the results are quite similar to the original orientation, Figure 4.48. The small changes in these results are within the confidence interval, based on the STD when the model is predicted multiple times, Figure 4.6 - 4.8. From these results is may therefore seem like the orientation of the building is indifferent. The orientation

will probably better impact the building if a less insulated building envelope was utilized or the exterior window shutters were removed.

Size of zones

The size of the zone may affect the accuracy of the prediction. In the experiments conducted, the small zones had more variations in indoor temperature than the larger ones, Figure 4.13. The upper limit of the confidence interval is, however, similar. Smaller zones will probably be more affected by internal and external gains than larger zones, as seen for the split Zone 12, making them harder to predict. This may be the reason for the more significant MAPE for Zone 4, 7, 20, and 22.

The temperature is more stable for Zone 12, 14, 18 and 19, compared to Zone 4, 7, 20 and 22, Figure 3.4, 4.12. The stable temperature may be why the MAPE is lower for these zones, Figure 4.1. However, the heating demand for Zone 12, 14, 18, and 19 are greater than the others, Figure 4.13, making it lightly that the temperatures of the other zones are more affected by external or internal heat gain.

In section 4.4.5 one meeting room, Zone 12, is split into two smaller offices, resulting in a more varying MAPE and increased and varying indoor temperature for the two new zones. The increase of variation may be due to the excessive use of equipment in the zone. On the other hand, it can also be due to the small size of the zone, which may be easier affected by internal heat gain. The test of the split zone, either way, results in a more varying indoor temperature for small offices than smaller rooms. This increased temperature variation may explain why Zone 12, 14, 18, and 19 have a lower MAPE than Zone 4, 7, 20, and 22. These results correspond to the results of Zeng et al. [29], where also offices were the most challenging to predict.

The increase of temperature variations was either due to the heavily equipped zone, the size, or a combination. Therefore, the experiment of the split zone should be redone, so the results of the different experiments could be separated. In the new experiment, the conditions for internal gains should be halved of the original zone. By utilizing this approach, it will be easier to separate the results of equipment use and the ones related to the size of the zone.

5.4 Climates impact on modeling

Analyzing Figure 4.53 - 4.56 it is clear that the building located in Oslo has the highest MAPE and Malaga the lowest. The indoor temperature for the different locations varies to some extend, Figure 4.57. For Oslo and Trondheim, the whiskers are below the desired temperature of 21°C. For Malaga, the temperature is never below this limit, which means that the indoor temperature in Malaga is similar for when the building is occupied and not, in contrast to Trondheim and Oslo. Since the HVAC conditions are similar for all cases, one can assume that no heating is needed in the building. This is confirmed in Figure, 4.58. The absence of heating in the building probably makes the prediction easier for the model due to one less parameter to take into account. The absence of space heating, including a small variation in indoor temperature, may be the main reason for the low MAPE for this location.

Regarding the results for the heat demand, The Malaga case does not have any, while Trondheim and Oslo have quite similar heating demands. Due to the lack of heating needed, the Malaga building probably has some cooling demand. Considering the indoor temperature reaches the maximum value for all zones, Figure 4.57. Information about the cooling demand is out of reach for the black-box model and may be one downside of utilizing a warmer climate with these particular input parameters. However, when analyzing the indoor temperature for the various zones, there is a slight variation between the Malaga zones, in contrast to the Oslo and Trondheim zones. The similar conditions for the building zone may also be a reason for the location's low MAPE.

When analyzing the parameter sensitivity for the Malaga building, the results are quite similar for all variables, except the daily time-index, which is of great importance. The parameter influence varies more for the other locations, where outdoor temperature stands out as necessary. The outdoor temperature may be a more valuable input parameter in cooler climates due to the larger temperature difference between set-point temperature and desired temperature. Since the lower limit of acceptable temperature changes depending on if the building is occupied or not, the gap between the two set-point temperatures will be more significant. However, the upper limit for indoor temperature is constant no matter if the building is occupied or not, making the temperature difference smaller throughout the week for temperate climates since conditions are similar at all times.

The results presented represent the model's performance when testing is conducted from October to December. At this time, the outdoor temperature is very low for the Nordic cities and tempered for Malaga. The low outdoor temperature leads to an increase of temperature difference between indoor and outdoor for these cases. While in Malaga, one can assume that the conditions are more similar to each other. If the testing was conducted during another season, it is reasonable to assume that the results would be different. During the summer, the conditions between inside and outside are much more similar for the Nordic cities, while for Malaga, the outdoor temperature is remarkably higher. Testing in this season will, therefore, probably result in better accuracy for cooler climates.

When testing is conducted in a different season, it is also reason to believe that the parameter importance changes. During this season, the solar radiation is probably much more prominent, and therefore, probably of more importance for all climates. For Nordic cities, the conditions between indoor and outdoor temperature are much more similar. The use of outdoor temperature as an input parameter is therefore probably of less importance during these seasons.

As seen in Subsection 4.1.1, the MAPE is higher for testing in a warmer season. This accuracy would probably be improved by conducting the training for parts of the warm season, for example, by starting the training period in mid-July and testing from April. Alternatively, training for a more extended period, so that the past summer is included in the training period.

5.5 Input parameters

The input parameters utilized in this experiment were chosen based on previous studies' parameters combined with the intuition of what parameters are essential to predict indoor temperature. As seen in Table 2.8 and 2.9, the input parameters mostly utilized by others are utilized in this thesis as well. The same goes for the input parameters of Wei et al. [24], Waseem et al. [54], and Wang et al. [31].

A wider variety of parameters should have been tested and validates to capture possible hidden gaps regarding utilized input parameters. Experiments of a much more extensive scale would, however, be both computationally expensive and time-consuming. The decision of only using the parameters utilized by others seems reasonable to get a wider variety of tests, based on the results indicating that four input parameters are sufficient to achieve an accurate prediction.

As seen in Section 2.5, few studies utilized indoor temperature as output in the data-driven model, making this a research gap. The parameter evaluation done by others may therefore not correspond to the answers found here. However, most of the studies aim to capture the dynamic of the building from an energy perspective. Heating and cooling account for a large share of the total energy use of buildings [9], and are therefore a central part of the energy dynamic of the building. Space heating and cooling are also strongly related to indoor temperature. Therefore, the findings of parameter evaluation and similar might be transferable to this study.

5.5.1 Feature elimination evaluation

In Section 4.1.2 the feature elimination is conducted three times for the Base Case. The results here vary to some degree, and the average STD for all parameters and zones regarding feature elimination is 0.030%. Therefore, a variation of this degree may be acceptable in other cases where feature elimination is conducted without claiming that the change in accuracy is due to the parameter. The average STD when all parameters are included is 0.028%, which is lower than the average STD when feature elimination is conducted. This strengthens the method of use and indicates that some parameters are necessary to achieve an accurate model.

When analyzing each parameter individually, the case where the daily time-index is missing stands out a great deal, both with a large confidence interval, wishers, and many upper outliers, Figure 4.15 - 4.18. For Zone 7, 12, and 22, the error is more outstanding than for Zone 8, which has many parameters with a more significant outbreak. These larger outbreaks of results may be due to the less insulated envelope, making the zone more sensitive to internal and external changes.

For Zone 8, the parameters relative humidity, wind, solar radiation, sky cover, hourly time-index, lighting, and occupancy have a lower MAPE than the case where all are included. This may indicate that these parameters are not crucial for an accurate model and can be neglected without sacrificing the accuracy for this zone. The other parameters may, however, be of greater importance.

As for Zone 7, 12, and 22, equipment, lighting, relative humidity, occupancy, wind, and outdoor temperature stands out as essential parameters, besides the daily time-index, 4.15 - 4.17. Most of these parameters have a higher MAPE than when all parameters are included, indicating that these parameters are of greater importance. As the IDA ICE is set up, the input parameter equipment includes information about lighting. One of these parameters may therefore be enough, as seen in the experiment with input combinations.

The feature evaluation of Zone 8 stands out remarkably from the others due to multiple parameters with better accuracy than when all parameters are included. This may be due to multiple reasons. However, the zone's most significant difference is the envelope, making the zone more sensitive to external changes, and meteorological values more critical. The glazed envelope has low thermal mass and u-value, making it miserable to store heat. Therefore, the envelope may be why this zone is much more sensitive to changes than the others. However, when analyzing the results in Table 4.4, most of the meteorological parameters have a slight negative impact on the model. However, this impact is tiny and within the STD of most parameters and may therefore be of coincidence.

When analyzing the results when the STD is considered, it is clear that the daily time-index is a parameter of colossal importance for this building. Other parameters of importance for the Base Case are the outdoor temperature, solar radiation, and equipment. The excellent result for daily time-index can be explained by the similar schedule for occupants and equipment, while the cool climate can justify the importance of outdoor temperature. The experiment in Section 4.4.5 showed that the equipment has a considerable contribution of internal gain compared to occupants. The immense contribution may explain their importance for temperature predictions.

Parameters that seem damaging for the model are sky cover, relative humidity, wind, hourly time-index, heat demand, and lighting. These parameters may be perceived as noise and are best to eliminate. Both sky cover and relative humidity affect the indoor temperature of the building to a small extend and are strongly related to solar radiation. The use of solar radiation may therefore be sufficient to cover the information given in these two inputs. The parameter lighting is included in the parameter equipment and may therefore be damaging as an individual parameter in addition to the equipment.

5.5.2 Combinations of inputs

When analysing the different combinations of inputs, Figure 4.14, "Combination 3" and "Time-index" clearly stands out as bad combinations. Both combinations have a higher MAPE than the other combinations and the case where all parameters were included. Both combinations miss the input parameter daily time-index, emphasizing the importance of this parameter, as stated earlier. Figure 4.19 - 4.22 illustrated that input combinations "Combination 3" and "Time-index" hold many upper outliers. These outliers may be caused by the lack of the input parameter daily time-index, which was the cause of the outliers in Figure 4.9.

Combination "Combination 2", "Meteorological" and "Zone data" all have equal or lower MAPE than the case with all input parameters. These results indicate that both meteorological values nor zone-related information are crucial for the model. The meteorological information may be of less importance due to the heavy insulation of the building. However, if another envelope was utilized in the testing period, their values might be of greater importance. The zone-related information may be redundant since all the parameters are closely connected to the time-indexes in the sense of schedules. If the equipment varies significantly, these parameters might be more valuable.

"Combination 2" stands out as the best combination of input. This may be due to a good combination of both time-index, meteorological, and zone-related information. Comparing the results of "Combination 2" with "Combination 1", it may seem like the parameters heat demand and lighting are not necessary, and that solar radiation is more valuable than relative humidity. This is based on their absence in "Combination 2".

5.5.3 Evaluation of the wrapper results

When analyzing the results of the wrapper method, the STD must be kept in mind. The bias of the wrapper method is to predict for all possible input combinations. Since there is uncertainty related to all the predictions conducted, and the prediction for each parameter combination is only conducted once for each input file, the results can be misleading due to coincidence. The STD for the MAPE related to multiple predictions is given in Table 4.2, and can give an indications of the randomness. However, as seen in Appendix A the STD varies for each parameter removed. Therefore, the STD related to each specific input combination is difficult to find without running the same prediction multiple times, which was not conducted.

The wrapper method is conducted three times with three different input files. Repetition of the same combination numbers for the different cases will strengthen the reliability of the combinations and make the results more trustworthy. Combination number 82 is repeated multiple times for the Base Case and TEK 87 buildings, both for the small private offices and the meeting rooms. In addition, combination number 83, which holds most of the same input parameters, is repeated multiple times for the Malaga building. These repetitions strengthen the importance of the input parameters included in these combinations: meteorological and time-indexes, plus equipment for 82 and heat demand for 83.

For the glazed lobby, both solar radiation and outdoor temperature are typical parameters in the best combinations. For the TEK 87 building, two combinations with a relatively low number of parameters get a good result. Therefore, it can be assumed that these parameters, outdoor temperature and hourly time-index, are of great importance for this case. For the Malaga building, the same thing occurs, but with the input parameter solar radiation.

The Base Case and TEK 87 building are located in Trondheim, which has a cool climate and is tested during the winter. The temperature difference between the indoor and outdoor conditions is, therefore, most likely relatively high. In addition, the zone examined has a glazed envelope, resulting in a large heat transfer from inside to outside. Information regarding the outdoor temperature is naturally an important parameter, which indicates the zone's heat loss. For the Malaga building, which is located in a temperate climate, the temperature is probably more similar between inside and outside, resulting in little heat transfer due to small temperature difference. It is, therefore, natural that outdoor temperature information is of less importance. However, solar radiation will increase the indoor temperature significantly and may therefore be a parameter of importance. For the buildings located in the Nordic climates, heat gain due to solar radiation is insignificant compared to the immense heat loss through the glazed envelope. Hence, this parameter may be of less importance for these cases.

For the Malaga building, Zone 14 and 18 got the same MAPE for the three best cases. This seems unusual and may be due to a hidden error. However, the difference in the other results for these zones indicates that the results may be due to coincidence. The other experiments with the Malaga building have utilized the same input file and generated different results for the two zones. This also strengthens the reliability of these results.

The best cases for the Malaga building, except combination number 82, do not include any meteorological parameters except diffuse radiation on horizontal. One can therefore assume that this is the most crucial meteorological parameter for temperate climates. The zone-related parameters most often occurring are heat demand and lighting. The importance heat demand seems somewhat strange since little heat demand is needed for this case during the testing phase, Figure 4.58.

For the Base Case, the parameters most often included in the best combinations are outdoor temperature, direct normal solar radiation, and the time-indexes. However, wind from east to west and relative humidity also occur multiple times for the meeting rooms. Combination number 82 is the most frequent combination number for this building and holds all meteorological variables. Most of these parameters may therefore be of importance for these zones. However, this can not be said for sure due to contradicting results in Section 4.2.1.

For the TEK 87 building, combination number 20 and 618 seems very promising, in addition to combination number 82. The two combinations include the outdoor temperature, wind from east to west, sky cover, time-indexes, and equipment information, which may be essential when less insulation is utilized. In addition, combination number 82 and the other common combinations for TEK 87 small office zones include all meteorological parameters, which is more critical when less insulation is utilized.

For the meeting rooms and private offices, almost all combinations with a good score include the daily time-index, and many also include the hourly time-index. When feature elimination was conducted, time-index parameters also got a good score. Based on the good results for the two different tests, one can assume that time-indexes, especially daily time-index, are essential input parameters for the schedule utilized in these experiments.

5.5.4 Connection between occupancy schedule and time-index

As seen in the experiment, the daily time-index varies largely, while the other parameters are more stable. When examining Figure 4.9 it is clear that the result contains many upper outliers when daily time-index are removed, compared to Figure 4.15 - 4.18. Explaining why the average MAPE varies more than the median for this case. These large amounts of outliers indicate a lack of stability, and the input parameter may be essential to achieve accuracy.

The occupants' schedule is random for each time-step throughout a week, multiplied by 52 to cover a whole year. This means that the occupants' schedule is identical every Monday, Tuesday, etc. Making the daily time-index more valuable than the hourly time-index since the patterns for each weekday is identical and not the pattern for each hour a week, which means that there is no pattern for 13.00 for all days in a week. A time-index combining both hour and day would, however, be the absolute best time-index. The use of extensive engineering methods can develop such time-index.

The type of schedule pattern utilized in the model will not be the case for an actual building. There the pattern will be more mixed between daily and hourly, and maybe also monthly time-index. The behavior of occupants tends to occur in patterns [13]. Therefore, a good time-index will be necessary for an actual building even though the patterns are not as straightforward as simulated.

Black-box models are trained to learn patterns in data. Simplifications regarding a schedule will therefore be remembered and use in its prediction. Therefore, the model will perform poorly in situations where the simplifications are not relatable to the actual happenings since it is not trained for these scenarios. This may, for instance, happen if occupancy deviates from a fixed schedule or heat gain from occupants vary to a large extent.

As mentioned in Section 2.1.3, the occupancy-related data are often simplified in studies due to challenges regarding accessibility. Due to privacy concerns, the data will still be challenging to collect after the model is developed. These challenges highlight the importance of a good time-index that can be used to gather information about the occupancy pattern. Such time-index is used as occupancy data in the study of Wang et al. [31]. Data related to the number of occupants attending each zone can be collected by the use of CO_2 sensors, such as in the study of Wei et al. [24]. Both of these parameters are easily assessable in buildings and can give a good representation of the occupancy.

A trend occurring is that indoor temperature increases as the week goes and then falls during the weekend. This temperature increase may be due to internal gain and heat stored in the thermal mass overnight, making it easier for the building to reach the desired temperatures the days after one weekday. For a residential schedule, the building is occupied every day. Therefore, the heat stored in the building mass is more constant since it cannot make large drops during weekends. This may also be a factor explaining the less importance of the daily time-index.

5.6 Suitable buildings for prediction models

The tests conducted indicate that there are specific buildings more suited for temperature prediction. The characteristics found suitable for prediction will be review in this subsection.

5.6.1 Characteristic related to building envelope and structure

Throughout the results, the perdition has had the best performance on buildings with a stable indoor temperature. Therefore, a confident characteristic with suitable buildings is a stable indoor temperature. A stable indoor temperature can be achieved with a large thermal mass, preferably combined with heavy insulation. A building with these properties will be affected by external changes to a small degree.

Glazed facades have a low U-value, i.e., have a high heat transfer rate. Therefore, the glazed envelopes often will be the primary heat transfer source through the building's boundary. Buildings with little glazed envelopes will probably be suitable buildings. For windows, the thesis has proven a more stable temperature for zones with few windows spread out on the external walls, compared to multiple windows on the same external wall. This finding was more prominent and is, therefore, more critical for high floors. Therefore, the location of a building's windows should be carefully evaluated, with these findings considered.

Shutters are an excellent tool for reducing external heat from solar radiation, and therefore a good characteristic for sufficient buildings. As seen in the experiment, the prediction performance of the southern zones decreased when shutters were removed; the performance for the other zones was similar to with shutters. The shutters will, either way, help keep a stable indoor temperature when installed, no matter room orientation, but for buildings north of the equator, southern facades are more exposed to solar radiation. If the building does not have good quality shutters, fewer windows on the southern facade are a good characteristic for buildings north of the equator.

The experiments conducted also indicate that small offices are more challenging to execute predictions for. Office buildings with more open landscapes and larger rooms will probably have a better prediction accuracy. As seen in the tests conducted, larger rooms are less affected by internal and external gain, leading to a more stable indoor temperature.

The prediction accuracy for the Malaga building was better than for the buildings located in Nordic cities. The increase of accuracy may be due to the season of the testing period, making the indoor and outdoor temperature conditions quite similar in Malaga. These conditions are of great advantage since the thermal time constant becomes lower when the temperature difference decreases. Therefore, a building located in a sheltered area may be more suitable due to a decrease in heat transfer by convection. On the other hand, a sheltered location may lead to problems during the summer where cooling is needed, and wind can be a great tool to execute natural ventilation. An optimal location for the building is therefore hard to find. However, buildings located in climates where the outdoor temperature is relatively stable throughout the day, or even year, seem like more suitable buildings.

5.6.2 Characteristics related to the HVAC system and use

As seen in the experiment, thermal mass is a good characteristic for good prediction performance. The thermal mass of the building does not only depend on the envelope; it can also be achieved by furniture. Therefore, heavily furnished, preferably with high thermal mass furniture, is a characteristic for suitable buildings for prediction. These types of furniture will increase the total mass of the building and make the building more similar to the Concrete case.

The difference in accuracy related to predictions of the Malaga building is probably strongly related to the high indoor temperature making the indoor conditions similar throughout the day. While for the buildings in Nordic climates, the HVAC setting was changed to a lower set-point value when the building was no longer occupied. Buildings with similar set-point temperatures throughout the day may therefore be more suited for prediction. Examples of buildings with these settings may be hotels, hospitals, residential buildings, or other buildings occupied most parts of the day.

Changing the HVAC settings to make the building more suitable for prediction may not be a good idea. This will increase the energy use of the building and contradict the original motivation. An evaluation regarding the desired outcome is therefore necessary before making the building less energy efficient.

The tests conducted indicate that the equipment affects zones predominantly, especially smaller ones. Therefore, buildings with a high turn-off rate of equipment, lighting, and other appliances will have a more stable indoor temperature. A high turn-off rate is therefore characteristic for buildings suitable for perdition. Buildings with presence control for lighting and other appliances will have a similar result and may also be suitable.

Another advantage of lighting and similar appliances connected to present control is that the input parameters are reduced. As seen in this study, the daily time index becomes the most valuable input parameter due to its strong connection to occupancy presents which further have a solid relationship to lighting, equipment, heat demand, and the number of occupants. If similar is done for an actual building, the parameters needed to conduct predictions will be reduced, making the model less time-consuming and computationally expensive.

Occupancy data is challenging to collect due to privacy concerns. Connecting other parameters to the occupancy by presents control will strengthen the occupants' patterns, making it easier for the model to learn them. This will simplify the collection of data without violating the occupants' privacy.

5.6.3 Modelling measures to increase prediction accuracy

As seen throughout the results, the daily time-index is the input parameter of most importance. The importance became extremely clear in the experiments in Section 4.6.2. Here one can see when the peaks of MAPE occur, and it a vague trend at the start or end of a weekend. A good representation of the time-index is therefore important to conduct accurate predictions.

A good time-index can be developed by merge both daily and hourly time-index. The merge will give a more detailed representation of the patterns occurring. The time-index can also be connected to a calendar, making it easier for the model to find the holidays when the building is not occupied. Improvements in the time-index will probably decrease the peaks occurring around weekends. A better representation of the occupants' schedule can be achieved by connecting each occupant's personal calendar to the time-index. However, this connection needs to be voluntary not to break any privacy concerns. The connection to personal calendars may better represent each occupants' energy pattern and make the indoor temperature more customized after each occupants' schedule.

The accuracy related to each time-step decreases after time-step two to five, i.e., 0.5hour to 1.25 hours ahead prediction. A prediction of this degree will therefore give the most accurate results. However, long-time predictions are more valuable than short-time since they can be used for finding the optimal scenario based on long-term consequences. Therefore, it is recommended not to predict for shorter than 0.5 hours ahead since this is the most accurate prediction available. Any desired predictions can be conducted for long-time predictions, but the values should be re-predicted closer to the happening to get the most accurate result possible.

Many meteorological parameters are affected by the sun, such as outdoor temperature, relative humidity, and solar radiation. The sun is strongly related to the hourly time-index since the rising and setting time occurs in a stable pattern throughout the year. Due to the sun's strong relation to both time-index and other meteorological parameters, a strong connection is developed connecting the two parameters. The connection between meteorological parameters and time-index contributes to explain the importance of this parameter.

The black-box model can also be connected to the meteorological forecast for buildings with lower thermal mass or less insulation. The forecast can improve the predictions due to more accurate information about the external conditions of the building. However, connection to meteorological forecast is probably unnecessary for buildings with advanced envelopes or located in temperate climates since the external environment influences them to a small degree.

6 Conclusion

The objective of this study was to investigate parameters affecting data-driven models for building energy predictions. Parameters studied include parameters of the data-driven model and general building parameters, respectively input parameters, the number of output parameters, building envelopes, locations, and internal gain. The study was conducted by testing a data-driven model with input data generated from a white-box model. The data-driven model applied is a hybrid multiple-input and multiple-output (MIMO) Long short-term memory (LSTM) model with indoor temperature as predicted output.

The findings in this thesis indicate that a stable indoor temperature is essential for accurate temperature predictions. Buildings with stable temperature profiles have heavy thermal mass, heavy insulation, reduced and spread out glazed facades, and exterior shutters on windows. These characteristics indicate that a high thermal time constant, resulting in smaller and slower changes in indoor temperature, is crucial for accurate temperature predictions.

Glazed envelopes have large heat transfer through the body, including transfer of solar radiation and space heating. Resulting in heat flows which can go both ways. These behaviors are challenging to predict due to the sensitivity of meteorological changes. When windows are located on the same wall, solar radiation at a given time is emphasized, resulting in intense external heat for a short period. Spreading out the windows will even out the external heat.

In the tests conducted, the set-point temperature varied based on occupancy. The temperature variations were amplified when the temperature difference between inside and outside increased. This resulted in challenging conditions for the model. Thus buildings with similar temperature conditions inside and outside or the same HVAC settings throughout the day will achieve better prediction accuracy.

The results also indicate that the input parameter daily time-index is highly significant. Time-index is a value describing the time. The index is used to learn patterns and is therefore strongly connected to occupants and their habits, including equipment, lighting, and HVAC systems. The parameter is also connected to meteorological parameters such as the sun and the parameters affected by it. A sufficient time-index is, therefore, crucial for achieving accurate predictions. Due to simplifications in schedules, the results may have been exaggerated in this thesis. However, due to the prominent results, it concludes that this parameter is vital.

The parameter evaluation indicates that time-index, equipment, and solar radiation are essential parameters for office buildings. Meteorological parameters are more important for buildings with less insulation and/or located in cool climates. Primarily, outdoor temperature, followed by the wind from east to west. For warmer climates, heat demand is one of the additional parameters resulting in a good score. This is, however, strange since the building utilized hardly uses any heat demand. Regarding solar radiation, "direct normal radiation" is essential for cool climates, and "diffuse radiation on horizontal surface" for temperate climates. For residential buildings, the daily time-index is less valuable.

Another finding of the thesis is that there is little or no communication between the zones. The lack of communication may be a drawback for the data-driven model or the building. However, this indicates that the modeling accuracy was not sacrificed by not utilizing a pure MIMO model for this thesis.

6.1 Further work

This subsection includes ideas for further work and potential focus areas for the future. The ideas presented will not be discussed further in this thesis since the topics are outside the scope.

- Conduct the wrapper method and/or feature elimination to a larger extent, multiple times and for more building types, to get more certain results. Other parameter evaluation methods should also be conducted due to the varying results for feature elimination and the wrapper method. Examples of methods that can be utilized are PCA, Filer, or other methods explained in Section 2.6.
- The findings in this thesis indicated that there is no communication between the zones, this can be investigated. The LSTM model can be tested for another building that is not perfectly heated to see how the results change. The insulation between the internal walls can also be minimized to see how this affects communication. Another possible experiment is to test this building for another data-driven model to see if the findings are transferable to other models.
- The experiment of splitting one zone into two should be reexamined with an equal amount of internal gain as the large zone. This will clarify the answers related to the effect of equipment and room size.
- Conducting these experiments with other output parameters could be of interest, since its degree of transferability will appear. Total energy use, energy demand, heating demand, or cooling demand, should be tested. These are the most utilized outputs, Table 2.9-2.8. Confirming the degree of transferable through different outputs would extensively minimize the need for research in potential research gaps, such as indoor temperature.
- The time-index showed to be of great importance for the data-driven model. Testing the model for å real building, instead of a simulated one, would clarify how much this parameter was affected by the simplifications of the IDA ICE model, and give more reliable results. The real building may also be able to discover possible gaps related to the use of generated input data.
- The data-driven model produced accurate results and seems to be a reliable tool. Implementing it in a real building and making it work with actual data would be the next natural step in this research. In the implementation, the set-point temperature should be implemented as an input and output temperature, and be controlled based on the predictions made in the data-driven model. The findings in this thesis can be used to reduce the input parameters for the data-driven models. Since sensors and similar equipment for data collection are expensive, this thesis's results may reveal potential cost savings when implementing the model.

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Appendix

The appendix includes additional information utilized to execute and evaluate the tests conducted in the thesis. The first part of the appendix includes the STD related to feature elimination. Further, the building standards utilized when creating a white-box model are included, followed by the code of the LSTM and the wrapper method. In addition, the main finding from the Project work [1] is included.

A Standard deviation of results

The standard deviation from the tests conducted in Section 4.1.2 is given i Table A.1 - A.2. The table illustrated that the variation is bigger for Zone 8 and the various zones' heat demand.

Table A.1: *Standard deviation of the feature elimination for the Base Case, for Zone 4, 7, 8, 12, and 14 [%]*

	Zone 4	Zone 7	Zone 8	Zone 12	Zone 14
All parameters	0.045	0.027	0.011	0.021	0.012
Outdoor temperature	0.037	0.030	0.040	0.002	0.002
Relative humidity	0.042	0.055	0.098	0.018	0.021
Wind	0.058	0.037	0.051	0.014	0.013
Solar radiation	0.031	0.033	0.103	0.011	0.009
Sky cover	0.036	0.037	0.161	0.010	0.008
Hourly Time-index	0.053	0.079	0.092	0.009	0.017
Daily Time-index	0.292	0.255	0.173	0.107	0.086
Equipment	0.055	0.051	0.056	0.009	0.017
Heat demand	0.080	0.110	0.120	0.031	0.047
Lighting	0.039	0.051	0.086	0.014	0.012
Occupancy	0.054	0.073	0.116	0.009	0.009

Table A.2: *Standard deviation of the feature elimination for the Base Case, for Zone 18, 19, 20, and 22 [%]*

	Zone 18	Zone 19	Zone 20	Zone 22
All parameters	0.029	0.013	0.038	0.058
Outdoor temperature	0.002	0.007	0.028	0.021
Relative humidity	0.011	0.018	0.035	0.016
Wind	0.018	0.022	0.031	0.054
Solar radiation	0.022	0.016	0.042	0.049
Sky cover	0.015	0.023	0.048	0.041
Hourly Time-index	0.014	0.017	0.015	0.044
Daily Time-index	0.091	0.103	0.246	0.273
Equipment	0.021	0.025	0.061	0.056
Heat demand	0.010	0.009	0.009	0.036
Lighting	0.009	0.008	0.021	0.016
Occupancy	0.021	0.023	0.076	0.069

B Building standards

This section includes some of the requirements for the building standards TEK 87, TEK 17 and Passive House.

B.1 TEK 87

The requirements regarding the building structure for TEK 87 is given in Table B.1.

Table B.1: *TEK 87 requirements for u-value when the indoor temperature exceeds 18°C [42]*

External wall	External roof	Floor to ground	External windows	External doors
$\leq 0.30\,\mathrm{W/(m^2K)}$	$\leq 0.20\,\mathrm{W/(m^2K)}$	$\leq 0.30\,\mathrm{W/(m^2K)}$	$\leq 2.40\,\mathrm{W/(m^2K)}$	$\leq 2.00\,\mathrm{W/(m^2K)}$

B.2 TEK 17

The requirements regarding the building structure for TEK 17 is given in Table B.2.

Table B.2: *TEK 17 requirements for u-value in buildings [42]*

External wall	External roof	Floor to ground	External windows & doors
$\leq 0.22\,\mathrm{W/(m^2K)}$	$\leq 0.18\,\mathrm{W/(m^2K)}$	$\leq 0.18\,\mathrm{W/(m^2K)}$	$\leq 1.2\,\mathrm{W/(m^2K)}$

B.3 Passive House

Criteria that must be met for a building to be considered a Passive House [96]:

- The space heating energy demand most not exceed $15\,\mathrm{kWh/m^2}$ of net living space or $10\,\mathrm{W/m^2}$ peak demand.
- The total energy used for heating, hot water, and domestic electricity must not exceed $60\,\mathrm{kWh/m^2}$ per year.
- In terms of Airtightness, a maximum of 0.6 air changes per hour at 50 Pascals pressure (ACH50), as verified with an onsite pressure test (in both pressurized and depressurized states).
- Thermal comfort must be met during all seasons, with less than 10% of the hours in a given year over 25°C.
- All opaque building components of the exterior envelope of the house must be well-insulated. For cool-temperate climates, this means a maximum u-value of $0.15\,\mathrm{W/m^2K}$
- The window frame must be well-insulated, with Low-E glazing and filled with argon of krypton. For a cool-temperate climate, the maximum u-value for windows is $0.80\,\mathrm{W/m^2K}$. The g-value must be around 50%.
- At least 7% of the heat from exhaust air must be recovered and transferred to the fresh air[96]. The efficiency of the heat recovery system in the passive house must be at least 70%[97].
- Uncontrolled leakages through gaps must be less than 0.6 of the total house volume per hour during a 50 PA pressure test.
- All thermal bridges must be minimized as far as possible.

C LSTM model

The following code is the MIMO MISO hybrid LSTM model utilized in this thesis. The model is made by PhD candidate Gaurav Chaudhary at NTNU.

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt
import tensorflow as tf
import os
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from math import sqrt

n_past = 384
n_future = 96
n_features_input = 54
n_features_output = 9
zonelist=[4,7,8,12,14,18,19,20,22]

numlayer = 100
dropout_factor = 0.3
epoch_num = 50
batch_num = 64

nameofcase = 'TRD_Concrete_PassivHus_Office_OccupancySchedule1'   #write this
    for every case
featuresremoved = 'none'   #ex 'A'
filenamecsv = r'InputFileTRDConcreteOfficeSCH1_'+featuresremoved+'.csv'

filenameident = 'past-'+str(n_past)+'_future-'+str(n_future)+'_'+nameofcase+'_'+
    featuresremoved

data_df=pd.read_csv(filenamecsv, sep=',', header=0,)
del data_df['Unnamed: 0']
data_scaled = data_df
scalers={}

for i in data_df.columns:
    scaler = MinMaxScaler(feature_range=(-1,1))
    s_s = scaler.fit_transform(data_scaled[i].values.reshape(-1,1))
    s_s=np.reshape(s_s,len(s_s))
    scalers['scaler_'+ i] = scaler
    data_scaled[i]=s_s

#DATA SPLIT
multiplier = 24*4
T_arr1 = 220 * multiplier
T_arr2 = 73 * multiplier
T_arr3 = (366-(T_arr1 + T_arr2)) * multiplier
arr1, arr2, arr3 = np.split(data_scaled, [T_arr1, (T_arr1 + T_arr2)])
train = arr1
validate = arr2
test = arr3

def split_series(series, n_past, n_future):
  # n_past ==> no of past observations
```

```
  # n_future ==> no of future observations
  X, y = list(), list()
  for window_start in range(len(series)):
    past_end = window_start + n_past
    future_end = past_end + n_future
    if future_end > len(series):
      break
    # slicing the past and future parts of the window
    past, future = series[window_start:past_end, :], series[past_end:future_end,
     :]
    X.append(past)
    y.append(future)
  return np.array(X), np.array(y)

#TRAIN VAILDATE TEST DATASET
X_train, y_train = split_series(train.values,n_past, n_future)
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1],n_features_input))
y_train = y_train.reshape((y_train.shape[0], y_train.shape[1], n_features_input)
    )
y_train=np.delete(y_train, range(0, n_features_input-n_features_output), 2) #
    assuming all output features are in end
X_validate, y_validate = split_series(validate.values,n_past, n_future)
X_validate = X_validate.reshape((X_validate.shape[0], X_validate.shape[1],
    n_features_input))
y_validate = y_validate.reshape((y_validate.shape[0], y_validate.shape[1],
    n_features_input))
y_validate=np.delete(y_validate, range(0, n_features_input-n_features_output),
    2)
X_test, y_test = split_series(test.values,n_past, n_future)
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1],n_features_input))
y_test = y_test.reshape((y_test.shape[0], y_test.shape[1], n_features_input))
y_test=np.delete(y_test, range(0, n_features_input-n_features_output), 2)
X_train.shape, y_train.shape, X_validate.shape, y_validate.shape, X_test.shape,
    y_test.shape

#LSTM MODEL
encoder_inputs = tf.keras.layers.Input(shape=(n_past, n_features_input))
encoder_l1 = tf.keras.layers.LSTM(numlayer, return_state=True, dropout=
    dropout_factor)
encoder_outputs1 = encoder_l1(encoder_inputs)
encoder_states1 = encoder_outputs1[1:]
decoder_inputs = tf.keras.layers.RepeatVector(n_future)(encoder_outputs1[0])
decoder_l1 = tf.keras.layers.LSTM(numlayer, return_sequences=True, dropout=
    dropout_factor)(decoder_inputs,initial_state = encoder_states1)
decoder_outputs1 = tf.keras.layers.TimeDistributed(tf.keras.layers.Dense(
    n_features_output))(decoder_l1)
model_e1d1 = tf.keras.models.Model(encoder_inputs,decoder_outputs1)
model_e1d1.summary()

#TRAINING MODEL
reduce_lr = tf.keras.callbacks.LearningRateScheduler(lambda x: 1e-3 * 0.90 ** x)
reduce_lr1 = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=7)
model_e1d1.compile(optimizer=tf.keras.optimizers.Adam(lr=0.00001, beta_1=0.9,
    beta_2=0.999, epsilon=None, decay=0.0, amsgrad=False), loss=tf.keras.losses.
    Huber())
history_e1d1=model_e1d1.fit(X_train,y_train,epochs=epoch_num,validation_data=(
    X_validate, y_validate),batch_size=batch_num,verbose=1,callbacks=[reduce_lr,
    reduce_lr1])
```

```
#SAVE MODEL
filename_h5 = 'Model_Epoch-'+filenameident
model_e1d1.save(filename_h5+"_E1D1_10min.h5")

#PREDICTING
pred_e1d1_ori=model_e1d1.predict(X_test)
pred_e1d1 = pred_e1d1_ori
y_test_scaled = y_test

for j in range(0,len(zonelist)):
    scaler = scalers['scaler_Zone '+str(zonelist[j])+'_tairmean']
    pred_e1d1[:,:,j]=scaler.inverse_transform(pred_e1d1[:,:,j])
    y_test_scaled[:,:,j]=scaler.inverse_transform(y_test[:,:,j])

def MAPE(Y_actual,Y_Predicted):
    mape = np.mean(np.abs((Y_actual - Y_Predicted)/Y_actual))*100
    return mape

#SAVING PREDICTION ERROR
f = open('All Errors_'+filenameident+'.CSV', "a")
zonelist=[4,7,8,12,14,18,19,20,22]
for i in range(0,len(zonelist)):
    for j in range(1,n_future+1):
        rmse1 = sqrt(mean_squared_error(y_test_scaled[:,j-1,i],pred_e1d1[:,j-1,i]))
        mape1= MAPE(y_test_scaled[:,j-1,i],pred_e1d1[:,j-1,i])
        mae1 = mean_absolute_error(y_test_scaled[:,j-1,i],pred_e1d1[:,j-1,i])
        print('Zone '+str(zonelist[i]),end=", ")
        print("Timestep ",j,end=", ")
        print('MAE : %.4f' % mae1,end=", ")
        print('RMSE : %.4f' % rmse1,end=", ")
        print('MAPE : %.4f' % mape1)
        f.write('Zone '+str(zonelist[i])+','+'Timestep '+str(j)+','+'MAE, '+str(round(mae1,4))+","+'RMSE, '+str(round(rmse1,4))+","+'MAPE, '+str(round(mape1,4))+"\n")
        print(i)
f.close()
```

D Wrapper method

The following code is the code for executing the wrapper method, which is utilized in this thesis. The code is made in collaboration with PhD candidate Gaurav Chaudhary at NTNU.

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt
import tensorflow as tf
import os
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from math import sqrt

n_past = 384
n_future = 96
numlayer = 100
dropout_factor = 0.3
epoch_num = 50
batch_num = 32
zonelist=[4,7,8,12,14,18,19,20,22]

filenamecsv = r'InputFileMalagaPassiveHouseOffice_All.csv'
mapefilename = 'Malagawrapper.csv'

###Import CSV data
data_df_original=pd.read_csv(filenamecsv, sep=',', header=0,)
del data_df_original['Unnamed: 0']
data_df_original.head()

###Import case data
case_df=pd.read_csv('wrapperMethodInoutFile.csv', sep=',', header=0)

###make file for MAPE
import csv
header1=[]
header2=[]

header1.append('Case Number')
header2.append('Case Number')

for i in range(0,len(zonelist)):
    for j in range(1,n_future+1):
        header1.append('Zone '+str(zonelist[i]))
        header2.append('Timestep '+str(j))

with open(mapefilename, 'a', newline='') as f:
    write = csv.writer(f)
    write.writerow(header1)
    write.writerow(header2)

for inum in range(1,883):

    casenum = inum
    xc=case_df.loc[casenum-1].values.tolist()
    xc = [x for x in xc if str(x) != 'nan']
    del xc[0]
```

```
    del xc[0]
    xc = [int(x) for x in xc]

    copyloc=[]
    for i in range(0,len(xc)):
        if 0<=xc[i]<=8:
            copyloc.append(xc[i])
        if 9<=xc[i]<=12:
            for x in range(0,9):
                copyloc.append(xc[i]+(x*4))
    for y in range(45,54):
        copyloc.append(y)

    data_df = data_df_original.iloc[: , copyloc].copy()
    data_df.head()
    n_features_input = len(copyloc)
    print(n_features_input)
    n_features_output = 9
    filenameident = 'past-'+str(n_past)+'_future-'+str(n_future)+'_Case'+str(
casenum)

    ###Scaling the values
    data_scaled = data_df
    scalers={}
    for i in data_df.columns:
        scaler = MinMaxScaler(feature_range=(-1,1))
        s_s = scaler.fit_transform(data_scaled[i].values.reshape(-1,1))
        s_s=np.reshape(s_s,len(s_s))
        scalers['scaler_'+ i] = scaler
        data_scaled[i]=s_s

    multiplier = 24*4
    T_arr1 = 220 * multiplier
    T_arr2 = 73 * multiplier
    T_arr3 = (366-(T_arr1 + T_arr2)) * multiplier
    arr1, arr2, arr3 = np.split(data_scaled, [T_arr1, (T_arr1 + T_arr2)])
    train = arr1
    validate = arr2
    test = arr3
    print(train.shape, validate.shape, test.shape)

    ###Converting the series to samples for supervised learning
    def split_series(series, n_past, n_future):
      X, y = list(), list()
      for window_start in range(len(series)):
        past_end = window_start + n_past
        future_end = past_end + n_future
        if future_end > len(series):
          break
        past, future = series[window_start:past_end, :], series[past_end:
future_end, :]
        X.append(past)
        y.append(future)
      return np.array(X), np.array(y)

    X_train, y_train = split_series(train.values,n_past, n_future)
    X_train = X_train.reshape((X_train.shape[0], X_train.shape[1],
n_features_input))
```

```
y_train = y_train.reshape((y_train.shape[0], y_train.shape[1], n_features_input))
y_train=np.delete(y_train, range(0, n_features_input-n_features_output), 2) #assuming all output features are in end
X_validate, y_validate = split_series(validate.values,n_past, n_future)
X_validate = X_validate.reshape((X_validate.shape[0], X_validate.shape[1], n_features_input))
y_validate = y_validate.reshape((y_validate.shape[0], y_validate.shape[1], n_features_input))
y_validate=np.delete(y_validate, range(0, n_features_input-n_features_output), 2)
X_test, y_test = split_series(test.values,n_past, n_future)
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1],n_features_input))
y_test = y_test.reshape((y_test.shape[0], y_test.shape[1], n_features_input))
y_test=np.delete(y_test, range(0, n_features_input-n_features_output), 2)

tf.keras.backend.clear_session()
encoder_inputs = tf.keras.layers.Input(shape=(n_past, n_features_input))
encoder_l1 = tf.keras.layers.LSTM(numlayer, return_state=True, dropout=dropout_factor)
encoder_outputs1 = encoder_l1(encoder_inputs)
encoder_states1 = encoder_outputs1[1:]
decoder_inputs = tf.keras.layers.RepeatVector(n_future)(encoder_outputs1[0])
decoder_l1 = tf.keras.layers.LSTM(numlayer, return_sequences=True, dropout=dropout_factor)(decoder_inputs,initial_state = encoder_states1)
decoder_outputs1 = tf.keras.layers.TimeDistributed(tf.keras.layers.Dense(n_features_output))(decoder_l1)
model_e1d1 = tf.keras.models.Model(encoder_inputs,decoder_outputs1)
model_e1d1.summary()

TRAIN = 1
if TRAIN:
    ###Training the model
    reduce_lr = tf.keras.callbacks.LearningRateScheduler(lambda x: 1e-3 * 0.90 ** x)
    reduce_lr1 = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=7)
    model_e1d1.compile(optimizer=tf.keras.optimizers.Adam(lr=0.00001, beta_1=0.9, beta_2=0.999, epsilon=None, decay=0.0, amsgrad=False), loss=tf.keras.losses.Huber())
    history_e1d1=model_e1d1.fit(X_train,y_train,epochs=epoch_num, validation_data=(X_validate, y_validate),batch_size=batch_num,verbose=1, callbacks=[reduce_lr,reduce_lr1])

HISTORY = 1
if HISTORY:
    ###Plot history
    plt.plot(history_e1d1.history['loss'])
    plt.plot(history_e1d1.history['val_loss'])
    plt.title("E1D1 Model Loss")
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend(['Train', 'Valid'])
    plt.show()

print('Casenumber is ',casenum)
```

```
SAVE_MODEL = 1
if SAVE_MODEL:
    ###Save model
    filename_h5 = 'Model_'+filenameident
    model_e1d1.save(filename_h5+"_E1D1_10min.h5")

USE_MODEL = 0
if USE_MODEL:
    from keras.models import load_model
    filename_h5 = 'Model_'+filenameident
    model_e1d1 = load_model(filename_h5+"_E1D1_10min.h5")

PREDICT = 1
if PREDICT:
    ###Predicting
    pred_e1d1_ori=model_e1d1.predict(X_test)
    pred_e1d1 = pred_e1d1_ori
    y_test_scaled = y_test
    ###Scaling back prediction
    for j in range(0,len(zonelist)):
        scaler = scalers['scaler_Zone '+str(zonelist[j])+'_tairmean']
        pred_e1d1[:,:,j]=scaler.inverse_transform(pred_e1d1[:,:,j])
        y_test_scaled[:,:,j]=scaler.inverse_transform(y_test[:,:,j])

SAVE_ERROR = 1
if SAVE_ERROR:
    ###Save error metrics data
    def MAPE(Y_actual,Y_Predicted):
        mape = np.mean(np.abs((Y_actual - Y_Predicted)/Y_actual))*100
        return mape
    allmape=[]
    allmape.append(casenum)
    for i in range(0,len(zonelist)):
        for j in range(1,n_future+1):
            mape1= MAPE(y_test_scaled[:,j-1,i],pred_e1d1[:,j-1,i])
            allmape.append(round(mape1,4))
    with open(mapefilename, 'a', newline='') as f:
        write = csv.writer(f)
        write.writerow(allmape)

tf.keras.backend.clear_session()
```

E Input combinations for Wrapper method

The following lines represental all the possible combinations the wrapper method was tested for. The Fist number represents the combination number, and the following number the output parameter, followed by the parameters included. The corresponding input for each number is given in Table 3.10.

```
 Output  Input
Case 1  13  0
Case 2  13  1
Case 3  13  2
Case 4  13  3
Case 5  13  4
Case 6  13  5
Case 7  13  6
Case 8  13  7
Case 9  13  8
Case 10 13  9
Case 11 13  10
Case 12 13  11
Case 13 13  12
Case 14 13  0 1
Case 15 13  0 2
Case 16 13  0 3
Case 17 13  0 4
Case 18 13  0 5
Case 19 13  0 6
Case 20 13  0 7
Case 21 13  0 8
Case 22 13  0 9
Case 23 13  0 10
Case 24 13  0 11
Case 25 13  0 12
Case 26 13  0 1 2
Case 27 13  0 1 3
Case 28 13  0 1 4
Case 29 13  0 1 5
Case 30 13  0 1 6
Case 31 13  0 1 7
Case 32 13  0 1 8
Case 33 13  0 1 9
Case 34 13  0 1 10
Case 35 13  0 1 11
Case 36 13  0 1 12
Case 37 13  0 1 2 3
Case 38 13  0 1 2 4
Case 39 13  0 1 2 5
Case 40 13  0 1 2 6
Case 41 13  0 1 2 7
Case 42 13  0 1 2 8
Case 43 13  0 1 2 9
Case 44 13  0 1 2 10
Case 45 13  0 1 2 11
Case 46 13  0 1 2 12
Case 47 13  0 1 2 3 4
Case 48 13  0 1 2 3 5
Case 49 13  0 1 2 3 6
```

```
Case 50 13 0 1 2 3 7
Case 51 13 0 1 2 3 8
Case 52 13 0 1 2 3 9
Case 53 13 0 1 2 3 10
Case 54 13 0 1 2 3 11
Case 55 13 0 1 2 3 12
Case 56 13 0 1 2 3 4 5
Case 57 13 0 1 2 3 4 6
Case 58 13 0 1 2 3 4 7
Case 59 13 0 1 2 3 4 8
Case 60 13 0 1 2 3 4 9
Case 61 13 0 1 2 3 4 10
Case 62 13 0 1 2 3 4 11
Case 63 13 0 1 2 3 4 12
Case 64 13 0 1 2 3 4 5 6
Case 65 13 0 1 2 3 4 5 7
Case 66 13 0 1 2 3 4 5 8
Case 67 13 0 1 2 3 4 5 9
Case 68 13 0 1 2 3 4 5 10
Case 69 13 0 1 2 3 4 5 11
Case 70 13 0 1 2 3 4 5 12
Case 71 13 0 1 2 3 4 5 6 7
Case 72 13 0 1 2 3 4 5 6 8
Case 73 13 0 1 2 3 4 5 6 9
Case 74 13 0 1 2 3 4 5 6 10
Case 75 13 0 1 2 3 4 5 6 11
Case 76 13 0 1 2 3 4 5 6 12
Case 77 13 0 1 2 3 4 5 6 7 8
Case 78 13 0 1 2 3 4 5 6 7 9
Case 79 13 0 1 2 3 4 5 6 7 10
Case 80 13 0 1 2 3 4 5 6 7 11
Case 81 13 0 1 2 3 4 5 6 7 12
Case 82 13 0 1 2 3 4 5 6 7 8 9
Case 83 13 0 1 2 3 4 5 6 7 8 10
Case 84 13 0 1 2 3 4 5 6 7 8 11
Case 85 13 0 1 2 3 4 5 6 7 8 12
Case 86 13 0 1 2 3 4 5 6 7 8 9 10
Case 87 13 0 1 2 3 4 5 6 7 8 9 11
Case 88 13 0 1 2 3 4 5 6 7 8 9 12
Case 89 13 0 1 2 3 4 5 6 7 8 9 10 11
Case 90 13 0 1 2 3 4 5 6 7 8 9 10 12
Case 91 13 0 1 2 3 4 5 6 7 8 9 10 11
 12
Case 92 13 1 2
Case 93 13 1 3
Case 94 13 1 4
Case 95 13 1 5
Case 96 13 1 6
Case 97 13 1 7
Case 98 13 1 8
Case 99 13 1 9
Case 100 13 1 10
Case 101 13 1 11
Case 102 13 1 12
Case 103 13 1 2 3
Case 104 13 1 2 4
Case 105 13 1 2 5
Case 106 13 1 2 6
Case 107 13 1 2 7
```

Case 108 13 1 2 8

Case 109 13 1 2 9

Case 110 13 1 2 10

Case 111 13 1 2 11

Case 112 13 1 2 12

Case 113 13 1 2 3 4

Case 114 13 1 2 3 5

Case 115 13 1 2 3 6

Case 116 13 1 2 3 7

Case 117 13 1 2 3 8

Case 118 13 1 2 3 9

Case 119 13 1 2 3 10

Case 120 13 1 2 3 11

Case 121 13 1 2 3 12

Case 122 13 1 2 3 4 5

Case 123 13 1 2 3 4 6

Case 124 13 1 2 3 4 7

Case 125 13 1 2 3 4 8

Case 126 13 1 2 3 4 9

Case 127 13 1 2 3 4 10

Case 128 13 1 2 3 4 11

Case 129 13 1 2 3 4 12

Case 130 13 1 2 3 4 5 6

Case 131 13 1 2 3 4 5 7

Case 132 13 1 2 3 4 5 8

Case 133 13 1 2 3 4 5 9

Case 134 13 1 2 3 4 5 10

Case 135 13 1 2 3 4 5 11

Case 136 13 1 2 3 4 5 12

Case 137 13 1 2 3 4 5 6 7

Case 138 13 1 2 3 4 5 6 8

Case 139 13 1 2 3 4 5 6 9

Case 140 13 1 2 3 4 5 6 10

Case 141 13 1 2 3 4 5 6 11

Case 142 13 1 2 3 4 5 6 12

Case 143 13 1 2 3 4 5 6 7 8

Case 144 13 1 2 3 4 5 6 7 9

Case 145 13 1 2 3 4 5 6 7 10

Case 146 13 1 2 3 4 5 6 7 11

Case 147 13 1 2 3 4 5 6 7 12

Case 148 13 1 2 3 4 5 6 7 8 9

Case 149 13 1 2 3 4 5 6 7 8 10

Case 150 13 1 2 3 4 5 6 7 8 11

Case 151 13 1 2 3 4 5 6 7 8 12

Case 152 13 1 2 3 4 5 6 7 8 9 10

Case 153 13 1 2 3 4 5 6 7 8 9 11

Case 154 13 1 2 3 4 5 6 7 8 9 12

Case 155 13 1 2 3 4 5 6 7 8 9 10 11

Case 156 13 1 2 3 4 5 6 7 8 9 10 12

Case 157 13 1 2 3 4 5 6 7 8 9 10 11 12

Case 158 13 2 3

Case 159 13 2 4

Case 160 13 2 5

Case 161 13 2 6

Case 162 13 2 7

Case 163 13 2 8

Case 164 13 2 9

Case 165 13 2 10

Case 166 13 2 11

Case 167 13 2 12

Case 168 13 2 3 4

Case 169 13 2 3 5

Case 170 13 2 3 6

Case 171 13 2 3 7

Case 172 13 2 3 8

Case 173 13 2 3 9

Case 174 13 2 3 10

Case 175 13 2 3 11

Case 176 13 2 3 12

Case 177 13 2 3 4 5

Case 178 13 2 3 4 6

Case 179 13 2 3 4 7

Case 180 13 2 3 4 8

Case 181 13 2 3 4 9

Case 182 13 2 3 4 10

Case 183 13 2 3 4 11

Case 184 13 2 3 4 12

Case 185 13 2 3 4 5 6

Case 186 13 2 3 4 5 7

Case 187 13 2 3 4 5 8

Case 188 13 2 3 4 5 9

Case 189 13 2 3 4 5 10

Case 190 13 2 3 4 5 11

Case 191 13 2 3 4 5 12

Case 192 13 2 3 4 5 6 7

Case 193 13 2 3 4 5 6 8

Case 194 13 2 3 4 5 6 9

Case 195 13 2 3 4 5 6 10

Case 196 13 2 3 4 5 6 11

Case 197 13 2 3 4 5 6 12

Case 198 13 2 3 4 5 6 7 8

Case 199 13 2 3 4 5 6 7 9

Case 200 13 2 3 4 5 6 7 10

Case 201 13 2 3 4 5 6 7 11

Case 202 13 2 3 4 5 6 7 12

Case 203 13 2 3 4 5 6 7 8 9

Case 204 13 2 3 4 5 6 7 8 10

Case 205 13 2 3 4 5 6 7 8 11

Case 206 13 2 3 4 5 6 7 8 12

Case 207 13 2 3 4 5 6 7 8 9 10

Case 208 13 2 3 4 5 6 7 8 9 11

Case 209 13 2 3 4 5 6 7 8 9 12

Case 210 13 2 3 4 5 6 7 8 9 10 11

Case 211 13 2 3 4 5 6 7 8 9 10 12

Case 212 13 2 3 4 5 6 7 8 9 10 11 12

Case 213 13 3 4

Case 214 13 3 5

Case 215 13 3 6

Case 216 13 3 7

Case 217 13 3 8

Case 218 13 3 9

Case 219 13 3 10

Case 220 13 3 11

Case 221 13 3 12

Case 222 13 3 4 5

Case 223 13 3 4 6

Case 224 13 3 4 7
Case 225 13 3 4 8
Case 226 13 3 4 9
Case 227 13 3 4 10
Case 228 13 3 4 11
Case 229 13 3 4 12
Case 230 13 3 4 5 6
Case 231 13 3 4 5 7
Case 232 13 3 4 5 8
Case 233 13 3 4 5 9
Case 234 13 3 4 5 10
Case 235 13 3 4 5 11
Case 236 13 3 4 5 12
Case 237 13 3 4 5 6 7
Case 238 13 3 4 5 6 8
Case 239 13 3 4 5 6 9
Case 240 13 3 4 5 6 10
Case 241 13 3 4 5 6 11
Case 242 13 3 4 5 6 12
Case 243 13 3 4 5 6 7 8
Case 244 13 3 4 5 6 7 9
Case 245 13 3 4 5 6 7 10
Case 246 13 3 4 5 6 7 11
Case 247 13 3 4 5 6 7 12
Case 248 13 3 4 5 6 7 8 9
Case 249 13 3 4 5 6 7 8 10
Case 250 13 3 4 5 6 7 8 11
Case 251 13 3 4 5 6 7 8 12
Case 252 13 3 4 5 6 7 8 9 10
Case 253 13 3 4 5 6 7 8 9 11
Case 254 13 3 4 5 6 7 8 9 12
Case 255 13 3 4 5 6 7 8 9 10 11
Case 256 13 3 4 5 6 7 8 9 10 12
Case 257 13 3 4 5 6 7 8 9 10 11 12
Case 258 13 4 5
Case 259 13 4 6
Case 260 13 4 7
Case 261 13 4 8
Case 262 13 4 9
Case 263 13 4 10
Case 264 13 4 11
Case 265 13 4 12
Case 266 13 4 5 6
Case 267 13 4 5 7
Case 268 13 4 5 8
Case 269 13 4 5 9
Case 270 13 4 5 10
Case 271 13 4 5 11
Case 272 13 4 5 12
Case 273 13 4 5 6 7
Case 274 13 4 5 6 8
Case 275 13 4 5 6 9
Case 276 13 4 5 6 10
Case 277 13 4 5 6 11
Case 278 13 4 5 6 12
Case 279 13 4 5 6 7 8
Case 280 13 4 5 6 7 9
Case 281 13 4 5 6 7 10

Case 282 13 4 5 6 7 11
Case 283 13 4 5 6 7 12
Case 284 13 4 5 6 7 8 9
Case 285 13 4 5 6 7 8 10
Case 286 13 4 5 6 7 8 11
Case 287 13 4 5 6 7 8 12
Case 288 13 4 5 6 7 8 9 10
Case 289 13 4 5 6 7 8 9 11
Case 290 13 4 5 6 7 8 9 12
Case 291 13 4 5 6 7 8 9 10 11
Case 292 13 4 5 6 7 8 9 10 12
Case 293 13 4 5 6 7 8 9 10 11 12
Case 294 13 5 6
Case 295 13 5 7
Case 296 13 5 8
Case 297 13 5 9
Case 298 13 5 10
Case 299 13 5 11
Case 300 13 5 12
Case 301 13 5 6 7
Case 302 13 5 6 8
Case 303 13 5 6 9
Case 304 13 5 6 10
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F Results from Project Work

The main results from the Project work [1] conducted this Autumn is presented in this section. The experiments conducted in the Project work were for a MISO LSTM model, which this thesis hybrid MIMO LSTM model is based on. The single zone utilized as an output in the Project work is a small office with one external wall facing north and an internal wall shared with Zone 8. The building utilized in the Project work quite similar to the Base Case of this thesis, with some new adjustments.

F.1 Ratio for data distribution

This subsection includes the results when different ratios for training, validation, and testing were tested. Table F.1 holds the average accuracy values for each ratio. Here the first value, testing, includes the data related to the start of the year, the validation of the following, and testing the end of the year.

Table F.1: *Accuracy with different ratios for training, validation and testing*

Train - Validate - Test	**RMSE** [C]	**MAPE** [%]	**MAE** [C]
20% - 40% - 40%	0,106	0,333	0,077
30% - 35% - 35%	0,137	0,426	0,100
40% - 30% - 30%	0,121	0,336	0,079
50% - 25% - 25%	0,171	0,684	0,153
60% - 20% - 20%	0,197	0,814	0,180
70% - 15% - 15%	0,135	0,424	0,096
80% - 10% - 10%	0,152	0,461	0,107

F.2 Accuracy for testing in different seasons

This subsection includes the accuracy for testing the model for different seasons. Table F.2 holds the average MAPE, MAE and RMSE values for this experiment. Here “Season 1” includes data from 01.01 - 30.04, “Season 2” 01.05 - 31.08, and “Season 3” 01.09 - 31.12.

Table F.2: *Average error with different seasons for different tasks*

Train(33%)	Validate(33%)	Test(33%)	**RMSE** [C]	**MAPE** [%]	**MAE** [C]
Season 1	Season 2	Season 3	0.086	0.274	0.061
Season 1	Season 3	Season 2	0.148	0.450	0.109
Season 2	Season 3	Season 1	0.153	0.490	0.119
Season 2	Season 1	Season 3	0.260	0.606	0.137
Season 3	Season 1	Season 2	0.389	0.965	0.258
Season 3	Season 2	Season 1	0.101	0.275	0.064

F.3 Time-stamp accuracy

This subsection includes results for test executed to find the error related to each time-stamp. Table F.3 hold the average RMSE, MAE and MAPE values.

Table F.3: *Average error with different time-step*

	RMSE [C]	MAPE [%]	MAE [C]
10 min	0.088	0.263	0.062
30 min	0.080	0.269	0.058
60 minutes	0.156	0.460	0.099

F.4 Parameter relevance

Table F.4 includes the results of the feature elimination conducted during the Project work [1].

Table F.4: *Average error related to each feature*

	RMSE [C]	MAPE [%]	MAE [C]
Outdoor temperature	0.131	0.324	0.072
Direct radiation	0.069	0.210	0.046
Radiation on surface	0.113	0.317	0.070
El. cooling	0.115	0.312	0.069
El. equipment	0.105	0.295	0.065
El. heating	0.093	0.252	0.055
El. lighting	0.121	0.335	0.074
El. mech. Supply air	0.148	0.404	0.089
Heat gain/loss	0.130	0.364	0.081
Number of occupants	0.101	0.284	0.062

Maria Solomon Langeland

Parameters relevance in data-driven models for building energy prediction

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Kunnskap for en bedre verden