Marko Masic

Doctoral Thesis

ISBN 978-82-471-1872-6 (printed ver.)
ISBN 978-82-471-1873-3 (electronic ver.)
ISSN 1503-8181

Doctoral theses at NTNU, 2009:233

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Science and Technology
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Printed by Tapir Uttrykk

Preface

This PhD thesis was completed at the Department of Energy and Process Engineering of the Norwegian University of Science and Technology (NTNU) from January 2006 to June 2009, and is part of the project ‘Life-Time Commissioning for Energy Efficient Operation of Buildings’.

First, I would like to thank my supervisor, NTNU professor Vojislav Novakovic, for leading me throughout my doctoral studies. His advice led me in the right direction, and his encouragement and optimism were priceless. Professor Novakovic has led several master and PhD projects in cooperation with West Balkan universities. I would like to thank him and Norway on behalf of those of us who get the opportunity to get a good education at NTNU.

I would like to thank the colleges from NTNU and SINTEF for valuable advice and unselfish support. The NTNU administrative staff was crucial in helping me adapt to working and living in Norway, so I would like thank all of the employees of the Department of Energy and Process Engineering.

Since a PhD degree is the completion of education, now is an appropriate time to thank my family for supporting me through all these years. I hope that they are as proud of me as I have always been of them. I would like to thank my primary and secondary school teachers Rizan Tasovic and Vojislav Tanovic. Last, but not least, I would especially like to thank the Todorovic family for all that we shared during these years in Trondheim.

Marko Masic

Abstract

This thesis has two main goals: (1) to develop a linear regression model of the heat consumption of space heating and ventilation systems and (2) to evaluate operation and maintenance problem detection, by comparing actual heat consumption and predictions gained through linear regression modeling.

This thesis discusses the influences that determine space heating and ventilation system heat consumption. Data with different resolutions capture heat consumption variations to different degrees. Data with higher resolutions introduce more information into calculations. However, the dynamic processes of heat transfer make data with higher resolutions less suitable for calculation than data with lower resolutions. This thesis evaluates the extent of different influences (outdoor air temperature, wind speed and solar radiation) through stepwise regression analysis of the heat consumption of six space heating and five ventilation systems. A comparison of the goodness of fit between calculations with data with different resolutions shows the extent of variation due to the heat transfer dynamic processes.

Heat consumption predictions for four ways of grouping data (hourly, hour-of-day grouping, mean values grouped by regimes and daily data) are compared. Calculations with daily data produced the most accurate predictions of heat consumption in analyses presented in representative literature and articles. There is a strong interest in producing hourly heat consumption predictions because they are more suitable for operation and maintenance problem detection. The heat consumption of HVAC systems operating with control regimes has not been evaluated in the relevant literature. Calculations with daily data collected from a system with control regimes might produce less accurate predictions than calculations with other data. This thesis analyzes excluding outliers to improve the accuracy of the model and explores necessary monitoring period length in order to obtain accurate predictions.

Heat transfer dynamic processes (the thermal storage effect) are generally considered to be insignificant in the literature for daily heat consumption. Introducing the time-lagged variable that describes changes in the mean daily temperature will show if the thermal storage effect significantly influences daily heat consumption.

A tool developed in Matlab is used for problem detection in the operation of nineteen buildings of Norwegian University of Science and Technology (NTNU). Linear regression calculations are incorporated in the tool. Operation and maintenance problems are detected by comparing actual and modeled heat consumption. The resulting predictions were accurate enough to recognize system operation faults. Even if modeled predictions were not precise enough due to the thermal storage effect, the tool user can interpret prediction errors by following outdoor temperature changes and corresponding heat consumption in parallel.

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List of symbols

A, B_1..B_3; b_0..b_3	Linear regression coefficients
BLC	Base level heat consumption [W]
β_0..β_3	Linear regression coefficients
CV	Coefficient of variation
c	Specific heat [KJ/kg·K]
Δp	Pressure difference [Pa]
ΔT	Time-lagged variable for one day temperature differences [°C]
$2\Delta T$	Time-lagged variable for two days temperature differences [°C]
HC, Q	Heat consumption [W]
NHC	Normalized heat consumption [%]
MBE	Mean bias error
R-student	R-student residual
R^2	Coefficient of determination [%]
R^2_{adj}	Adjusted coefficient of determination [%]
$R^2_{overall}$	Overall coefficient of determination [%]
ρ	Density [kg/m^3]
Q_{PRED}	Modeled prediction of heat consumption [W]
T, T_{out}	Outdoor air temperature [°C]
T_{IN}	Indoor air temperature [°C]
τ, T_{SET}, CPT	Change point temperature [°C]
S	Solar radiation on vertical surface [W/m^2]
SSS	Sequential sum of squares [W]
V	Flow rate [m^3/s]
W	Wind speed [m/s]
W^*	Member of wind independent variable

1 Introduction

1.1 Background and motivation for research

Heating, ventilation and air conditioning (HVAC) monitoring systems are becoming more commonly used in commercial buildings. Although monitoring of these systems has become wide-spread in recent decades, there is still a lack of knowledge and tools which would fully utilize the plethora of monitoring data. The price of sensors and other accompanying equipment has dramatically fallen, and the use of information technology has also spread in this field. However, our knowledge of how to use available monitoring data is still insufficient. Data are often hard to analyze due to a lack of information about the HVAC system and the characteristics of the building itself, non-documented changes in the HVAC system, and weaknesses in the HVAC system maintenance. Logical questions are: ’’Is it possible to determine how the system functions by analyzing past data? Is it possible to utilize monitoring data in order to bridge the lack of information about the HVAC system?’’ Other fields, in which economic interests and safety concerns were present, have successfully used monitoring for decades. In an era when energy has become a central question of the further development of human society and an independence issue for every country, focusing on energy savings is not only reasonable, but necessary.

This PhD thesis is financed by the ‘Life-Time Commissioning for Energy Efficient Operation of Buildings’ project, which is conducted by the Norwegian University of Science and Technology (NTNU) in Trondheim, Norway and SINTEF. The main goal for this project is to develop, verify, document and implement suitable tools for functional control of energy and climatic conditions in buildings under continuous operation during the entire operational life of the building. This should improve energy efficiency and ensure a rational use of energy and a sound indoor environment.

For most developed counties, energy use is equally distributed between industry, transportation and buildings. Energy waste due to poorly maintained HVAC systems is estimated to be 15% to 30% in commercial buildings. Despite efforts to improve energy efficiency, energy use in the commercial buildings sector is constantly increasing (Brambley et al. 1988, MacDonald et al. 1988). Since we already have ‘hardware’ (existing monitoring systems) and basic knowledge developed for other industries, it is clear that development of those technologies should be the first choice in efforts to reduce energy use and the release of greenhouse gasses.

Fault detection and diagnostics (FDD) were first developed in industries such as nuclear power plants, where high concerns about safety exist. Recently, because of increasing energy prices and concerns about greenhouse gas emission, this method has become more urgent for HVAC systems. This technique can alarm if a fault appears (detection) and can show where a fault has appeared (diagnostics). There are different ways to detect a fault. One way is to compare actual and predicted heat consumption. Predicted heat consumption can be obtained through calibrated simulations or other modeling methods. Although predictions gained through calibrated simulation are more precise, building a simulation model is time intensive, so other methods are often preferable.

Reading and understanding monitoring data is difficult and time consuming. Building energy use is a function of weather, building use, building characteristics and HVAC characteristics. Their influences overlap over minutes, hours, days, weeks and seasons, so it is difficult to determine if changes in heat consumption are a result of change of weather or other influences. Graphical tools can help to better understand HVAC system operation and to distinguish the influences of each variable.

This thesis belongs to the whole building diagnostics field. An HVAC system is analyzed together with building and weather by modeling building energy use as a function of weather. This approach can be considered as a ‘top-down’ approach. Building energy use is examined in the presented method by comparing modeled and actual heat consumption to determine if any indications of faults exist. This approach is expected to reveal larger problems, such as an energy consumption increase of 5% or more. The main focus in the thesis is developing an accurate enough model so that energy use increases can be spotted. This method cannot diagnose where problem appears in the HVAC system. The proposed method should be one of the first steps in the monitoring process. If we imagine a doctor during initial contact with a patient, he will first ask the patient about symptoms that he or she can describe. If the doctor cannot explain the patient’s condition, or if he has doubts regarding a more serious illness, he will, for example, take a blood sample from the patient for further diagnosis.

There are different methodologies that can be used to model building heat consumption (HC). It is common sense that people lose their interest as technology becomes more complicated. Calibrated simulations, building energy models based on artificial neural networks or Fourier series are generally difficult to understand because their physical meaning is not obvious. Although calibrated simulations are superior to linear regression (LR) regarding accuracy and broader opportunities, the physical perspicuity that LR offers makes it preferable for building diagnostics. The ‘Great Energy Predictor Shootout II’ (Haberl et al. 1996) was conducted in order to compare the accuracy of different methods that predict hourly HC. LR, among five evaluated methods, took second place, so this method is competitive with other methods.

Although calibrated simulations were not included in this competition, because predictions had to be made based only on HC and weather data, it can be concluded that LR is also advantageous for calibrated simulations. LR requires far less effort to develop the model, and information about building or its HVAC system is not needed.

1.2 Objectives

The main focus in this thesis is how to develop an accurate enough LR model so that increases in building energy use can be spotted. This thesis emphasizes heat consumption of space heating and ventilation systems. Other energy uses, such as building lighting, are not analyzed. HC depends on weather and the dynamic performance of both the HVAC system and the building. LR in this thesis uses weather parameters, such as outdoor temperature, solar radiation and wind speed, as independent variables of the LR model in order to model HC as the dependent variable. Due to the dynamic performance of both the HVAC system and building, instantaneous values of HC do not correspond exactly with the mentioned independent variables. Mean values of HC over 15 minutes, hourly, daily, weekly and monthly intervals describe variations introduced by dynamic performance at different levels.

The dynamic performance of HVAC equipment in the literature in generally assumed to be covered by hourly mean values, since response times are much shorter than an hour (Reddy et al. 1995). Due to concern that dynamic characteristics of HVAC system on the 15 minutes level can be important, modeling at this interval was not considered in this thesis. The literature suggests that the thermal storage effect of a building is not significant at the daily interval. Time constants of typical buildings are around one day, so thermal storage effects average over daily variation (ASHRAE 2001, Katipamula et al. 1998).

To identify operational and maintenance (O&M) problems, hourly HC is considered to be the most appropriate (Claridge et al. 1994; Liu et al. 1994) because of their higher time resolution. In ASHRAE (2001), it is claimed that steady-state models (that do not consider thermal mass effects) are proper for daily models, but not for hourly models. However, LR is used by many authors to model HC at an hourly level. Hourly modeling can be achieved by regressing all hourly data collected from one control regime. If there is no difference between day and night operations, all hourly data are regressed together. The other way to model hourly data is to collect data in 24 hour sets: the hour-of-day (HOD) model. Since weekend and day operations are different, the HOD model distinguishes between them, so there are 48 sets of data. The HOD model proved to give more accurate predictions than models with hourly data (Katipamula et al. 1998, Katipamula et al. 1995), so it is preferable for modeling hourly consumption. The daily model produced the most accurate HC predictions for space heating systems operating without control regimes (Katipamula et al. 1998, Katipamula et al. 1995). Generally, the hourly model introduces more variability, so it is expected that a more detailed model will give more accurate predictions. However, this accuracy can be lost due to thermal storage effects. Hourly models are more appropriate for O&M problems detection than daily models. To choose between hourly and daily intervals for modeling HC represents a trade-off between opportunities for O&M problem detection and model accuracy. It can be concluded that these two time resolutions are the most attractive for investigation since they are appropriate for O&M problem detection, so this thesis will focus on these time intervals.

HVAC systems are often operated with control schedules that differ for day and night operation. This issue was not considered in the literature when daily HCs were modeled. Night temperature is less relevant for daily HC because night operation is reduced for most buildings. In order to properly cover this variation, a day is divided into two parts corresponding to the regimes schedules. Mean values of HCs are modeled for each part of the day according to the mean values of independent variables. It is expected that this model should give more accurate predictions than the daily model.

Most scientific efforts in the last two decades in this field have been carried out by a group near Texas A&M University in the United States (USA). Air-side HVAC systems are traditionally used in the USA for commercial buildings. HVAC systems with radiator heating prevail in Norway because of little need for cooling. A ventilation system is used for fresh air and additional summer cooling with heat pumps. In Europe, commercial buildings are heated with radiators more often than in the USA. So far, LR models of air-side HVAC systems in the literature have been proposed mainly by American authors. This thesis will focus on HVAC systems with radiator heating and ventilation. Radiator heating has a longer response time, so whether or not it is possible to model hourly HC will be determined. All system heat consumption analyzed in this thesis involves space heating with radiators.

This thesis presents the background on how HC of radiator heating and ventilation systems vary with different independent variables. The effects of weather, thermal storage, building use and HVAC system performance will be evaluated. In ASHRAE (2001), it is claimed that regressing outdoor temperature provides an accurate enough prediction of space heating consumption, so there is no need to introduce solar and wind influences in the model. This assumption will be verified. Special emphasis will be placed on investigating how time delays introduced by thermal storage influence HC. The thermal storage effect is less significant for daily resolution than for hourly resolution. By averaging hourly data to mean daily values, some information is lost (Katipamula et al. 1995). As a result, hourly predictions should be more accurate. However, due to thermal storage effects, this was not the case in the analysis conducted so far. The authors did not address this as a reason, but this will be proved later in this thesis.

Literature resources claim that three to six months of monitoring history is necessary to model daily heat consumption (Kissock et al. 1993). However, there is no reliable evaluation of the necessary monitoring period to model hourly heat consumption. This issue will be analyzed for radiator heating and ventilation systems in this thesis.

Excluding outliers (residuals) improves the accuracy of the model. Excluding outliers can be automated through standard statistical methods by recognizing residuals. Data points with unexpected values can be excluded manually by the developer of the model. The accuracy of the model will be evaluated when the residuals are excluded.

The second issue covered in this thesis, in addition to modeling HC, is how to use proposed method in practice. Different sensors are used to measure the indoor environment, the state of equipment and energy meters. Although operators fully understand the HVAC system operation and there are a wide variety of measurements, it is still not fully clear how the HVAC system interacts with its surrounding, i.e., the building and weather. The energy signature line is the primary, and often only, tool in monitoring systems that shows this interaction. The aim of this thesis is to develop a tool to be used for interpreting HVAC system functioning regarding the interaction between the HVAC system and its mentioned surrounding.

Different players involved in HVAC system monitoring ‘seem not to speak the same language’. Monitoring system operators cannot fully understand signals from the systems that they follow. Engineers, who developed the monitoring system and are often involved by contract to maintain and further develop monitoring system, do not understand operators. What these three parties need is a ‘common language’. When they start to understand each other, all will be engaged and technology will be improved. The tool developed for this thesis is intended to improve communication. Furthermore, introducing whole building diagnostics would cover the communication gap that exists between different stages of the building life cycle (from HVAC system design, through its installation, to its operation).

Next, questions and objectives are named in order to summarize all the objectives of this thesis:

- How do different influences determine HC for radiator heating and ventilation systems at different time resolution levels?
- Develop a tool which will enable HC modeling through LR and enable O&M problem detection.
- Which time resolution gives the best predictions of HC?
- Can the LR model be improved by excluding outliers?

- What is the necessary monitoring period duration in order to obtain a precise HC model?
- Is it possible to detect O&M problem with radiator heating and ventilation by comparing predicted and actual HC?
- Can the developed tool improve comprehension of HVAC system operation and improve communication between operators and other players involved in monitoring building energy?

1.3 Specific contributions from this thesis

These are the most significant contributions from this thesis:

- LR model is developed for modeling radiator and ventilation heating, which has never been done before.
- LR models are developed for eleven buildings in order to evaluate outdoor temperature, solar radiation and wind speed as independent variables. Outdoor temperature was the most significant independent variable for both ventilation and radiator heating systems. Wind speed was insignificant for model accuracy. The sun was far less important than outdoor temperature for most of the buildings with radiator heating. Although it is not expected that solar radiation will affect ventilation heating, the sun was a significant factor for modeling ventilation heating of two buildings. There are large areas organized as glass atriums in those buildings.
- HOD model is more accurate than the hourly model for both space heating and ventilation systems. The LR model with mean values is more accurate than the daily model for both space heating and ventilation systems.
- This thesis proves that the daily level thermal storage effect is significant. Introducing a time-lagged variable that describes changes in the outdoor temperature improved the accuracy of heat consumption predictions significantly for the daily model.
- Deviations between actual and modeled hourly HC are higher than deviations for daily HC due to thermal storage effects. However, dynamic performance of the system can be interpreted by following the ratio between actual and modeled HC and the hourly change of outdoor temperature in parallel.
- Thermal storage effect is more significant for space heating than for the ventilation system.
- Excluding outliers with the recommended statistical method did not prove to be a reliable tool for improving LR model accuracy.
- Three months of monitoring history are enough for LR modeling of space heating and ventilation system HC.
- A tool with a graphical user interface proves that detection of O&M problems is possible with the proposed method. Nineteen NTNU campus buildings are analyzed with the developed tool.
- Regarding improvement of communication, both operators and author of this thesis understood the performance of the analyzed HVAC systems in the same fashion, so it can be concluded that the developed tool helped improve communication.

1.4 Thesis organization

Chapter 2 presents the reasons for building energy monitoring. Further, different methodologies of modeling building heat consumption are presented. LR as a statistical methodology is described. At the end of the chapter, an overview of results from the relevant literature regarding modeling HC through LR is presented.

The rest of the thesis follows the order of the questions named in subchapter 1.2. Chapter 3 addresses the first question - How do different influences determine HC for radiator heating and ventilation systems at different time resolution levels? The article written by Liu and Claridge, “Is the Actual Heat Loss Factor Substantially Smaller than You Calculated?” is summarized in detail in order to better understand the effects of thermal mass, which is crucial in modeling hourly HC. Different data groupings are discussed in order to predict how different influences will be covered with different resolution models. Finally, outliers among the monitoring data are defined.

Chapter 4 addresses the second of the questions and objectives - Develop a tool which will enable HC modeling through LR and enable O&M problem detection. First, the basic concepts used in the proposed method are explained. The proposed method is implemented in the developed tool. The features of the developed tool are described. Finally, the functions incorporated in the tool that enable different LR calculations are described at the end of the chapter.

In Chapter 5, each of the data groupings are analyzed separately both for space and ventilation heating. The third, fourth and fifth questions mentioned in subchapter 1.2 are addressed. At the end of chapter, new independent variables are introduced into the LR model, which describe the space heating dynamic performance.

Chapter 6 addresses the last two of questions mentioned in subchapter 1.2. Detailed analysis is presented for one of the buildings on the NTNU campus. Analysis results are presented for eighteen more buildings regarding O&M problems.

Chapter 7 provides the conclusions and recommendations for further work.

2 Different methodologies for using HVAC monitoring data in analysis of building energy use

2.1 Overview of building energy monitoring issues

There are four reasons for building energy monitoring (ASHRAE, 2003):

- Determining energy end-use
- Specific technology assessment
- Savings measurement and verification (M&V)
- Building operation and diagnostics

Energy end-use is gained by monitoring the energy consumption of individual building energy systems. Its goal is to determine separate energy consumption in buildings, and it is used for load forecasting, confirmation of energy conservation opportunities and simulation calculations.

The goal of specific technology assessment is to evaluate the performance of certain technology or retrofit measures; it uses more detailed sub-metering.

The goal of M&V projects is to verify energy savings gained through retrofits. Energy uses from periods before and after the retrofit are compared. Since weather varies through these periods, weather normalization is necessary and is typically done with linear regression. Actual savings are calculated as the difference between the post-retrofit energy consumption gained from pre-retrofit period model and the post-retrofit energy consumption (Kissock et al., 1998). The word 'verification' in the title of this thesis does not refer to M&V applications; rather, it is used in the sense of determining if the HVAC system operates properly.

This thesis is a part of the building operation and diagnostics field. The goal of collecting data for building operation and diagnostics is to identify O&M problems or indoor air quality problems. Typical procedures for the residential sector are manual procedures, such as (1) flue gas analysis to determine furnace gas efficiency or other procedures to determine air conditioners, refrigerators and equipment efficiency, (2) a fan pressurization test to locate and measure building air tightness, and (3) infrared thermography to determine thermal characteristics of building envelope. In commercial buildings, HVAC equipment is more complex than in residential buildings so there are many more procedures for equipment diagnosis and building performance analysis. Identification of O&M problems is the first step in the process of improving the energy efficiency of an existing building. O&M measures are considered to be no-cost or low-cost measures. Most measures include turning-off equipment when the building is unoccupied, adjusting temperature settings and using efficient system operation strategies. The relevant literature gives the results of implementing O&M measures, which gave significant results. For example, Claridge et al. (1994) identified four million dollars in savings by implementing O&M measures.

2.1.1 Fault detection and diagnostics

The other way to identify O&M problems, opposed to manual equipment inspection, is automated fault detection and diagnostics (FDD). There are two approaches: ‘down-top’ and ‘top-down’. The ‘down-top’ approach is based on analysis of HVAC component performance, while the ‘top-down’ approach observes the entire HVAC system. The most logical parameter for the ‘top-down’ approach to describe overall HVAC system performance is overall heat consumption. Energy use intensity (EUI) is the annual building energy consumption divided by the conditioned floor area. It represents a benchmark of building energy use. Monthly EUI can detect billing errors, improper operation of equipment during unoccupied hours and a seasonal space-conditioning problem (Haberl and Komor 1990a). In addition to EUI, there are more parameters that can be used to characterize building energy use (Haberl and Komora 1990a) and identify O&M problems.

Most research effort thus far has focused on ‘down-top’ analysis. The operation of HVAC components is checked by rules of proper and improper performance, which are implemented through algorithms. The other way to implement a ‘down-top’ approach is based on physical models of the components. An advantage of this approach is that faults can be detected and the cause of a problem can be diagnosed. For most ‘top-down’ methods, diagnostics are not possible. However, the ‘down-top’ method ‘cannot see the overall picture’, i.e., the interaction between the building and HVAC system. The FDD-based on calibrated simulations can ‘see’ both interactions between the building and HVAC system and the performance of HVAC components. However, this method requires significant effort to develop a calibrated simulation model, so it is still not widely used in practice.

The 1973 oil embargo put energy conservation in focus, so during the 1970’s and 1980’s, the first significant efforts to monitor building energy were made. Research in the FDD field started later than research for other monitoring issues (late 1980’s). Other industrial fields, like the nuclear, aerospace, defense and automotive industries, began research and application of FDD decades ago. This accumulated knowledge can be used for HVAC systems. The objective of the FDD process is to detect faults and diagnose their causes before additional damage to the system or loss of service occurs. FDD assisted by continuous monitoring is called automated FDD. Diagnostics include isolation of a fault and fault identification. Isolation of a fault includes determining the type and location of a fault. Fault identification includes evaluation of the size and severity of fault. In the most cases, the detection system runs continuously, while the diagnostic system is triggered if a fault is detected.

Automated FDD can be used for three purposes: commissioning a new HVAC system, operation and maintenance (Katipamula 2005). Initial commissioning should guarantee that the system is installed and operates correctly. Most actions include visual inspection and functional testing, which are performed manually. It is possible to implement automated FDD methods through short-time data collection.

During building operation many problems are not detected if only the inside air quality is controlled, because automatic controllers compensate for faults so that occupants experience no discomfort. This leads to an increase in energy consumption and operating costs. A building automation system (BAS) provides a set of data that describes the operating parameters of the HVAC system, but operators only check space temperatures and adjusting set points. Because of this, operational problems are often not detected, or if they are not diagnosed, operators turn off automatic control. FDD procedures should help operators detect and identify problems.

Automated FDD can be used for condition-based maintenance. This FDD feature predicts when a fault will appear, and HVAC components can be changed before problem appears.

FDD methods can be classified as *prior knowledge* methods and *completely empirical* methods. The prior knowledge methods use models based on first principal (quantitative methods) or expert knowledge, which is implemented through rule based algorithms (qualitative methods). The completely empirical methods are also called 'black-box' models. They use measurement data from monitoring history without prior knowledge of the physical significance of variables used for modeling.

Most FDD procedures were developed during the 1980's and 1990's to investigate HVAC&R components ('down-top' approach). During the 1980's, procedures for FDD's of vapor-compressor-based refrigeration were developed. During the 1990's, research focused more on building systems, such as air-conditioners, heat pumps and air handling units (AHU's). Those procedures use measured temperature and pressure at various locations in a system to determine the thermodynamic relations between them. In the early 1990's, the International Energy Agency (IEA) conducted the Annex 25 research project, which investigated using simulations for FDD. In the mid-1990's, the U.S. Department for Energy (DOE) founded a project that developed a tool for detecting faults in whole-buildings and major systems (Brembley et al. 1998, Katipamula et al. 1999). Katipamula et al. have developed a tool that is based on a set of rules, which are implemented through the algorithm. The algorithm checks the operation of AHU through a decision tree structure (if-then-else structure) that implements the engineering rules (expert system) and first principal of thermodynamics.

Whole-building diagnostics are a 'top-down' approach. The performance of the entire HVAC system is examined. This approach can spot large problems, e.g., those which increase energy use by 5% or more. This should be the first step of any building diagnosis. The first effort in the whole building diagnostics approach started with calculating building heating use through the degree day method. This method was meant to predict heating use, not diagnose it. It assumes that heating use has a linear dependence on the outside temperature. Later methods continue to follow this assumption.

NAC (weather-adjusted normalized annual consumption of a building) describes heating-related and non-heating-related consumption. This parameter was introduced by the Princeton Scorekeeping Method (PRISM) (Fels 1986). The method is based on linear regression, and it calculates three parameters that define heating-related and non-heating-related consumption. This method introduced the concept of change point temperature. Over some outside temperature, there is no need for heating, since internal and sun heat gains are higher than the heating demand. Over this temperature, energy use is related only to tap-water consumption, if heat consumption is regressed. If an HVAC system uses electricity for heating or cooling, it is possible to determine base-level electricity consumption by regressing electricity use. Energy consumption defined by PRISM is:

$$Q = \alpha + \beta(\tau - T_{out})_{+} \tag{1.1}$$

where the terms are:

α – base level heat consumption, which is related to tap-water consumption

β – slope of heating-related heat consumption

τ – change point temperature

T_{out} – outdoor temperature

The '+' sign indicates that if T_{out} is higher than τ, heat consumption is equal to the base level. A linear regression calculation procedure that calculates α, β and τ is presented in subchapter 3.4. Linear regression in the PRISM method uses monthly heat consumption, so the temperature data are adapted to this calculation. Linear regression calculation is done through monthly values from the equation:

$$F_i = \alpha + \beta H_i(\tau) + \varepsilon_i \tag{1.2}$$

where F_i is the average daily consumption through a month and ε_i is a random error term. Heating degree-day per day for the ith month - $H_i(\tau)$, is calculated according to equation

$$H_i(\tau) = \sum_{j=1}^{N_i} (\tau - T_{ij})_+ / N_i \tag{1.3}$$

where N_i is the number of days during a month. NAC is calculated according to:

$$NAC = 365\alpha + \beta H_0(\tau) \tag{1.4}$$

where H_0 is the heating degree-days for base τ in a typical year. In addition to heating, the PRISM method can be used for cooling. Haberl and Komor (1990a) used PRISM to determine heating, cooling and base-level electricity consumption by categorizing consumption: base level plus cooling (PRISM cooling only, CO), base level plus heating (PRISM heating only, HO), base level plus heating and cooling (PRISM heating and cooling, HC) and base level only (a flat consumption profile). With this method, they found which portion of energy is used for which purposes. Also, through use of PRISM they recognized changes in HVAC performance during the monitoring history.

Equation 1.2 is solved through linear regression, which is a mathematical tool that is widely used in engineering and scientific practice. By solving a system of linear equations, it gives a function with linear dependence between the dependant variable and one or more independent variables. The dependant variable $\hat{y}$ is estimated from the equation of the form:

$$\hat{y} = b_0 + b_1 x_1 + \cdots + b_n x_n \tag{1.5}$$

where:

x_1, x_2,… x_n - n independent variables

b_0, b_1,…b_{0n} - n+1 regression coefficients

$\hat{y}$ - dependent variable

The results of linear regression calculation are regression coefficients. Independent variables can be single variables or any function of single variables. If a model has linear coefficients, it is called a *linear regression* model. This type of model will be used exclusively for further analysis. If a model has only one independent variable, it is called a *simple* or *simple-variate* linear regression (SLR) model; otherwise, it is a *multiple* or *multivariate* linear regression (MLR) model. Calculation of linear regression coefficients is rather simple, and it simply requires solving of linear equation system. Many commercial program packages have functions that support linear regression.

‘Top-down’ analysis can be also done by using different models of building energy use. HVAC performance can be described through different models: for example, calibrated simulations, artificial neural networks, Fourier series, or linear regression. These methods are called inverse modeling methods. Modeling improves heat consumption prediction accuracy by including additional terms that describe building heat consumption. By comparing actual building energy use with a prediction gained through a model, system operation faults can be detected. Inverse modeling methods can be also used to model HVAC components, which are used in ‘down-top’ approach analysis. Although this approach is more detailed than the ‘top-down’ approach it misses interactions between the building and HVAC system.

2.2 Inverse modeling methods (ASHRAE 2001)

Energy use can be modeled by forward modeling or inverse modeling. Forward modeling is used to design and optimize HVAC systems. Inverse modeling is used for existing buildings or components. Inverse modeling is preferable for the four mentioned purposes associated with building energy monitoring. A model is defined by input variables that act on the system, properties and structure of system, as well as output variables that describe response of the system to the input variables. The purpose of forward modeling is to determine output when the first two components are known. A system does not need to exist to be modeled, so this approach is used in the design stage. This approach is based on mass and energy balances and requires understanding and implementing various natural phenomena. Forward modeling of building energy use begins with defining building geometry and the physical characteristics of building materials and a description of the building location. This stage describes the building heating and cooling loads. Next, secondary equipment and operation schedules are defined. The secondary system distributes heating, cooling and ventilation to the conditioned space. Building loads are than translated into secondary equipment loads. The last stage is primary equipment, which refers to central plant equipment. Energy loads on this stage should meet loads on the secondary level. This way is defined *forward simulation* model. There are many commercial simulation programs, such as EnergyPlus, BLAST, and DOE-2.

Inverse modeling determines system parameters when input and output variables are known. Input data can be gained by experiment – intrusive data. Such data lead to more accurate models. Nonintrusive data can be obtained from normal system operation. The model contains a relatively small number of parameters because of the limited information. Although, inverse models are less complex than forward models, inverse models can give more accurate predictions of future system performance, since the model is developed from data gained from an existing building. Inverse modeling is less labor-intensive than modeling through simulations. Developing a simulation model for existing building requires a blueprint of the building and its HVAC system. Through the calibration process, it is possible to tune the simulation model to match the performance of the HVAC system of an existing building. Despite its advantages, the inverse modeling concept has still not been widely adopted in the building professional community.

2.2.1 Classification of inverse modeling methods

Inverse modeling methods are classified according to the level of detail they require and the approach in handling input and output variables as empirical or 'black-box' methods, calibrated simulations and 'gray-box' methods. These approaches require different levels of effort and expertise. According to their complexity, they provide different model accuracy and opportunities for analysis. The 'black-box' models are based on regression between measured energy use (output) and influential parameters (climatic variables and building occupancy) (input). Single-variate and multivariate linear regression, change point, Fourier series and artificial neural network (ANN) models are in this category. Model formulation requires little effort. This approach is most widely used in the inverse modeling method. It can be used to model building energy use and equipment. It is appropriate for detecting equipment and system faults, but it is of limited value for diagnostics.

Calibrated simulations represent a developed simulation model that is tuned or calibrated to match measured variables. Although there were serious efforts to adopt forward simulation programs, truly calibrated models have been achieved in only a few applications. Katipamula and Claridge (1993) and Liu and Claridge (1998) have developed a simplified simulation model that performs calibration simulations much more quickly.

'Gray-box' methods employ a physical model that is fitted to the structure of the building or HVAC system it represents. Model parameters are then identified through statistical analysis. For example, in the short-term energy monitoring method (STEM) (Subbarao 1988), steady-state load coefficients are calculated through experiments with an electric heater maintaining a steady interior temperature overnight. A cool-down period is used to get information about building thermal storage. Parameters gained from these two experiments are then used to develop a model, which provides extrapolation to long-term performance. The other 'gray-box' methods are multistep parameter identification, thermal network, autoregressive moving average model, modal analysis and differential equations.

Inverse modeling methods can be also classified as *time-integrated* or *steady-state* methods and *dynamic* methods. Time-integrated methods are based on algebraic equations of building energy balance. For them is important that the time step is longer than the response time of the building and HVAC equipment in order to average variations. The intention of dynamic methods is to capture dynamic thermal storage effects.

2.2.2. Steady-state and dynamic models

Steady-state models are appropriate for monthly, weekly and daily data. For finer time steps, dynamic models are necessary. They capture effects such as building warm-up and cool-down. Dynamic models contain time-lagged variables. For nonlinear effects, such as air infiltration, time-integrated methods should not be used. Linear regression, which is used in this thesis, is a steady-state method. Steady-state models are used for both building and equipment modeling. Single-variate, multivariate, polynomial and physical models are all steady-state models.

2.2.2.1 Single-variate steady-state models

Single-variate models use only one independent variable for linear regression; they are most widely used. Outdoor temperature is the most significant driving force for building energy use (Fels 1986, Kissock et al. 1993 and Katipamula et al. 1994) on monthly and daily time scales, so it is used as the only independent variable in the single-variate model. The PRISM model is based on the change point concept. This model has three parameters that define energy use: α, β and τ (Eq. 1.1). In its simplest form, the change point temperature is fixed at 18.3°C. If either heating or cooling is always needed, it is possible to use a two parameter model (α and β). Three parameter models are typical for single-family houses that use natural gas for space heating and domestic water heating. The four parameter (4-P) model (Ruch and Claridge 1991) is based on monthly mean temperatures, and it has a slope below and above the change point. This model is suitable for modeling energy use of buildings with electric cooling and heating. The five parameter (5-P) model can be used if both cooling and heating are measured by the same meter. It has two change points and one base level consumption.

An advantage of single-variate models is that they can be easily automated if monthly utility billings and average daily temperatures are available. This model was also applied to daily data (Kissock et al. 1998). The model, in this case, should be adapted to weekday and weekend use by separating the data. Steady-state single-variate models are less accurate if dynamic effects (e.g., thermal mass) or influences other than outdoor temperature (solar gains, humidity, wind) have more influence on building energy use. This model generally works better with heating than with cooling, because cooling is more influenced by outdoor humidity and solar gains. Systems operating in an on-off cycle with part loads are also less suitable for these models. These models are most appropriate for buildings with heat consumption that has strong linear dependence on outside temperatures, e.g., residential buildings. For commercial buildings, there are higher internal gains, and in some cases, simultaneous heating and cooling exists, which introduces nonlinearity effects. Thus, the four parameter model is more suitable.

The major advantage of steady-state models is of the ability to evaluate normalized annual consumption (NAC). NAC is used to evaluate energy conservation retrofits. Energy conservation savings can be gained by comparing NAC gained by multiplying parameters gained from the pre-retrofit and post-retrofit periods by the weather conditions for the average year. Typically, ten to twenty years of weather data are necessary to obtain average yearly weather conditions.

2.2.2.2 Multivariate steady-state models

Multivariate steady-state models are a logical extension of single-variate models. There are two approaches for this kind of modeling: change-point regression models and Fourier series models. Change-point regression models do not capture diurnal and seasonal cycles of HVAC operation. Reddy et al. (1995) presented formulation of these models for air-side HVAC equipment. The Fourier series is a trigonometric polynomial, so its formulation should better match to diurnal and seasonal cycles (Dhar et al. 1998). The variables included in these models are outdoor air dry-bulb temperature, solar radiation and outdoor specific humidity. If some of these variables vary slightly, their introduction in the model will not significantly improve the goodness of fit. These variables change the parameter that represents constant load if they are not presented in the model. In commercial buildings, internal gains are significant. They are difficult to measure because of their complexity. Reddy et al. (1999) have proved that monitored electricity used by lighting and equipment can be a surrogate for internal sensible loads.

There are several standard methods for selecting significant variables of a multivariate model. The model should be as simple as possible, because more complex models require more monitoring and more work to handle the data. In addition, if some variables are correlated (multicollinearity), it can cause poorer model accuracy. A rule of a thumb is that if the correlation between two independent variables is higher than the correlation between either of the variables with the dependent variable, multicollinearity is important (Draper and Smith 1981). Principal component analysis (PCA) is a method to overcome the multicollinearity problem. The PCA method re-expresses independent variables of the linear regression formulation with synthetic variables, which represent a linear combination of original variables.

Multivariate steady-state models have proved to be accurate for daily time scales and slightly less accurate for hourly time scales. Grouping data into hourly bins corresponding to each hour of the day (hour-of-day – HOD) improves the accuracy of the hourly model (Katipamula et al. 1995, 1998).

2.2.2.3 Polynomial and physical models

Polynomial models are widely used as pure statistical models to express performance of equipment such as pumps, fans and chillers. Model formulation is based on theoretical knowledge, but it does not involve physical properties during model formulation (black-box model). Pump capacity and efficiency are expressed as a polynomial consisting of measured pump pressure, flow rate and pump electrical power input. Fan electricity consumption is expressed as a polynomial of the supply air mass flow. For chillers, compressor electrical power consumption is correlated with the thermal cooling capacity, and the temperature on condenser inlets and evaporator outlets.

Physical models, in contrast to polynomial models, are physically based on thermodynamic lows. The first principal of thermodynamics is frequently used, so these models are often called first principal models. Only a few models have been estimated considering building energy use. There are more studies that model equipment performance. For example, chiller COP is expressed by measured values of thermal cooling capacity and the temperature on the condenser inlets and evaporator outlets. In contrast to the polynomial model, physical models express COP according to its physical meaning.

2.2.2.4 Dynamic models

There are two classes of dynamic models: macro-dynamic (whole building models) and micro-dynamic models (HVAC components). They enable the monitoring duration to be reduced, increase model accuracy and reveal interactions within the system. They are usually used for modeling with hourly and sub-hourly data and traditionally require the calculation of a set of differential equations. Their disadvantage is their complexity and that they require detailed measurements to tune the model. Unlike steady-state models, they usually require user knowledge about the building and HVAC system being modeled. There are four types of dynamic models: thermal network, time series, differential equation and modal models. An artificial neural network is a statistical method. In this approach, the algorithm is intuitive, so it does not follow programmed rules. The weights of net elements are adjusted iteratively, or ‘trained’, so that the set of input variables produce the desired set of output variables. An iteration refers to an input/output pair.

3 Modeling building heat consumption through linear regression

3.1 Variables defining building heat consumption

The factors defining building heat consumption can be grouped into four groups:

1. Weather parameters:
   - Outdoor air temperature
   - Solar radiation
   - Wind speed
2. Building characteristics:
   - Wall thermal characteristics
   - Air tightness around windows
3. Building use:
   - Heat released by occupants, lights and other electrical appliances
   - Opening of windows
4. Performance of HVAC system components and its control

Figure 3.1 presents these factors. Heat flux due to a difference between the indoor and outdoor temperature partly accumulates in the walls.

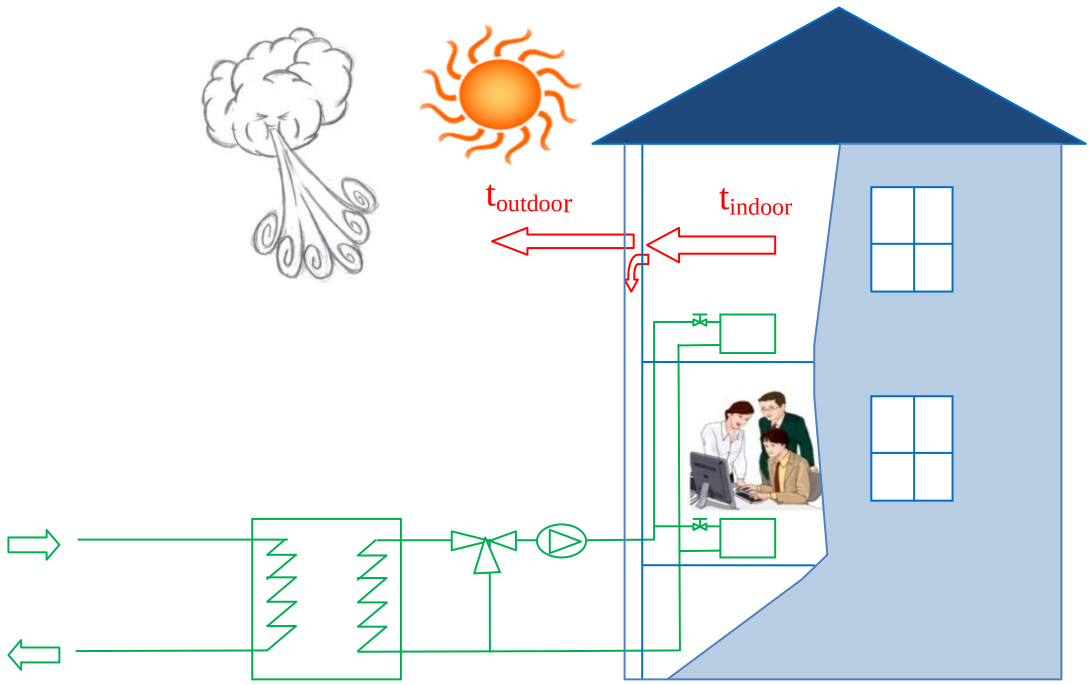

Figure 3.1 Simplified scheme of radiator heating system

There are many other factors that could influence building energy consumption. The presented factors are mentioned because they are the most important. It is obviously impossible to obtain a perfect building heat consumption model by comprising all independent variables. Some factors are measurable, like climate factors, some are unpredictable and un-measureable, like building use or HVAC malfunctions, and some are hard to model, like the performance of HVAC system components. However, with some simplifications, a rough figure of building thermal performance can come close enough to reality.

Inverse modeling uses measurable input and output variables to determine a mathematical description of system. A flow chart of building energy use inverse model is presented in Figure 3.2. Weather and internal heat gains (generated by building use) represent disturbances to the system, which are covered by the HVAC system in order to maintain the indoor environment within the desired limits. Heat loads caused by weather and internal heat gains are input variables, while delivered heat is the output variable. An equation that represents the dependence of delivered heat on the independent variables indirectly explains the performance of a building and HVAC system.

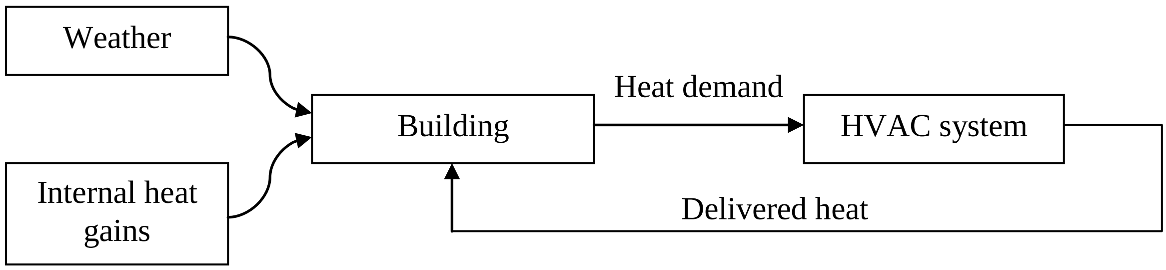

Figure 3.2 Flow chart of inverse model of building energy use

Weather data are easily available and measurable, so they represent the choice for independent variables. Changes in these parameters highly determine building heat consumption. Figure 3.3 presents building heat consumption and the corresponding outdoor air temperatures for one control regime in a building at the NTNU campus. The line gained through simple linear regression, known as an *ET* line or *energy signature* line, has two parts: a horizontal component corresponding to the time period when heat consumption did not depend on outdoor temperature and a slanted component. The horizontal part corresponds to heat consumption for tap water preparation. It is obvious that heat consumption depends linearly on the outdoor air temperature. However, there are deviations from the ET line that are a consequence of other influences. The LR model, which would cover all variations of heat consumption, would represent a flat surface in an n-dimensional space corresponding to *n* independent variables. Independent variables can also be other weather parameters, such as air humidity or an overcast sky. In the case of cooling, air humidity is an important factor. Since cooling will not be considered in the thesis, air humidity is not included in the LR model. A building releases radiant energy into space with a clear sky. An overcast sky could be introduced in the LR model as an independent variable. However, those data were not available.

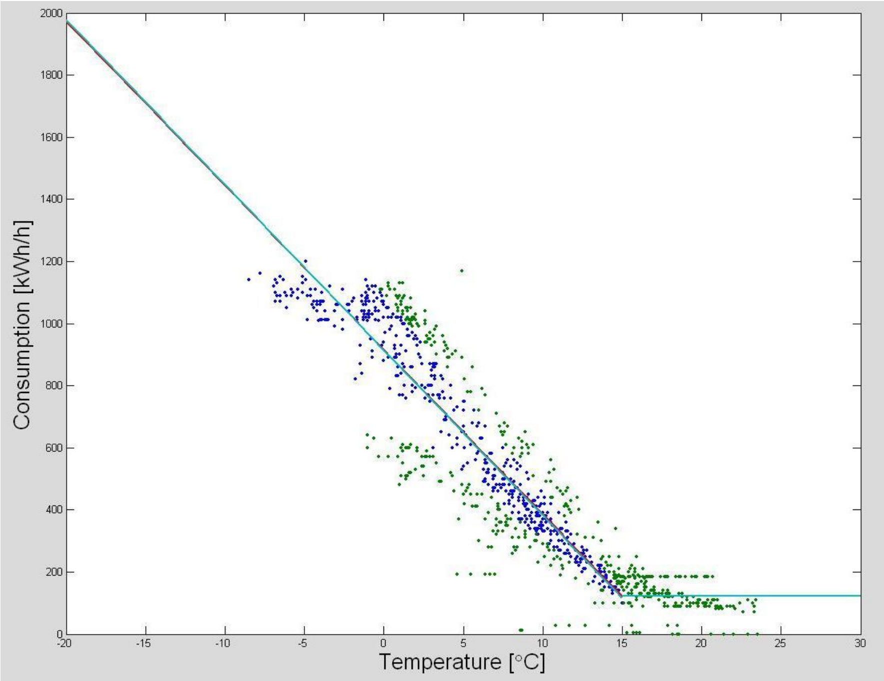

Figure 3.3 Energy signature line for one control regime

As mentioned earlier, the primary interest for O&M problem detection is modeling hourly and daily heat consumption. Some hourly and sub-hourly variations of different parameters that influence building heat consumption are averaged at the daily level. For example, if heat gains released by occupants have similar values from day to day, introducing that parameter as an independent variable will not increase the accuracy of the daily model. These heat gains will decrease the linear regression coefficient corresponding to constant heat consumption, but will not influence the slope of the ET line (Figure 3.3). It can be assumed that these gains are covered on the daily level by averaging. At hourly intervals, occupancy of the building changes throughout the day, so introducing this individual variable would increase the accuracy of the hourly model. Heat released by lighting changes throughout the year as the length of a day changes, so daily models do not take this influence into account through averaging. The HOD model covers better hourly patterns of building use than the hourly model. It will be analyzed whether or not the influence is averaged in the daily model.

Night outdoor temperature is less relevant for daily HC if night operation is reduced. In order to properly cover this variation, a day is divided into two parts corresponding to the different control regimes. For each part of a day, the mean HC is modeled according to the mean values of the independent variables. It is expected that this model (mean values grouped by regimes) should give more accurate predictions than the daily model. Different ways of grouping data are presented in the next subchapter.

The building envelope stands between weather influences and building inside space (Figure 3.4). Characteristics of the building envelope determine the time delay between weather changes and the corresponding change in building heat demand. The building envelope simultaneously conducts and accumulates heat. In the case of steady-state conditions, accumulation is equal to zero. Thermal storage has no influence on the steady-state conditions, so building heat demand is directly proportional to the difference between outdoor and indoor temperature. Thermal storage appears with changes in outdoor or indoor temperature, and it lasts until steady-state is re-established. However, the outdoor temperature is never constant, so thermal storage effect always exists. Its magnitude depends on the thermal capacity of the walls and the magnitude of the outdoor temperature change. For sun radiation, if we imagine a case in which the building will be under the influence of the same amount of solar radiation, thermal balance will be accomplished after some period of time, so instantaneous values of solar radiation correspond to heat gains. However, sun radiation is never constant (except for nights), so the thermal storage effect always exists in this case. Nonlinearity due to the thermal storage effect appears with changes in weather. The indoor air temperature changes under occupied to unoccupied conditions, for example, during the morning start of the HVAC system after the night temperature setback. Changes in the outdoor temperature also introduce nonlinearity. If the outdoor temperature falls, heat demand is lower than the heat demand for steady-state conditions. The level of this effect depends on the heat capacity of walls. Instantaneous values cannot be used for modeling due to thermal storage effects. Averaging instantaneous values covers variation introduced by thermal storage effects.

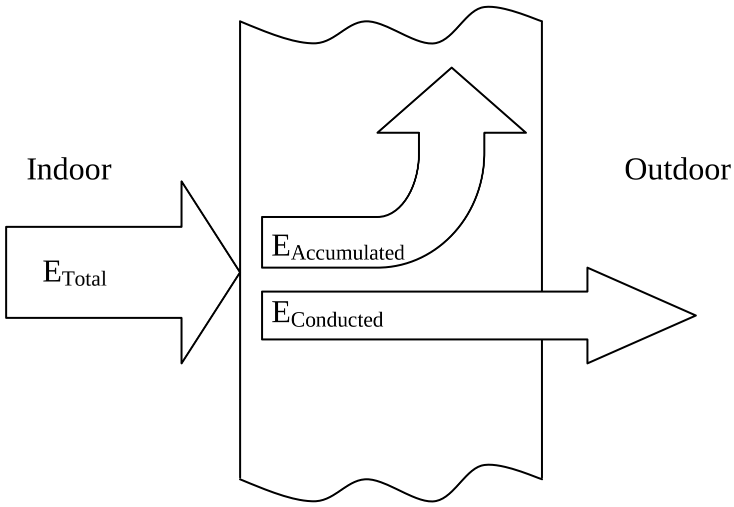

Figure 3.4 Heat transfer through wall

Building use decreases heat demand because of heat gains from occupants, lights and other electrical appliances. These influences are hard to measure. Reddy et al. (1999) introduced monitored electricity consumption as a surrogate for total internal gains. Since those data were not available, linear regression models developed in this thesis did not consider this surrogate.

The use of a building dictates HVAC system operation. The occupancy of the building mainly determines the HVAC system control regimes. Weekends and holidays are periods when the system works with reduced operation in commercial buildings. A model of the thermal performance of the building should follow different HVAC system operation regimes, which are also patterns of building use through grouping the data. This means that both use of the building and its control can be covered by one model. The aim is to cover all mentioned factors defining building heat consumption through one model. Although some factors and their effects on building heat consumption are not presented as independent variables in the linear regression model, they can be considered in model by grouping the data. For example, if occupants open windows at the same time when they come to work and close it when they leave, this effect can be covered if the data are grouped such that they follow the control regimes, since control regimes follow the building occupancy.

Control of the HVAC system determines how much energy is delivered to the building. Some space heating systems control the amount of delivered energy based on climate parameters, such as outdoor air temperature and wind speed, while some maintain constant indoor parameters. The extent to which disturbances will be covered by HVAC system it is up to its control, so some disturbances will influence heat consumption, while some will not. For instance, if a building space heating system has control based on measuring outdoor air temperature and wind speed, solar radiation is not relevant, i.e., it does not influence building heat consumption. Regression parameters regarding solar gains will not be significant in the regression model in this case.

The question is how effective is the HVAC system control. It operates with time delays. Because of this, and the mentioned nonlinearities, it is better to average data on hourly and daily intervals instead of working with instantaneous values to avoid the effects of time delays. HVAC components also introduce time delays due to thermal storage effects. Water and air have to pass distances inside a building through pipes and ducts, which demands time. All these time delays are considered to be shorter than an hour, so that averaging should cover those effects.

3.2 Grouping of data for linear regression

It is common for HVAC system control regimes to follow division of a day into working hours and nonworking hours. During weekends, the system usually works with reduced operation. The first regime in Table 3.1 is used during working hours (from $7^{\underline{h}}$ to $16^{\underline{h}}$), while the second is used during weekday nights. Regimes 3 and 4 correspond to weekend operation. Often, regimes 2, 3 and 4 are all the same. A time period corresponding to one regime during a day will be referred to as *regime period* for the remainder of this document. If nonlinearities did not influence HVAC system behavior, the best way to group data for linear regression would be to take instantaneous values of dependent and independent variables from each regime. Much more variation would be taken into account this way than if daily data would be used. The closest case to instantaneous values which will be analyzed is to take mean values of data for every hour. Since time delays of HVAC components are shorter than an hour, the influence of components is averaged and will not be discussed further. Selecting a data resolution that gives the most accurate prediction of heat consumption represents a trade-off between taking as much information as possible into consideration and excluding effects that cannot be modeled (for example thermal storage effects) by averaging.

In the case of hourly mean values, we have 10 points from every weekday for regime 1, and 14 points for regime 2 for the scheme presented in Table 3.1. For every weekend day, we have 7 points for regime 4 and 17 points for regime 3. For 70 days in the monitoring history, i.e. 10 weeks, there are 500 points for regime 1 and 700 points for regime 2 and 340 points for regime 3 and 140 points for regime 4. This grouping method will be referred to as *hourly data grouped by regimes* or just *hourly data* for the remainder of this document.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
M	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
T	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
W	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
T	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
F	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
S	3	3	3	3	3	3	3	3	4	4	4	4	4	4	4	3	3	3	3	3	3	3	3	3
S	3	3	3	3	3	3	3	3	4	4	4	4	4	4	4	3	3	3	3	3	3	3	3	3

Table 3.1 Example regime schedule for one week

The second way to group data is to calculate mean values from more hourly data corresponding to each control regime. If we take mean values from data shaded with blue in Table 3.1, this would give one data point. Mean values for one week are presented in Table 3.2. For example, the first point corresponding to weekday night regime value of corresponding heat consumption is:

$$Q_{2.1} = (\sum_{i=1}^{6} Q_i + \sum_{i=17}^{24} Q_i)/14 \tag{3.1}$$

The first data point corresponding to weekday day regime value of corresponding heat consumption is:

$$Q_{1.1} = \sum_{i=7}^{16} Q_i /10 \tag{3.2}$$

In the case of 70 days, 50 data points correspond to the first regime, 50 points to the second regime, 20 points to the third regime and 20 points to the fourth regime. We avoid effects of heat accumulation and time delays in the HVAC system by averaging data, but we lose information content. Insid e a regime period (e.g., the period shaded with blue in Table 3.1), events appear that correspond to building use and have certain patterns; for example, turning on lights or opening windows. These patterns mostly follow HVAC control regimes, so averaging hourly data by regime periods should cover those events. This way of grouping will be referred to as *mean values grouped by regimes* or just *mean values* for the remainder of this document.

The third way of grouping data is to divide every weekday into 24 periods and to divide every weekend day into 24 periods. This grouping of data is presented in Table 3.3. With this method, we will get 48 groups of data corresponding to 48 equations. This way of grouping is called the hour-of-day (HOD) grouping. In the case of 70 days, we have 50 data points for every weekday hour and 20 data points for every weekend hour. Patterns of both building use and climatic influences are covered better through HOD data than with hourly data. Building warming-up and cooling-down introduces time delays, so the grouping in Table 3.1 will not cover this effect; thus, it is expected that grouping in 48 groups will capture these effects better than the grouping in Table 3.1. The problem with this way of grouping data is that it requires a longer monitoring period in order to obtain accurate linear regression coefficients. This way of grouping will be referred in the further text as *HOD grouping*.

<table>
<tr><th></th><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>6</th><th>7</th><th>8</th><th>9</th><th>10</th><th>11</th><th>12</th><th>13</th><th>14</th><th>15</th><th>16</th><th>17</th><th>18</th><th>19</th><th>20</th><th>21</th><th>22</th><th>23</th><th>24</th></tr>
<tr><td>M</td><td colspan="6">2.1</td><td colspan="10">1.1</td><td colspan="8">2.1</td></tr>
<tr><td>T</td><td colspan="6">2.2</td><td colspan="10">1.2</td><td colspan="8">2.2</td></tr>
<tr><td>W</td><td colspan="6">2.3</td><td colspan="10">1.3</td><td colspan="8">2.3</td></tr>
<tr><td>T</td><td colspan="6">2.4</td><td colspan="10">1.4</td><td colspan="8">2.4</td></tr>
<tr><td>F</td><td colspan="6">2.5</td><td colspan="10">1.5</td><td colspan="8">2.5</td></tr>
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<tr><td>S</td><td colspan="8">3.2</td><td colspan="7">4.2</td><td colspan="9">3.2</td></tr>
</table>

Table 3.2 Grouping of data with mean values grouped by regimes

The fourth way of grouping that will be analyzed is modeling with mean daily data. The four suggested grouping methods do not represent all possible ways to group the data. Mean values over a week or month of building energy consumption could also be used. These grouping methods were used a lot in practice previously, but more in the sense of predicting building energy consumption than for fault detection. They can be used for fault detection, but with the obvious disadvantage that they cannot show when precisely the fault appears. However, Katipamula et al. (1995) proved that predicting building energy consumption with data grouped on monthly basis gave less accurate predictions than predictions based on using daily or hourly data. Daily values of independent parameters hide variations during a day that exist in the hourly and HOD model, so it is expected that hourly models should give more precise predictions. However, Katipamula et al. (1995) proved that the daily model gives more accurate prediction than two hour models for analyzed systems.

To summarize, all groupings have their advantages and disadvantages. Models with different groupings are more accurate in some senses but inaccurate in others. The presented four groupings should cover all the analyzed effects and will be used in the further analysis. Hourly models are more suitable for O&M problem detection, so they will be preferable if they are also the most accurate model. However, daily models have proved to be more accurate so far in the published research.

	1	2	3	4	5	6	7	8	9
M	1.1.1	1.2.1	1.3.1	1.4.1	1.5.1	1.6.1	1.7.1	1.8.1	1.9.1
T	1.1.2	1.2.2	1.3.2	1.4.2	1.5.2	1.6.2	1.7.2	1.8.2	1.9.2
W	1.1.3	1.2.3	1.3.3	1.4.3	1.5.3	1.6.3	1.7.3	1.8.3	1.9.3
T	1.1.4	1.2.4	1.3.4	1.4.4	1.5.4	1.6.4	1.7.4	1.8.4	1.9.4
F	1.1.5	1.2.5	1.3.5	1.4.5	1.5.5	1.6.5	1.7.5	1.8.5	1.9.5
S	2.1.1	2.2.1	2.3.1	2.4.1	2.5.1	2.6.1	2.7.1	2.8.1	2.9.1
S	2.1.2	2.2.2	2.3.2	2.4.2	2.5.2	2.6.2	2.7.2	2.8.2	2.9.2

Table 3.3 HOD grouping

3.3 How are different groupings expected to cover different effects that define building heat consumption?

The goal of a heating system is to maintain constant indoor air temperature. Complex interaction between building, indoor air and weather introduces more nonlinearity in the space heating demand model than in the ventilation heating model. Changes in the outdoor temperature almost immediately influence ventilation system heat consumption, so the thermal storage effect is not significant. Because of this, the ventilation system is more appropriate to model than the space heating system. The radiator heating system and ventilation systems will be discussed separately because of their different natures.

3.3.1 Radiator space heating system

A simplified scheme of a radiator heating system is presented in Figure 3.1. The presented system gets heat from a district heating system. A furnace can supply the demanded heat instead of the heat exchanger. The simplified system is presented because response times of its components are shorter than an hour, so no special assumptions are needed to analyze their performances.

All the influences that determine consumption of a space heating system will be discussed. Different data groupings cover those influences to varying degrees. The daily model averages influences that affect HVAC performance on hourly and sub-hourly levels. The sense of HOD grouping is not to average time delays due to thermal storage effects or variations of heat consumption that appear because of building use, but to follow patterns that appear from day to day.

3.3.1.1 Weather and its interaction with the building

Difference between indoor and outdoor air temperature is the main driving force of heat transfer through the building envelope. It is a common sense that building heat consumption is a linear function of outdoor temperature for steady-state conditions. If heat accumulation is neglected, heat transfer equation through the flat wall becomes Fourier's law, which represents the dependence between heat flux and the difference between outdoor temperature and indoor temperature multiplied by conductivity k.

$$q = -k\frac{\Delta T}{\Delta x} \tag{3.3}$$

Due to changes in the indoor or outdoor temperature, nonlinear members involving heat accumulation of walls must be introduced in Equation 3.3. Changes in the indoor air temperature are a consequence of using the building: for example, different temperature settings for day and night. Changes in the outdoor temperature also introduce nonlinearity.

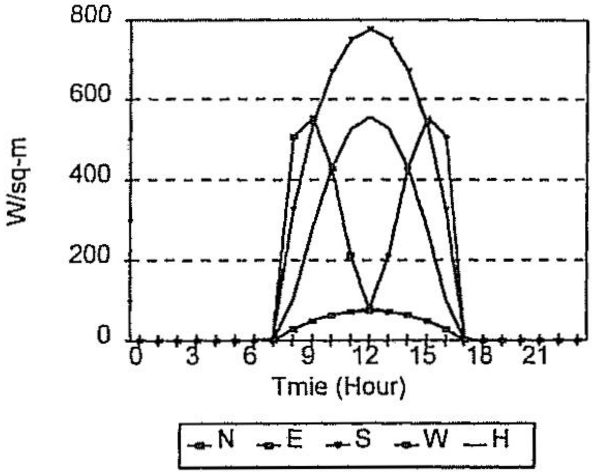


Figure 1 *Solar gain factors on each facet and roof.*

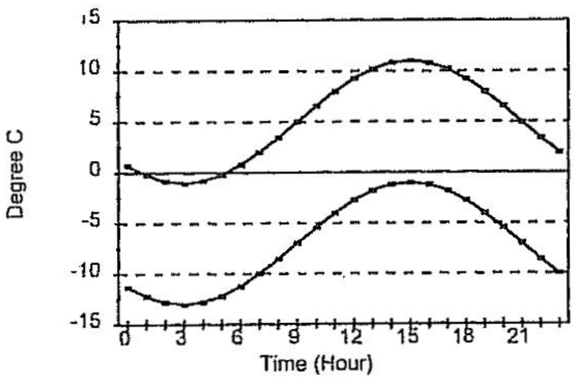


Figure 2 *Ambient temperatures used in the analysis.*

Figure 3.5 Solar radiations and outdoor temperatures during two days used in simulation model analysis conducted by Liu and Claridge (1995)

Other weather parameters besides outdoor temperature also influence building heating demand. Sun penetrates a building through the windows and this energy has to be accumulated first in the walls and furniture in order to be released to the indoor air. This generates a delay between the sun's influence and its effect on indoor air temperature. Window orientation makes the problem even more complicated. If windows are oriented, for example, to the west, sunny morning weather will not contribute much solar gain. Such a building is more sensitive to afternoon sun, i.e., coefficients of linear regression will be higher for the afternoon if the HOD model is used.

Liu and Claridge (1995) discussed the effects of thermal storage on changes of building heat demand throughout the day. They developed a simulation model for a building with medium weight walls. They discussed (1) positive and negative contributions to heat demand from heat accumulated and released by the wall, which corresponds to outdoor temperature changes; (2) decrease of building heat demand due to heat released from walls, which corresponds to solar radiation that entered the building through windows; and (3) decrease of building heat demand due to heat released from walls, which corresponds to solar radiation that is accumulated in the opaque building envelope. The building has the same window area on each of the walls, so sun orientation plays no role. Building ventilation is low, and infiltration is not considered in the simulation model. Internal gains are not considered in the model.

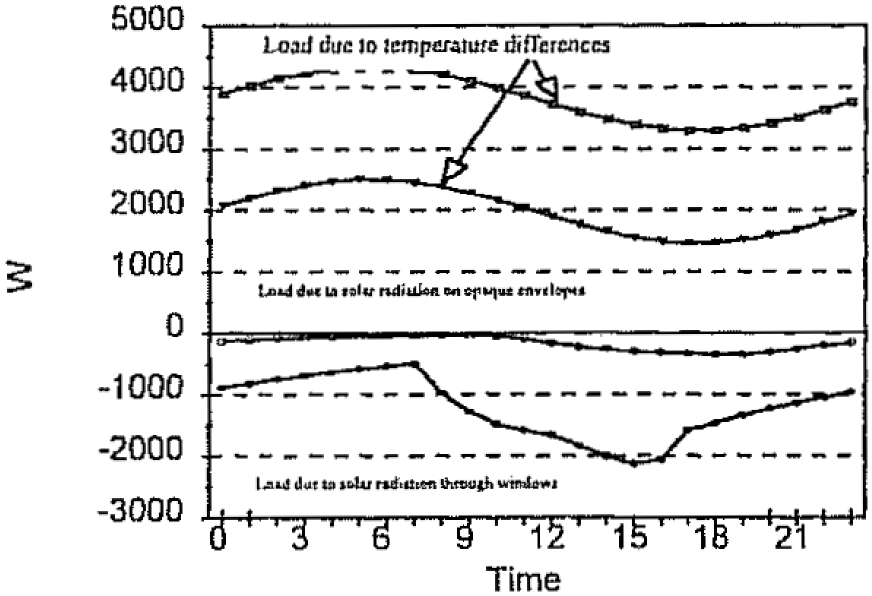


Figure 3.6 Heating load profiles (Liu and Claridge 1995)

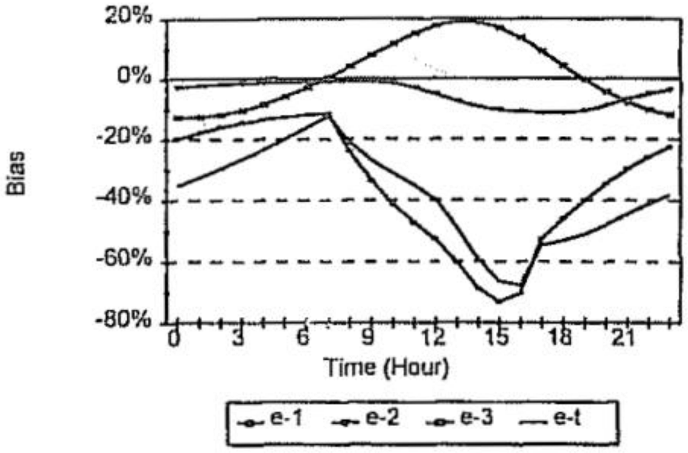
Solar radiation and outdoor temperatures during two characteristic days are presented in Figure 3.5. One day is a cold winter day and the other one can be considered to be a mild winter day. Solar radiation is the same for both days. Figure 3.6 presents heat loads due to (1) temperature difference, (2) solar radiation on opaque envelope, and (3) solar radiation through windows. Heat loads due to temperature difference are presented with two curves corresponding to milder (daily average temperature +5°C) and colder days (daily average temperature -7°C). Those heat loads are calculated with the transfer function method. Maximum heat loads due to temperature differences appears between $5^{\underline{h}}$ and $6^{\underline{h}}$, although the minimum temperature is at $3^{\underline{h}}$, due to the thermal storage effect. Both solar radiation heat loads are negative because they decrease heat demand. Although a day lasts from $7^{\underline{h}}$ to $17^{\underline{h}}$, solar radiation heat loads exist through the whole day because solar radiation energy is accumulated in the walls and is not completely released, even at $7^{\underline{h}}$ when the new day starts. Although solar radiation is at its maximum at $12^{\underline{h}}$, maximum solar radiation heat loads appear around 15^{h}. Ratios between three heat loads and heat load due to temperature difference (steady-state conditions) are presented on Figure 3.7 for cold and mild days. Three ratios are:

$$\varepsilon_1 = E_{solar\text{-}window} / (T_{room} - T_{out})UA \tag{3.4}$$

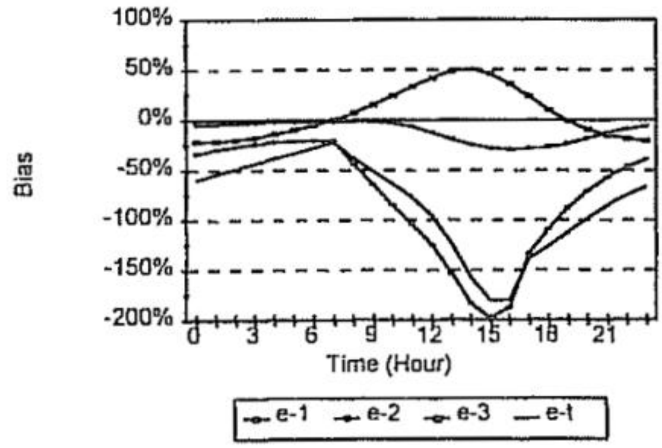
$$\varepsilon_2 = E_{solar\text{-}opaque} / (T_{room} - T_{out})UA \tag{3.5}$$

$$\varepsilon_3 = [E_{Temp} / (T_{room} - T_{out})UA] - 1 \tag{3.6}$$

Ratios (bias on Figure 3.7) represent deviations of real heat demand due to three influences from heat demand calculated for steady-state assumed conditions.



(a) Daily average temperature –7 C



(b) Daily average temperature –5 C

Figure 3.7 Bias due to neglecting solar gains through windows e-1, solar gains through opaque walls e-2, accumulated heat due to change of outside temperature e-3 and total bias e-t (Liu and Claridge, 1995)

Due to the thermal storage effect, which appears due to outdoor temperature changes, heat demand does not correspond completely to the difference between indoor and outdoor temperature. During the evening and night, heat is released from the walls, so heat demand is 13% to 0% lower than it would be with the steady-state case in the period between midnight and 7^{h} for a relatively cold day. For milder day, this decrease is even more apparent. Over the same period of day, the heat demand is from 21% to 0% lower. During morning and afternoon, demand is higher than calculated from the steady-state case because the walls are heated after a cold night. A 20% increase in heat demand is the maximum for a cold day, and a 50% increase for a mild day. A mild day is more sensitive to changes in outdoor temperatures because heat demand is lower for mild days. However, changes of outdoor temperatures are assumed to be the same (temperature curves are parallel, Figure 3.5), so heat accumulations due to outdoor temperature changes for two days have close values. This means that the ratio ε_3 will be much higher for the mild day in the afternoon than for the cold day; thus, thermal storage effect is much more significant for mild days.

The e-2 curve is closer to 0% than the e-1 curve, since heat gains through opaque walls are lower than solar gains through windows, as shown in Figure 3.6. The ratio ε_2 varies from -3% to -1% for nights for cold days and from -5% to -2% for nights for mild days. During the afternoon, the maximum value of ε_2 is -12% for cold days and -25% for mild days. Mild days are more sensitive to thermal storage effects than cold days for solar radiation.

Solar gains through windows are higher than heat losses due to the difference between outdoor and indoor temperature calculated for the steady state case for mild days between $11^{\underline{h}}$ and $18^{\underline{h}}$, so e-1 is lower than -100% in this period. For colder days, the solar influence is not as significant as for mild days, but it still has high significance.

The total bias, e-t, is the sum of the three biases. Its value is negative for both days. It varies from -17% to -65% for the cold day and from -20% to -180% for the mild day. This shows the extent of the error from modeling the heat load with only the difference between indoor and outdoor temperature.

The conclusion presented by Liu and Claridge (1995) is that the thickness of thermal insulation can be decreased due to thermal storage effects, since the thickness of thermal insulation is chosen according to the lowest temperatures that appear during the night. Although this is not an issue, results from this article are presented to show effects of thermal storage on the hourly changes in building heat demand. It is assumed that the indoor temperature is constant during the day. A night temperature setback introduces inside temperature changes, so the thermal storage effect will be even more significant.

The LR model with different data grouping will consider the effects of thermal storage to varying degrees. The simplest case for analysis is to assume that the HVAC system operates with only one control regime (there is no temperature setback during nights and weekends), which is the case analyzed by Liu and Claridge. In this case, the data grouping with mean values is the same as modeling with daily data. Modeling with hourly data would be a worse choice regarding thermal storage effects. If there is no solar influence, it is expected that hourly predictions of HC will be higher than real HC at night. During late morning and afternoon, hourly predictions of HC will be lower than the true HC.

The HOD model should be better than the hourly model, since changes in outside temperature as well as changes in solar radiation follow the same pattern every day. The maximum temperature appears around $15^{\underline{h}}$. Liu and Claridge (1995) have shown that at $15^{\underline{h}}$ 50% of heat delivered by the space heating system accumulates in the walls on mild days. The HOD model will account for this, and it will increase the predictions in late morning and afternoon and decrease predictions at evening and night. However, temperature differences between day and night vary from day to day, so the thermal storage effect is not fully covered by this grouping. Also, HC increases during late morning and afternoon (decrease of HC during evening and night) are more significant for mild days, so models with a whole year of data cannot fully consider this phenomenon. Solar radiation also follows a pattern during the day. However, day length varies through the year (especially in Norway), so the HOD model will probably underestimate solar influence if the calculation is conducted with a whole year's worth of data. It is better to model data from a monitoring period when the length of day was constant in order to better estimate the solar influence with the HOD model. The building used in simulation was developed by Liu and Claridge and does not have a dominant orientation. However, since the sun orientation is changed during the day, the hourly model cannot follow this change. The HOD model is also, in this case, superior to the hourly model because the LR coefficient for solar influence can be higher for hours, which corresponds to the same position of the sun and dominant building orientation.

The daily model should best cover thermal storage effects. Areas between a-3 bias and 0% over and under 0% are approximately equal for the cold day case (Figure 3.7). For the mild day case, it seems that area over 0% is larger than area under 0%, so it is expected that, for cold days, predictions should be more accurate than for mild day. Regarding solar radiation, this model should fully cope with change of day length, as opposed to the HOD model. However, since it is proved that accumulated solar radiation is released the day after, even the daily model could not fully cover the effects of thermal storage. The daily model averages effects of changes in the sun's orientation. However, even this model does not cover fully change if the building is not equally oriented on all sides. During the spring, days are much longer than in the winter. It can happen that the sun does not reach a window during winter, and it reaches a window in spring, so outdoor solar radiation will not correspond to solar energy that entered building.

The aim of the model that uses mean values is to average variations, like the model with daily data. Variation due to thermal storage effects is presented in Figure 3.7. The thermal storage effect due to changes in outdoor temperature increases heating demand between $7^{\underline{h}}$ and $18^{\underline{h}}$, compared to the heating demand that would exist in steady-state case. Since these are working hours, and control regimes follow working hours, the thermal storage effect due to changes in outdoor temperature is covered by this grouping. For non-working hours, thermal storage decreases heating demand, and those hours belongs to the night regime. Regarding solar radiation, grouping the data by day and night will follow decreases in building heating demand due to solar radiation (Figure 3.7). The day regime will have a more significant decrease of heat consumption due to solar radiation. However since the length of day varies significantly, especially in Norway, daily variation of released accumulated solar radiation will also change significantly during a year. As a result, a courser resolution (daily model) will be preferable in this case.

Regarding wind, air enters a building through opened windows or gaps. The wind instantaneously decreases indoor air temperature, i.e., increases heating demand, so there is no delay between the moment when air has entered building and the moment of change of heating demand. Because of that, hourly and HOD models should be preferable to the daily model and the model with mean values grouped by regimes, since they explain more variation. The air tightness of the building can be changed over the course of a day. For example, occupants often open windows on weekday mornings to air offices. It is obvious that there is a certain time pattern of opening windows during the day, which can be covered if linear regression is conducted with the HOD model. The daily model averages these events, so it covers them. Opening windows also introduces a complicated fluid dynamic phenomenon that causes penetration of outdoor air. Later, a method will be presented to cover changes in the nature of the natural ventilation phenomena. Wind direction can be also very important. The geometry of the building and its surrounding makes the building more ‘vulnerable’ to wind from certain directions. However, wind direction was not considered in this thesis.

It cannot be directly estimated how models with different data groupings will cover different effects. The presented theoretical considerations assume how influences will be covered with different data groupings. Those assumptions will be checked through the analysis of goodness of fit and contributions of different independent variables to the accuracy of LR models with different data groupings.

3.3.1.2 Building use

Heat released by occupants, lights and equipment decreases building heat demand. Heat released by occupants and equipment almost immediately increases indoor air temperature. Radiant heat gains from lights are released from the walls for hours after turning-off the lights.

Building use is not presented in the LR model as an independent variable, although it is possible to introduce electricity use as its surrogate (Reddy et al. 1999). Heat gains introduce change points into the LR model (Figure 3.3) and decrease the constant component of the linear regression model for the temperature-sensitive part of the operation. Hourly variation of heat gains from occupants, lights and equipment are indirectly covered by grouping of data into regimes, since regimes follow working hours. Daily data average hourly heat gains. Mean values also properly average internal heat gains since regimes follow working hours. Hourly data are also grouped by regimes. However, if occupant behavior follows a certain pattern through the working hours, the HOD model will better cover this pattern than the hourly model. The problem for the hourly model is thermal storage effect for radiant heat from lighting. The HOD model will consider the thermal storage effect, by reducing heat demand for hours when accumulated radiant heat is released. Because of this, the hourly model can be considered as the worst in covering lighting heat gains.

Change point temperatures are calculated for hourly data and mean values for each regime separately from hourly heat consumption and temperatures, which is a correct representation of internal heat gain due to building use, since control regimes follow building occupancy. Calculations with HOD data and daily data calculate change point temperatures from hourly data separated into weekdays and weekends. Although weekends correspond with unoccupied hours, the difference in occupancy between nights and days for weekdays is not treated, which makes this way of calculating change point temperatures less accurate than calculations for hourly data and mean values.

Hourly data are separated in the data below and above the change point during calculations of mean values grouped by regimes and calculations of mean daily data. LR is conducted for temperatures under the change point, so introducing data points with temperatures over the change point would deteriorate accuracy. The thermal storage effect is more significant for higher temperatures, so the LR model will have difficulty coping with higher temperatures.

As stated previously, all of the mentioned effects are not separately analyzed in the discussion of LR models. Goodness of fit of models calculated for same monitoring period with different groupings are compared in order to conclude which model gives the best results.

3.3.1.3 Performance of HVAC system components and HVAC system control

The HVAC system and its control stand last in the flow chart presented in Figure 3.2. None of the HVAC system parameters are independent variables in the inverse model. However, the performance of the HVAC system follows the performance of the overall system presented in Figure 3.2. The HVAC system control maintains indoor climate within the desired limits, so it represents a ‘bridge’ between the building and its HVAC system.

The radiator heating systems consist of a heat exchanger or furnace supplying hot water to the system, pipes connecting components, pumps, radiators and accompanying control equipment. Relevant literature claims that the response times of all these components, as well as their controls, are shorter than an hour, so all the effects are averaged over the hour or day time period. This means that the HVAC components and control should not be concerned with hourly and daily level modeling. Radiator space heating is not analyzed with regard to inverse modeling in representative literature. There are models of air-side space heating. Radiator space heating has a longer response time than air-side space heating, because of the slower mixing of indoor air.

For components that are controlled by an on-off principle, if a parameter difference that defines on-off operation is wide, the response time is longer. If heat is produced by a furnace with a high accumulation of hot water, its response time can be relatively high. This can be especially significant for partial load operation, i.e., for warmer days. The mentioned control issues regarding response times are not checked in this thesis, but should be addressed in the future.

Night temperature setback makes the night outdoor temperature less relevant than the day outdoor temperature for daily heat consumption. This means that a regression that uses daily values is not accurate. The purpose of the mean values grouped by regimes is to cover different performances of the HVAC system properly during day and night operation. However, nonlinearity effects due to thermal storage can be better covered with more coarse time resolutions. All the discussed effects overlap over in time, so goodness of fit of LR models with different groupings will show how models cope with them.

The other issue of night temperature setback is that the thermal storage effect appears, just as it appears due to changes in the outdoor temperature (discussed in subchapter 3.3.1.1). The daily model and model with mean values grouped by regimes should cover this effect through averaging. The HOD model should cover this effect by increasing heat consumption for hours at the beginning of the daily regime and decreasing heat consumption for hours at the beginning of the night regime. Hourly models will not cover this effect.

3.3.2 Ventilation system

With a space heating system in which the indoor temperature is maintained by thermostatic radiators, there are the building envelope, radiators, pipes and heat exchanger connected to the district heating (or furnace), which stand between climatic influences (disturbances) and the primal energy carrier – district heating hot water (or fuel). Because of this, there is a time delay between disturbances and heat consumption. Outdoor air is taken directly into the ventilation system and heated to a set temperature, so the air temperature influences heat consumption without time-delay. Opposite to space heating, outdoor temperature (the most important influence) directly affects heat consumption of the ventilation system, i.e., the building envelope does not stand between them.

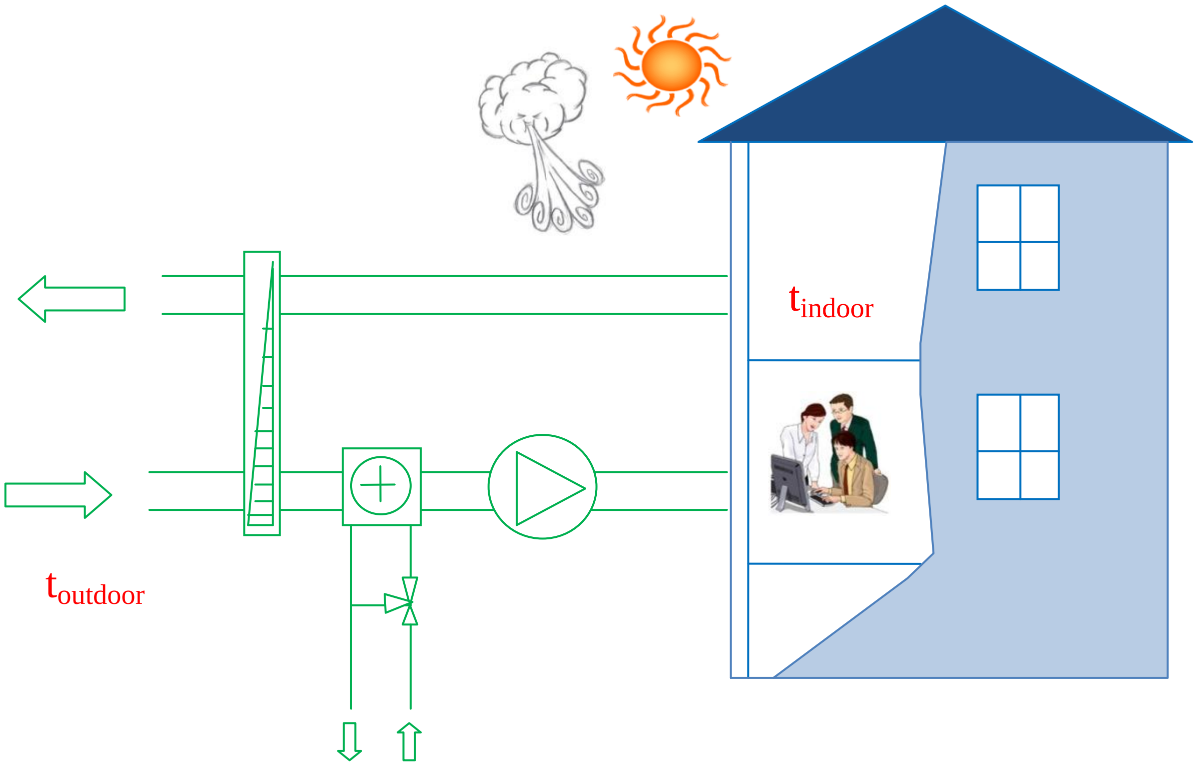


Figure 3.8 Simplified scheme of ventilation system with economizer

A ventilation system with an economizer uses indoor air to preheat outdoor air (Figure 3.8) so in this case, the amount of used energy depends of occupancy and other parameters that define heat gains. In the case of variable air volume systems, the amount of air depends on space occupancy. Variable air volume systems will not be analyzed.

Ventilation systems keep the air temperature constant behind the ventilator. Changes of outdoor temperature will directly and linearly influence heat consumption without any time delay. The only time delay that exists is inside the heat exchanger. Because of this, the hourly model has the same ability to cover temperature variation as the HOD model. The model with mean values averages deviations in the temperature, so information about the variation of temperature is lost through the averaging process. That is why the hourly model and the HOD model should be more precise. Decreases in heat consumption during unoccupied hours are much more significant for the ventilation system than for the space heating system. Since the daily model uses night temperatures as equally significant as temperatures that correspond to occupied hours, predictions of the daily model can be significantly inaccurate.

Unlike outdoor temperature, sun heat gains will not directly influence heat consumption. Solar influence will increase the indoor air temperature, so return air with higher temperature will decrease heat consumption by operation of the economizer. The solar influence has delays and involves nonlinearity due to accumulation of heat inside the building. The indoor temperature is maintained with space heating. If heat gains are higher than heat losses, the temperature will rise over the set indoor temperature. It can also rise over the set value if the space heating control does not react fast enough. In these cases, the economizer will utilize heat from heat gains. It is not possible to model this scenario through LR. However, part of the heat gains that decrease ventilation heat consumption will be covered. The thermal storage effect discussed in subchapter 3.3.1.1 also matters in the case of ventilation heating. The same conclusions regarding the ability of different data groupings to cover solar radiation as for space heating apply to the ventilation system. Solar radiation accumulated in walls releases for hours. The hourly model is expected to be the worst in the sense of covering thermal storage effects. The HOD model will follow the daily pattern of thermal storage effects. The daily and model with mean values average variation due to thermal storage effect. Daily model is expected to better consider the solar influence than the model with mean values grouped by regimes.

Wind is expected not to have influence ventilation system heat consumption, since space heating will compensate for infiltration losses before the indoor temperature decreases.

Heat gains from occupants, lights and other electrical appliances do not directly decrease ventilation heating. Just as for sun, this heat can be utilized only if the indoor temperature rises over the set value. The LR model will cover part of this variation. As for space heating, the HOD model is preferable to the hourly model, because of its ability to cover the building use patterns. The daily model and the model with mean values that average variation due to heat gains take it into account in this way. Regarding ventilation components and their control, response times are shorter than an hour, so they should not influence the accuracy of models with hourly and daily resolutions.

Goodness of fit of the LR model of ventilation system is expected to be better than for space heating, since thermal storage effects due to temperature change are not significant for ventilation heating. Since outdoor temperature is the most important factor defining space heating heat consumption, covering thermal storage effects is expected to be crucial for accuracy of LR models.

The measured heat consumption modeled in this thesis, was a combination of heat consumption of the ventilation and space heating systems and heat consumption of the ventilation system. There were no measurements that corresponded only to the heating system. Since the LR model is the same for both ventilation heating and space heating, modeling of the mixed heat consumption is correct. Some of the analyzed buildings have electric heating, so their heat consumption corresponds to ventilation heating. Since heat consumption for these buildings also have change points, this heat consumption could also be used for tap water preparation. The presence of a change point means that the change point model should be used.

3.4 Simple linear regression model with outdoor temperature as independent variable

It is common sense that the building heat consumption is a linear function of outdoor air temperature. Outdoor temperature is the main driving force that influences building energy use (ASHRAE 2001). Previous studies (Fels, 1986; Kissock et al., 1993; Katipamula et al., 1994; Reddy et al., 1997) have shown that outdoor air temperature is the most important factor, especially at the monthly and daily time scales. The hourly time scale involves heat accumulation effects. Dynamic models try to capture the effects, such as building warming-up or cooling-down through sending time-lagged variables into a model. They are designed to be more appropriate for FDD’s with an hourly time scale. However, building such a model demands extensive expertise of the users and detailed measurements to tune the model. Steady-state models do not consider the effects of heat accumulation. Those models are appropriate for analysis with monthly, weekly and daily data (ASHRAE 2001). In this thesis, steady-state models with hourly data will be also used. A comparison of goodness of fit for models with different data groupings will show if different influences defining building heat consumption are captured.

Steady-state models are mostly used for predicting building energy use. Their use in FDD’s is considered to be unreliable. Of special concern in this case is the mild weather, when the consumption is more sensitive to other influences, such as occupancy and solar influences. Despite this, steady-state methods, such as the degree-day method, give quite precise results for the prediction of annual heating energy consumption. Typical buildings have time constants that are about one day, so averaging consumption on a daily basis gives good results. The building heat consumption during mild weather is small, so relatively high errors have small effects on annual consumption (ASHRAE 2001).

Two characteristic periods of building heat energy consumption can be recognized in Figure 3.3: a period when it depends on the outdoor air temperature and a period that corresponds to base level consumption. In the latter period, there is no need for heating because internal heat gains are sufficient to maintain indoor air temperature at or above the desired indoor temperature or the outdoor air temperature was higher than the desired indoor temperature. Base level consumption includes energy requirements for tap water heating. In the case of electric heating, the same meter will register electricity consumption for all appliances in the building; thus, base level consumption will also include electricity for lighting and other equipment in the building. Fels (1986) expressed expected energy consumption for the building as:

$$Q = \alpha + \beta(\tau - T_{out})_{+} \tag{3.7}$$

where:

α - base level consumption (BLC), or constant term

β – heat-loss rate, or slope term

τ – heating reference temperature or change point temperature

T_{out} – outdoor air temperature

+ – indicates zero if the term is negative

The heating reference temperature or change point temperature is influenced by the indoor temperature and internal heat gains of a building. The heat-loss rate β depends on the conductivity of the walls and air tightness of the windows. Solving the linear regression formulation (equation 3.7) assumes that τ is a known value, since only two regression coefficients, α and β, can be calculated. It is discussed by Fels (1986) that assuming τ as 18.3°C, which was usual in practice, can lead to unreliable values of the base level and heat-loss rate. The change point temperature (CPT) was lower than 18.3°C for all analyzed buildings in this study, confirming this claim.

In order to determine τ, it is possible to make different trial calculations with different τ values and to select the one which gives the highest value of the coefficient of determination (R^2). That procedure is expressed in the algorithm presented by Kissock et al. (2003). It uses a two-part grid-search method to find the CPT corresponding to the highest R^2. In the first step, ten different values of CPTs are tried by dividing the whole temperature interval by ten. For value which gives maximum R^2, a finer grid (ten new CPTs) is introduced around it in the second step. This method is used later in many analyses, and it never demonstrated numerical instability.

This method was used in the thesis to determine the CPT, but was slightly modified. For all temperatures between the lowest temperature and 20°C, the coefficients of determination were calculated. The calculation giving the highest coefficient of determination gives the CPT. When this method was used in this thesis, the defining slope term was accurate, even in the cases when only data from the winter were used.

3.5 Evaluation of possible improvements to the LR model by introducing wind speed and solar radiation as independent variables

Other influences, such as solar radiation and wind can be introduced in the multiple linear regression model. These models are logical extensions of the simple LR model. Measured solar radiations and wind speeds are readily available data. They were found on the Norwegian metrological institute (www.met.no) web-site for this thesis, along with the outdoor temperature. ASHRAE (2001) claims that, except outdoor temperature, other influences do not contribute significantly to the building heat consumption. The purpose of subchapter 3.5 is to determine the necessity of introducing a multiple linear regression model.

3.5.1 Evaluation of the solar radiation influence on building heat consumption

Solar gains can be significant in Norway, especially during the spring when the outdoor temperatures are still low. In this period, the sun is low in the sky, and days are long, which results in high solar gains. This causes lower heating demand in April and especially in May. Table 3.4 presents deviations of monthly heat consumption from predictions gained from the simple LR model. Heat consumption is the overall heat consumption of monitored buildings at Gloshaugen campus in Trondheim, which comprises approximately 20 buildings. It can be concluded from Table 3.4 that the lowest deviation of consumption appeared in May for every analyzed year.

	2003	2004	2005	2006	2007
March	-1.43	-13.54	-0.71	1.70	-2.24
April	-10.36	-0.28	-8.72	-1.05	-8.85
May	-13.10	-21.44	-18.87	-8.33	-16.26
October	-3.54	-2.55	-5.73	-2.83	-4.21
November	2.54	1.61	-4.02	6.72	3.11

Table 3.4 Monthly deviations of actual overall heat consumption from predicted overall heat consumption for the NTNU Gloshaugen campus in Trondheim (%)

	2003	2004	2005	2006	2007
March	3.27	2.42	0.03	-3.70	3.46
April	5.16	7.37	5.64	5.29	4.76
May	8.78	8.73	7.16	8.63	8.16
October	3.89	6.16	5.32	6.72	6.45
November	2.77	1.00	2.67	4.14	3.34

Table 3.5 Mean monthly temperatures for Trondheim in period 2003-2007 (°C)

Mean temperatures for the months listed in Table 3.4 are presented in Table 3.5. From Table 3.5, it can be concluded that April and October have similar mean monthly temperatures. However, solar gains in Norway are higher in April than in October. This resulted that the monthly mean deviations for April had, in most cases, lower values than for October. The mean value of the monthly deviations is -7.24% for April and -3.77% for October. As it is expected, monthly deviations for May are even lower than for April due to higher solar gains. The mean value of the monthly deviations for May is -14.4%. In the spring of 2004, the heating system did not operate correctly, so values for spring 2004 are not taken into the calculation of the mean values of monthly deviations for April and May. Heat consumption in this period did not correspond to outdoor temperature for many days. If we exclude 2004, there is an obvious pattern in Table 3.4 that monthly deviations decrease from March to May and increase from October to November as a consequence of solar gains. The conclusion is that solar radiation influences building heat consumption, so including it into the multiple LR model is reasonable.

3.5.2 Evaluation of wind influence on building heat consumption

Wind influence is analyzed for January and February during the period 2003-2007 in order to avoid overlapping with the influence of solar radiation gains. Sun heat gains in January and February can be neglected in Norway. Actual overall heat consumption of the Gloshaugen campus and its predictions modeled through simple LR are compared. Heat consumption and outdoor temperature data were collected for 5 years. Table 3.6 presents the numbers of days when the day-mean wind velocities were within the given limits. Absolute deviations in Table 3.6 represent mean daily deviations of the overall heating demand from the predicted values of daily heating demand for the days when mean wind speeds were within given limits. For the entire analysis period (January and February 2003-2007), the mean deviation from the predicted value of the heating demand was 5.25%, i.e. heat consumption was 5.25% higher than predicted. This is reasonable and expected since we can see from the Table 3.4 that monthly deviations are positive during the winter and negative during the spring and fall, due to solar influences. The last column in Table 3.6 shows the relative deviations, which represent absolute deviations reduced by 5.25%. Since relative deviations are positive, it can be concluded that wind caused the increase in the heat consumption.

	Number of days	Absolute deviations (%)	Relative deviations (%)
$4 < v < 5.5$ (m/s)	30	6.0	0.75
$5.5 < v < 7$ (m/s)	21	8.15	2.9
$v > 7$ (m/s)	11	8.08	2.83

Table 3.6 Mean deviations from predicted values of overall heating demand for Gloshaugen campus as a result of higher wind influence

Days with mean wind velocity between 4.0 and 5.5 m/s appeared in 30 of 295 days, which represents 10.2% of days in analyzed period. Wind velocities from this interval did not significantly increase the heat consumption, only by 0.75%. Wind velocity between 5.5 and 7.0 m/s appeared in 21 of 295 days, which presents 7.1% of days in the analyzed period. The corresponding relative deviation of 2.76% should not significantly influence the accuracy of the analysis conclusions based on the model that did not take wind influence into consideration. It was expected that velocity higher than 7 m/s will result in a greater increase in heating demand. However, due to statistical error caused by the low number of these events, this did not happen. Although wind influence did not appear to be as significant for overall heat consumption of Gloshaugen campus as solar influence, it is possible that for some buildings this influence is more significant. Thus, both solar radiation and wind will be included in the multiple linear regression model which will be presented in the next subchapter.

3.6 Building a multiple linear regression model

Heat consumption of building is influenced by outdoor climatic parameters: temperature, solar radiation and wind. Other influences are captured in the LR model by grouping the data as discussed in subchapter 3.3.

Heat consumption for the summer period is defined only by consumption of tap water. Those consumption are excluded from the multiple linear regression model by recognizing CPT and base level heat consumption, which was presented in subchapter 3.4. This means that linear regression is performed only for data points with outdoor temperatures lower than the CPT. The linear regression formulation presenting the dependence of the building heat consumption on outdoor climatic parameters is:

$$Q = A + B_1 \cdot (T_{SET} - T) + B_2 \cdot W^* \cdot (T_{IN} - T) + B_3 \cdot S \tag{3.8}$$

where variables in the equation are:

A and B – regression coefficients

T_{SET} – change point temperature

T – outdoor temperature

W^* – wind speed

T_{IN} – indoor temperature

S – solar radiation on vertical surface

If the outdoor temperature is higher than T_{SET}, that point in the monitoring history is excluded from the linear regression calculation. As a consequence, (T_{SET}-T) is always positive, which causes B_1 to also be positive. This suggests that, if outdoor temperature T is lower, heat consumption is higher. $B_1 \cdot T_{SET}$ is a constant value, so T_{SET} can be excluded from the formulation. Other authors did not introduce CPT in the LR model. If T_{SET} were to be excluded, the regression coefficient A would be higher. However, it is more physically understandable to formulate the LR model as in equation 3.7. Predictions gained through the LR calculation would be the same for both models. B_2 is also positive. B_3 is negative.

The same LR formulation is used for both space heating and ventilation systems. Regarding ventilation heating, a change point also appears in this case. Internal heat gains and solar gains increase indoor air temperature. If the amount of heat delivered to fresh air through the economizer is greater than the heat needed to heat the fresh air to the set temperature, additional heating is not necessary.

3.6.1 Presentation of wind influence in the linear regression model

Regarding wind influence, there are two defining parameters: wind speed and the difference between indoor temperature (T_{IN}) and outdoor temperature (T). T_{IN} is constant. T_{SET} is always lower than T_{IN}, due to heat gains of buildings, such as solar gains and internal gains. Since the values of T are lower than T_{SET} used in linear regression, (T_{IN}-T) is always positive. Since wind speed is also positive, B_2 is also positive. In all conducted calculations, T_{IN} is fixed at 20°C, but that value could be changed in the program if there is a need to do so. Regarding wind speed, the amount of air entering a building is a function of many factors, such as the characteristics of windows and doors, the position of building, and the configuration of the building. Air infiltration is nonlinear when estimated from wind speed and the indoor/outdoor temperature difference (ASHRAE 2003). Generally, from Bernoulli the equation, it is known that flow is linearly dependant on $\Delta p^{1/2}$. Determining Δp is rather complicated. Todorovic (2005) defines heat losses due to natural ventilation as:

$$Q = V \cdot c \cdot \rho \cdot (T_{IN} - T) \qquad (3.9)$$

where:

V – air flow rate

c – specific heat of air

ρ – density of air

T_{IN} – indoor air temperature

T – outdoor air temperature

Air flow rate is gained from the equation:

$$V = \Sigma(a \cdot l) \cdot (\Delta p)^{2/3} \tag{3.10}$$

where:

a – permeability of air gaps

l – length of air gaps

Δp – pressure difference on inner and outer side of air gap

However, Δp is rather complicated to determine, so equation 3.9 is simplified to:

$$Q = \varepsilon_h \cdot H \cdot (T_{IN} - T) \tag{3.11}$$

where:

ε_h – correction for building height

H – building characteristics

If the building characteristics are not known, this rather complicated procedure for determining natural ventilation heat losses becomes even more complicated. Also, characteristics of openings change during the day because, for example, windows can be opened by an employee arriving at work in the morning, which makes analysis of hourly heat consumption meaningless. That is why heat demand for natural ventilation is expressed as an estimated function of wind speed W^* in equation 3.7. Figure 3.9 presents a house and wind, which makes an eddy behind it. Due to the eddy, lower pressure appears behind the house. Opening the window on the side of the building exposed to the wind will bring high penetration of cold air. With low wind speed, the inside air in the upper part of the building will go out due to indoor thermal overpressure (Todorovic). It is obvious that natural ventilation is a complicated phenomenon, and that heat losses due to natural ventilation cannot be expressed simply by wind speed. A couple logical choices for W^* were tried, and the expression giving the highest value of R^2 was selected. Three expressions for W^* are included: $W^{1/2}$, W and W^2.

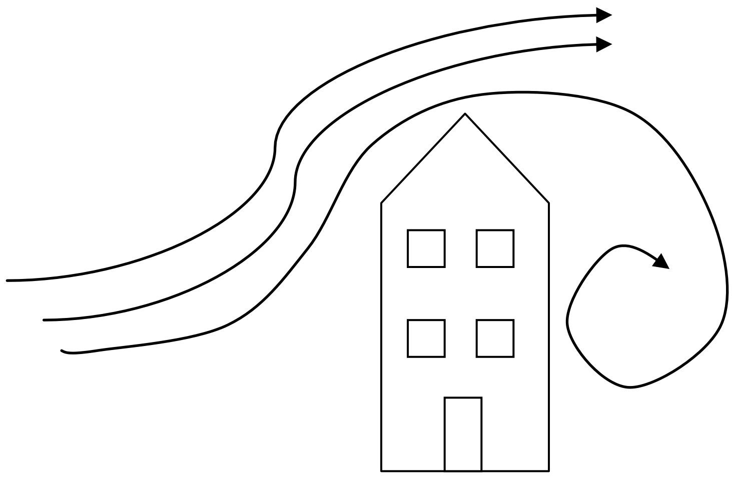


Figure 3.9 House exposed to wind

3.6.2 Presentation of solar radiation influence in the linear regression model

Solar radiation on vertical surface is regarded as representative for calculation of solar heat gains, since solar radiation energy mostly enters a building through windows. Other authors used global horizontal radiation in multiple linear regression models (Katipamula et al. 1995). S in equation 3.7 is solar radiation on vertical surface. In order to calculate projection of solar radiation on vertical surface, sun elevation angle has to be found for every hour. Solar radiation on vertical surface is calculated from solar radiation on horizontal surface and cotangent of sun elevation angle α_{SUN}:

$$S_{VERTICAL} = S_{HORIZONTAL} \cdot \mathrm{ctg}(\alpha_{SUN}) \tag{3.12}$$

Sun elevation angle is calculated from equation:

$$\sin \alpha_{SUN} = \cos h \cdot \cos \delta \cdot \cos \Phi + \sin \delta \cdot \sin \Phi \tag{3.13}$$

where:

h - hour angle in the local solar time; 0° indicates noon and 180° indicates midnight

δ - current sun declination; $\delta = -23.45 \cdot \mathrm{COS}(360/365) \cdot (N + 10)$, where N is the number of days since January 1st

Φ - local latitude, 63.6° for Trondheim

Hourly values of sun elevation angle in Trondheim for the three weeks in March, April and May are presented on Figures 3.10, 3.11 and 3.12. For the high latitude as Trondheim has, it is evident that days last shortly in the winter and long in summer. From Figures 3.11 and 3.12, it is obvious that, for most days in April and May, the sun has an elevation angle between 0° and 30°, which causes a significant amount of sun radiation energy to enter buildings through windows. The mean day temperatures in Trondheim can be under 5°C in May, so space heating is needed. Mean monthly temperatures in March, April and May for Trondheim are presented in Table 3.5. The sun influence is evident in this period, so the combination of these two driving forces determines the heat consumption of buildings.

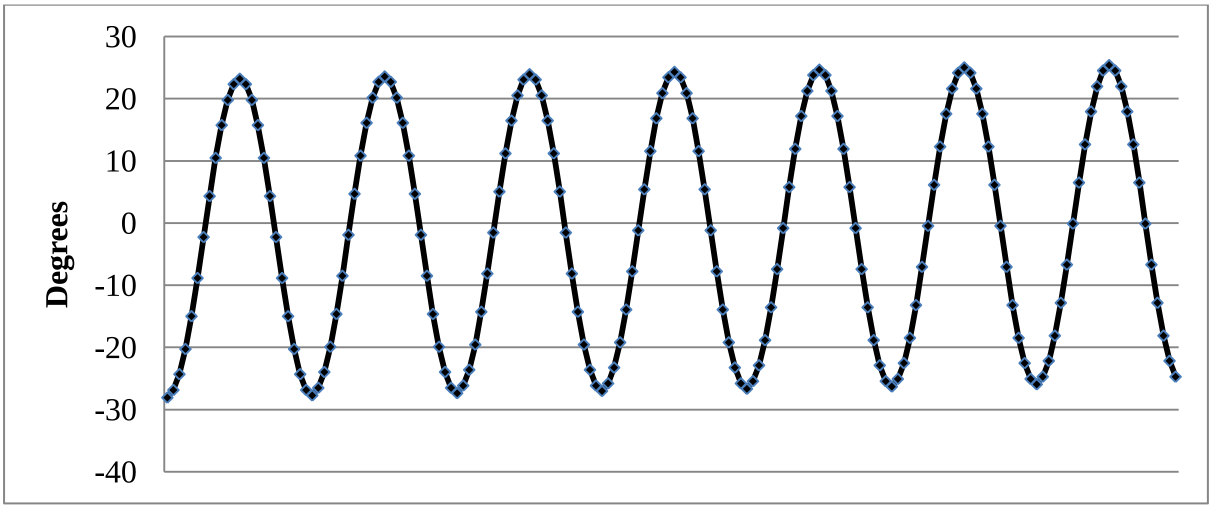


Figure 3.10 Hourly values of sun elevation angle from March 15 to March 21

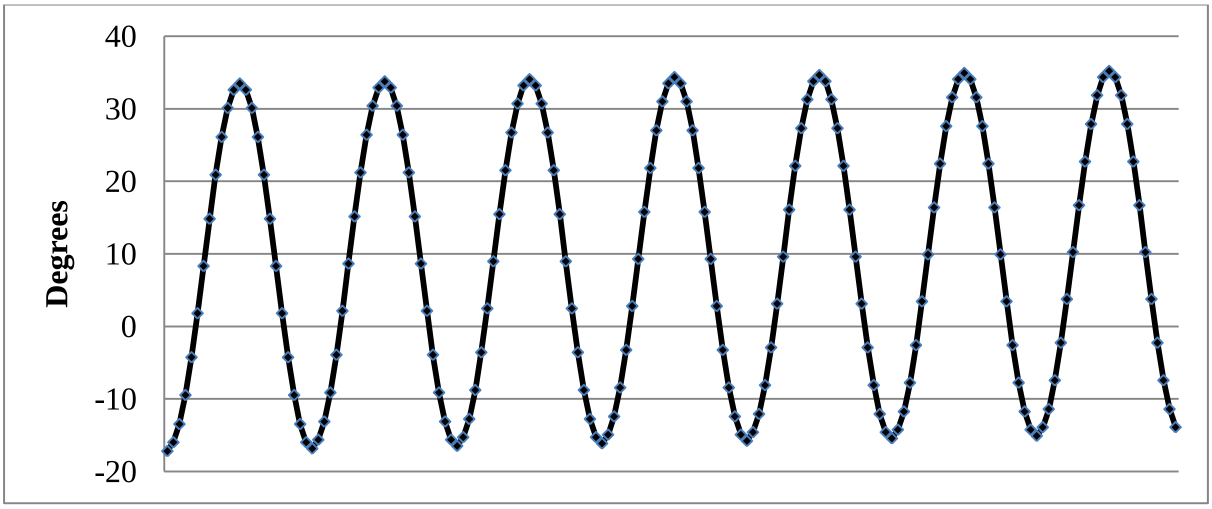


Figure 3.11 Hourly values of sun elevation angle for the period April 15 to April 21

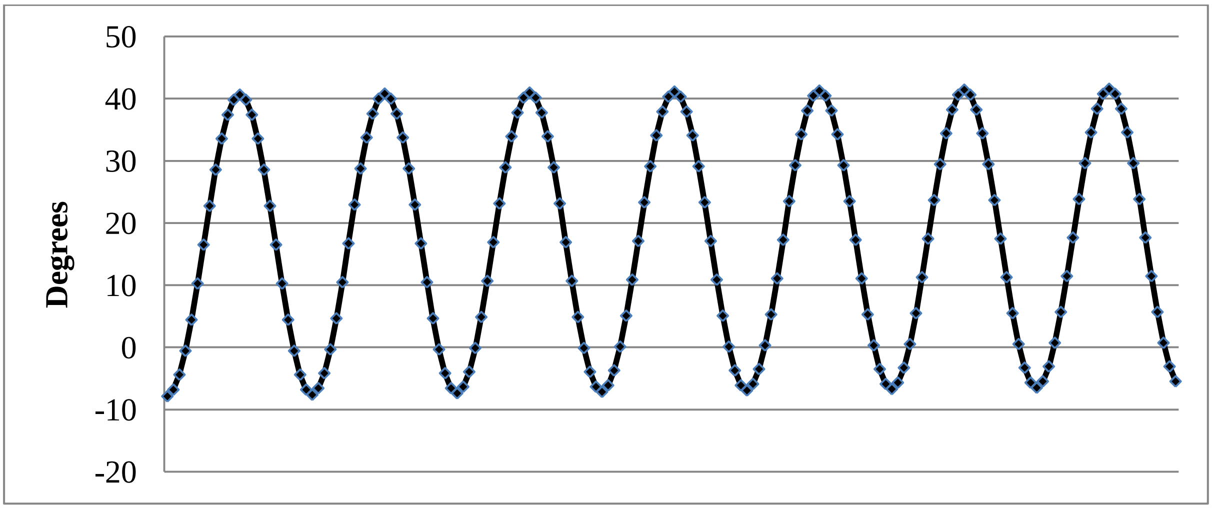


Figure 3.12 Hourly values of sun elevation angle for the period May 15 to May 21

The hourly values of solar radiation on the horizontal surface for May 21, 2007 measured in Tronheim are presented in Table 3.7. Negative values appear due to radiation from the surface to the space during the night. Solar radiation is evidently the highest at noon. However, if those values are corrected by the cotangent of sun elevation, we get a different picture. Hourly values of solar radiation on the vertical surface for the same day are presented in Table 3.8. Due to low sun elevation angles, higher values appeared, not at noon, but in the morning and afternoon. The maximum appeared, surprisingly, at $22^{\underline{h}}$. This value does not seem to be realistic. The calculated angle of the sun elevation at $22^{\underline{h}}$ is 0.707°. For such a low angle, the cotangent has high value. For example, the cotangent of 1° is 57.32. This problem would introduce instability in the regression model. For such small values of sun elevation angle, there is a high probability that the building would be in the shadow of its surrounding. Thus, a correction is introduced which replace the cotangent of sun elevation for small sun elevation angles. The correction is used instead of cotangent for sun elevation lower than 9° (Figure 3.13). For sun elevation lower than 2°, solar radiation is excluded as a parameter from linear regression because the building is probably in shadow, so the correction is equal to 0. For the other values of sun elevation, corrections are smaller than the cotangent of sun elevation, especially for small angles. For 9°, cotangent and correction have same value.

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Solar radiation	-1.4	-0.8	-0.7	0.1	6	35	52	83	144	198	292	447
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Solar radiation	386	577	745	533	488	507	200	91	58	54	2.5	-2.9

Table 3.7 Hourly values of solar radiation on a horizontal surface for May 21, 2007 (W·h/m^2)

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Solar radiation	0	0	0	8	61	175	164	190	254	288	369	519
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Solar radiation	436	671	943	775	861	1150	632	451	586	4418	0	0

Table 3.8 Hourly values of solar radiation on vertical surface for May 21, 2007 (W·h/m^2)

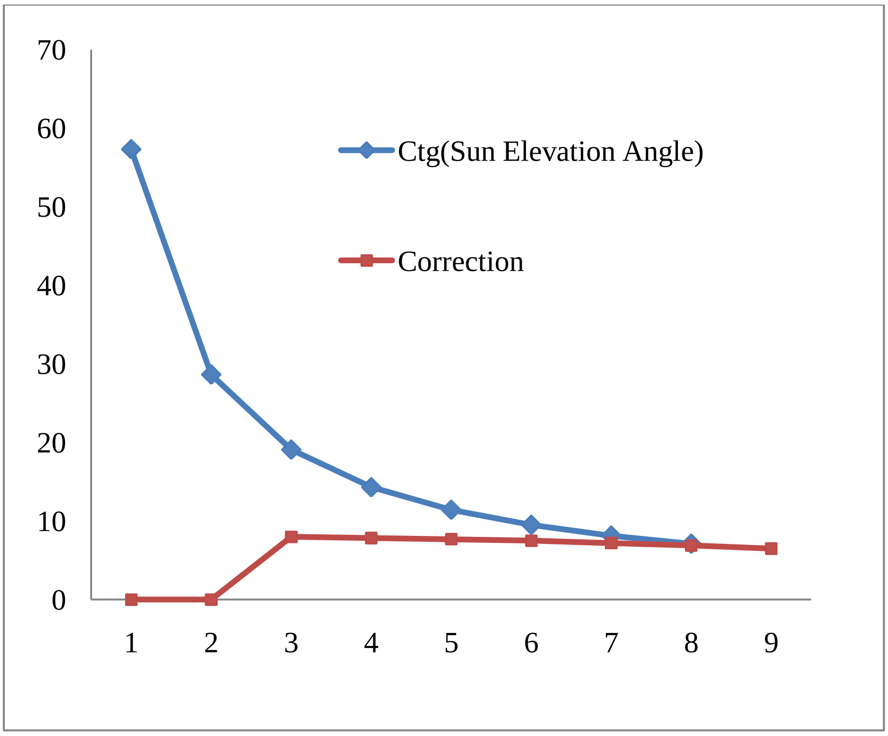


Figure 3.13 Correction of sun elevation angle cotangent

3.7 Model improvement by excluding outliers

Outliers (residuals) appear due to a HVAC system malfunction or measurement errors. There is interest in identifying outliers and repeating the calculation with the set of data that does not contain outliers. There are two ways to recognize and exclude outliers from the data used in linear regression modeling and both are used in this thesis: (1) manual - through visual inspection of diagrams and (2) automated - inspection of the R-student residual statistic. A graphical user interface tool offers the possibility for both methods to be used to exclude data suspected to be outliers.

Manually excluding outliers is done by inspecting deviations of measured heat consumption from their predictions which are gained from the linear regression model. If the deviation is high, that suggests that outliers exist. *Normalized heat consumption* (NHC) is a measure of the consumption deviation from the modeled consumption, which is used in this thesis to recognize faults in HVAC system operation or to recognize operation changes in the monitoring history. NHC represents the ratio of real and modeled heat consumption:

$$NHC=Q_{REAL}/Q_{MODEL}\ [\%] \tag{3.14}$$

If we analyze hourly data for one control regime from one of the analyzed buildings at the university campus in Trondheim, we recognize that some data points deviate from the modeled consumption, which is represented by a line (Figure 3.14). The presented line is the energy signature line in the case of simple linear regression. In this case, Q_{MODEL} represents the point on the energy signature line that corresponds to outdoor air temperature. Normalized heat consumption is presented by percent; thus, 100% implies that the modeled and real consumption have the same value. If normalized consumption deviates significantly from 100%, this indicates a fault in the HVAC system operation.

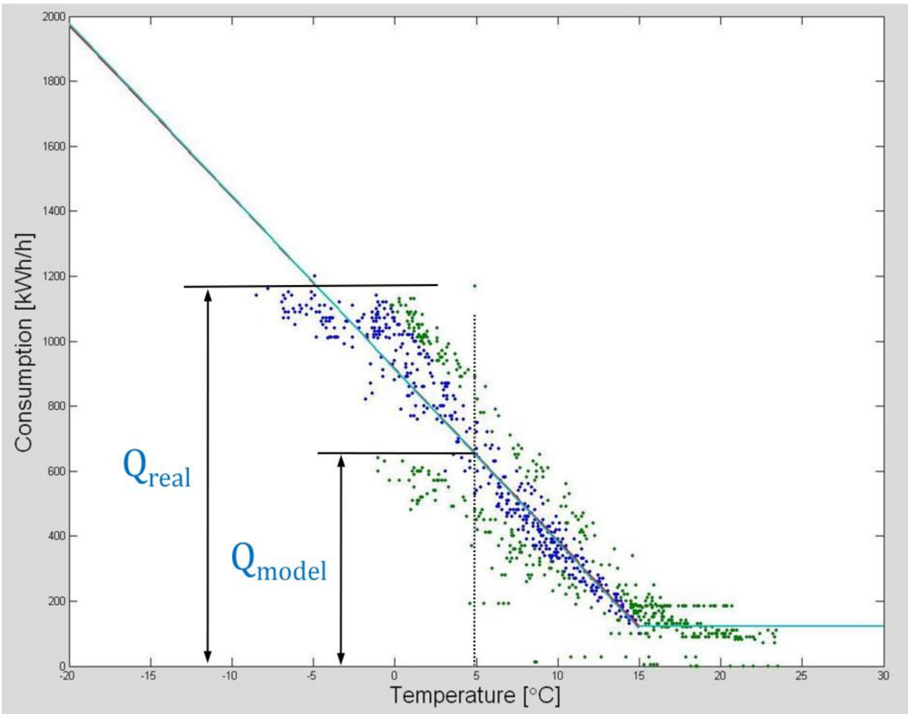


Figure 3.14 Energy signature line referring to one control regime for one of the buildings in the university campus in Trondheim

A normalized heat consumption diagram (Figure 3.15) is formed when normalized heat consumption are put in a 3-D diagram, where normalized heat consumption for every hour of a day are presented in one row. It presents normalized consumption for each hour of the analyzed monitoring period. If the model were perfect and captured all influences on building energy consumption, and if the system were to operate without any faults, normalized heat consumption diagram will look like a flat horizontal surface placed at 100%. Three peaks with strong red color on Figure 3.15 represent faults in the system operation. After identification of outliers, they can be excluded manually by the tool enabled in the graphical user interface of the developed program.

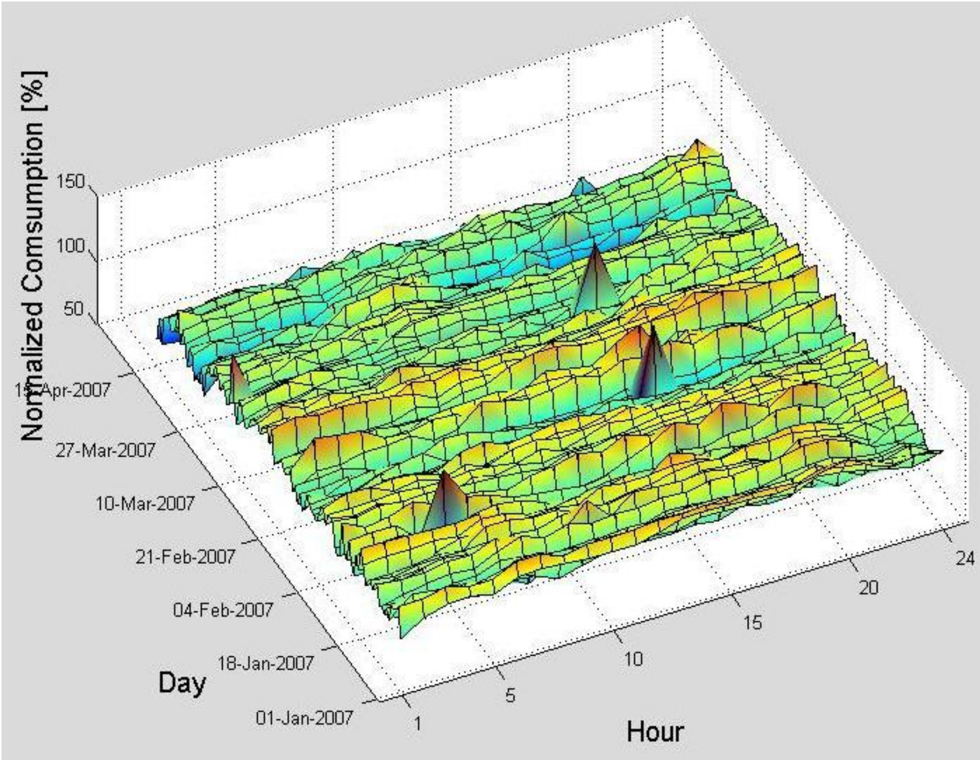


Figure 3.15 Normalized heat consumption 3-D diagram for one of the buildings at the university campus in Trondheim

Even if the system functions without any faults, it is not possible to build a perfect model that captures all events in system operation. Thus, normalized consumption diagrams have ‘hills’ and ‘valleys’, which represent the imperfection of the model and faults in the system operation. The user of the tool should not conclude that deviation from 100% is a result of a system operation fault before checking if the model has captured all relevant effects. With different models (simple or multiple linear regression models), different data groupings and varying the length of modeled monitoring period, some consumption that at first appear to be too high or too low could be proven to be normal.

The second way of recognizing residuals is to inspect R-student residuals for each observation. Calculation of R-student residuals enables outlier identification to be implemented in a computer program, i.e., excluding outliers can be automated. In Walpole et al. (2007), R-student residuals and studentized residuals are imposed as statistics that are used as diagnostic tools. These statistics identify observations where the error is higher than expected. Observations with R-student residuals higher than 2 are proposed to be outliers in the Minitab help (computer tool for statistic analysis). Equitation for R-student residuals, which is used in the developed tool, is taken from Walpole et al. (2007):

$$t_i = \frac{e_i}{s_{-i}\sqrt{1-h_{ii}}} \tag{3.15}$$

where

i – number of observations

e_i – difference between the value of the dependent variable and the predicted value from the model for the i-th observation

s_{-i} – estimate of the error standard deviation, calculated without the i-th observation

h_{ii} – diagonal element of the HAT matrix

After calculating the R-student residuals, data with high residuals are eliminated from the dataset, and linear regression calculation is repeated.

3.8 Normality testing

Deviations of measured heat consumption from their predictions gained through linear regression are random events, so they should be normally distributed. Violation of this assumption indicates systemic error. Figure 3.16 presents a normal probability plot. This graph shows whether or not the data are normally distributed. It assumes normally distributed data, so the vertical axis is scaled according to a normal distribution. It is expected that a normal distribution has a mean value of 50% of the range of dependent variable. Residuals should follow the straight line if the distribution is normal.

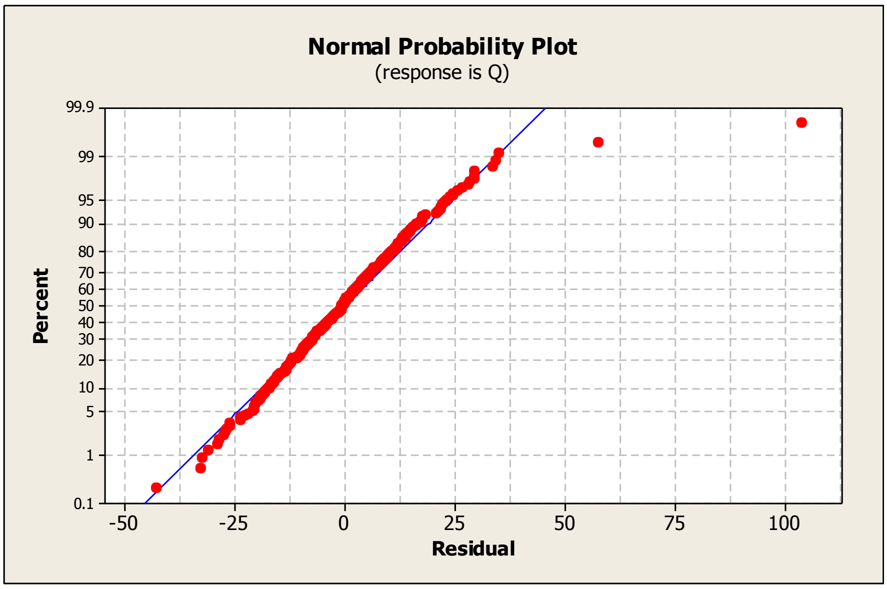


Figure 3.16 A normal probability plot of heat consumption linear regression for the Gamle kjemi building at the university campus in Trondheim

Figure 3.16 is a normal probability plot of heat consumption linear regression for one of the buildings at the university campus in Trondheim. Linear regression calculation is conducted on the dataset, which included heat consumption, outdoor temperature, products of wind speeds and indoor/outdoor temperature differences, and solar radiation on the vertical surface (according to equation 3.7). It is obvious that some points deviate from the straight line on Figure 3.16. Those points are outliers. Their R-student residuals are higher than R-student residuals for the other data points. If we exclude points with R-student residuals higher than two from the second calculation data, we will get a normal probability plot presented on Figure 3.17. Outlier identification is conducted again after the second calculation. If there are still data points that do not fulfill criteria that their R-student residual are lower than two, the calculation should be repeated until all data points fulfill the criteria. This procedure was conducted in Minitab.

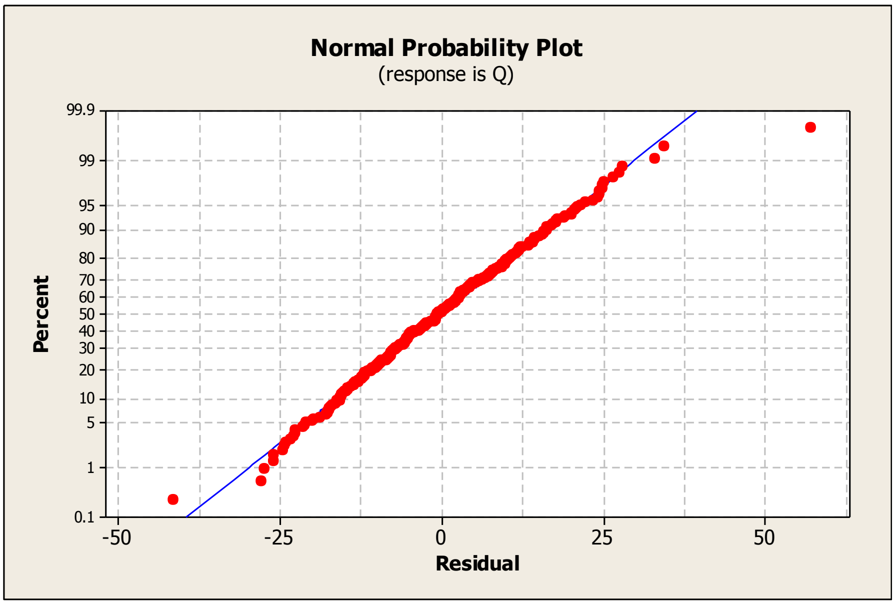


Figure 3.17 Normal probability plot of heat consumption linear regression for the Gamle kjemi building at the university campus in Trondheim with data corrected by removing residuals

After excluding outliers and conducting a second linear regression, new residuals appeared because the model became more accurate. After a third calculation, the graph in Figure 3.18 is obtained. It is obvious that outliers are excluded. Data follow the straight line except at the ends of range. This type of deviation is characteristic for data that do not fully follow a normal distribution. If points are distributed in the shape of a letter S (this is called a fat or short tail) (Figure 3.19), it is suggested in NIST/SEMATECH that there is serious doubt about the normal distribution of the analyzed phenomenon. If the data points follow a straight line in the center and only the ends have an S shape (long tail), as is the case in Figure 3.18, it is suggested that the distribution is satisfyingly close to normal.

Checking the normal probability plot represents normality testing. A normal distribution imposes the assumption that all events that cause deviations of a dependent variable from the model are random. From Figure 3.18, it can be concluded that a normal distribution exists for heat consumption of the analyzed building.

Figures 3.20, 3.21 and 3.22 are residual plots for the three independent variables of equation 3.7. The residual plot is the most used tool for detecting violations of the assumption of homogeneous variance. If higher residuals are concentrated for some values of an independent variable, the variance is not homogeneous. Since residuals are randomly distributed on Figures 3.20, 3.21 and 3.22, there is no systematic deviation from a normal distribution. Figures 3.18, 3.20, 3.21 and 3.22 confirm the assumption that all events that cause deviations are random for analyzed heat consumption of the Gamle kjemi building; this allows the linear regression to be performed according to equation 3.7. The same analysis is conducted for the heat consumption for more university campus buildings in Trondheim. To conclude, heat consumption can be modeled by linear regression according to equation 3.7. The method proposed in this thesis for building energy performance analysis does not use the residual plot to analyze residuals. For operators that should analyze HVAC performance, normalized heat consumption plots (Figure 3.15) are more convenient.

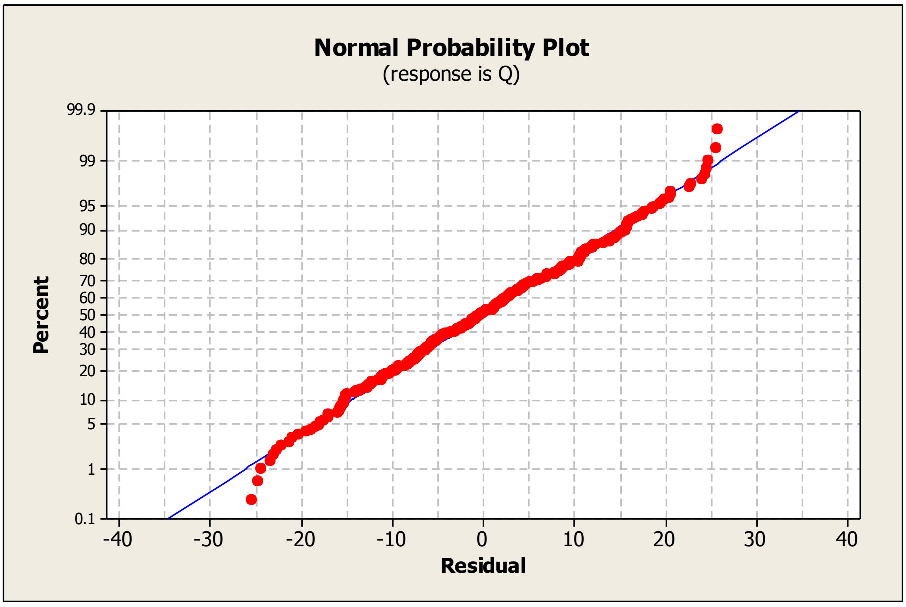


Figure 3.18 Normal probability plot of heat consumption linear regression for the Gamle kjemi buildings at university campus in Trondheim after third calculation

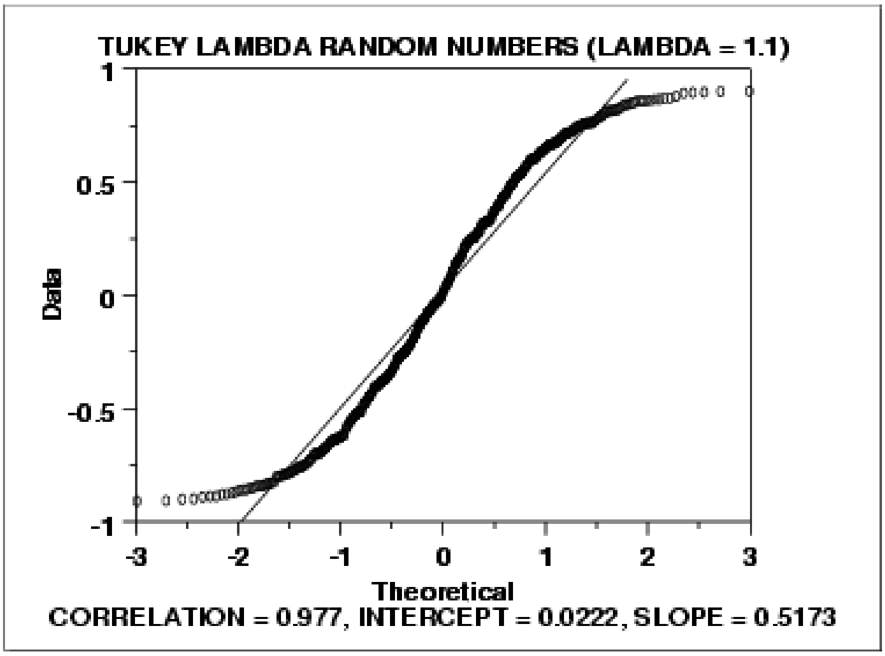


Figure 3.19 Normal Probability with fat or short tail (NIST/SEMATECH)

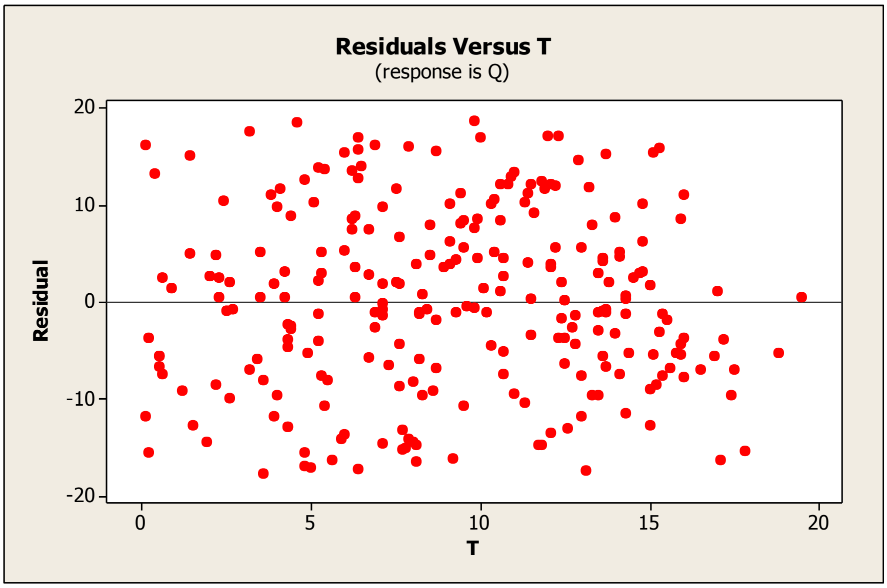


Figure 3.20 Residual plot for temperature member (T) of equation 3.7 for heat consumption linear regression of the Gamle kjemi building

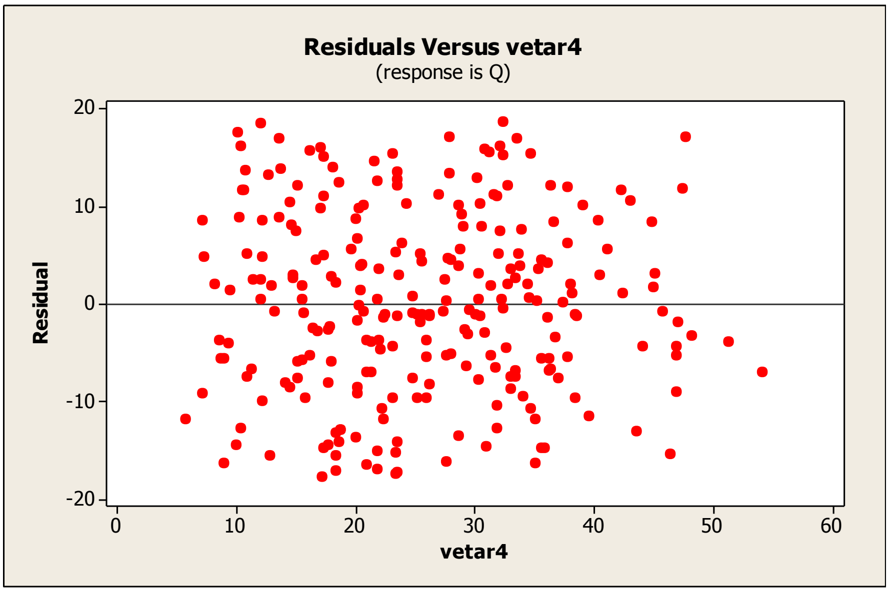


Figure 3.21 Residual plot for wind member (vetar4) of equation 3.7 for heat consumption with a linear regression of the Gamle kjemi building

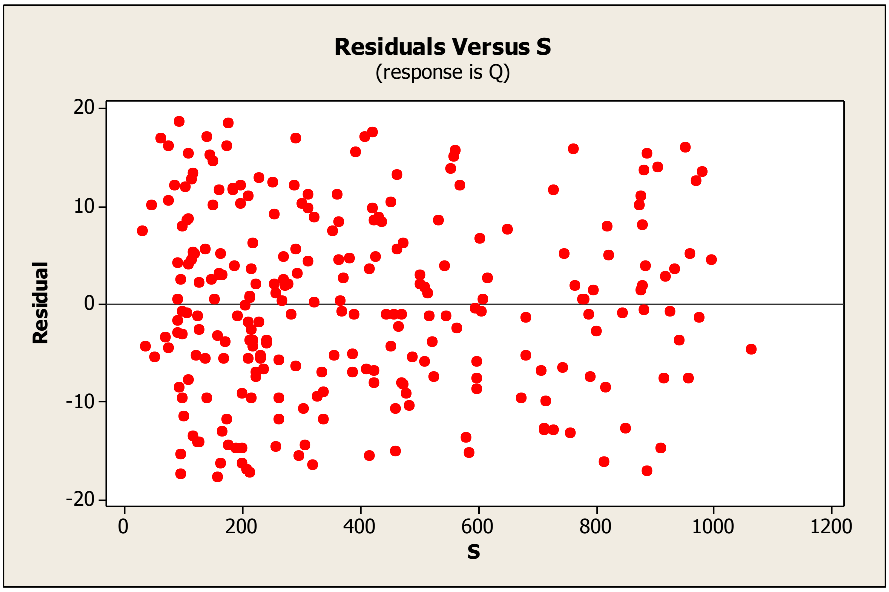


Figure 3.22 Residual plot for solar radiation member (S) of equation 3.7 for heat consumption linear regression of the Gamle kjemi building

3.9 Overview of relevant literature regarding modeling of heat consumption of HVAC systems through linear regression

This thesis is based on a linear regression to model HVAC system heat consumption. Other authors have also discussed this issue, and their results will be presented. There is no linear regression formulation in the literature for radiator space heating and ventilation heating. However, a formulation similar to those presented in literature can be used for this purpose.

Reddy et al. (1995) gave a formulation for a linear regression model of a heating and cooling load for air-side HVAC systems, terminal reheat and duct-duct systems, under both constant and variable air volume operation. Katipamula et al. (1994) gave a linear regression formulation for cooling energy consumption of dual-duct constant volume (DDCV) and variable volume (VAV) systems. The LR formulation is (Katipamula et al., 1994):

$$E_c = a + bT_0^{\cdot} + cI + dIT_0 + eT_{dp}^{+} + fq_{sol} + gq_i \tag{3.16}$$

where:

- T_o - dry-bulb outdoor temperature
- I - indicator variable that indicated if the outdoor temperature is greater than the change point
- T_{dp}^{+} - outdoor air dew-point temperature; it is set to zero if T_{dp} is lower than the surface temperature of the cooling coil
- q_{sol} - solar radiation
- q_i - internal heat gains

Multiple linear regression assumes that regression variables are independent of each other. This problem is known as multicollinearity. A rule of thumb (Draper and Smith, 1981) is that if the simple correlation between two independent variables is larger than the correlation between one or either independent variable with the dependent variable, multicollinearity effect may be important. Correlation coefficients presented in Table 3.7 for one of the buildings in Texas show that the correlation between T_o and q_{sol} is higher than the correlation between E_c and q_{sol}. It is expected that a sunny day will be followed by higher outdoor temperatures. Other correlations were insignificant.

Variable	T_o	T_{dp}^{+}	q_{sol}	q_i	$\dot{E}_c$
T_o	1.00	0.66	0.39	0.32	0.88
T_{dp}^{+}		1.00	0.00	0.05	0.80
q_{sol}			1.00	0.56	0.32
q_i				1.00	0.43

Table 3.7 Correlation coefficients between E_c and independent variables of the linear regression model (Katipamula et al., 1994)

Katipamula et al. (1994) conducted calculations with daily and hourly data for the DDCV and VAV system of a university building at Texas A&M University. Individual contributions of independent variables are evaluated through stepwise regression. Results of the stepwise regression are presented in Table 3.8 for calculation with daily and hourly data. The partial coefficient of determination (partial R^2) measures contributions of each independent variable. Partial coefficients of determination are obtained from simple linear regressions. The partial R^2 of T_o explains the greatest variation (87.1% for daily and 76.5% for hourly calculation). The contribution of the outdoor dew-point temperature is much lower, but it is still significant. Contributions of internal gains and solar radiation are far less significant. Since the change point did not exist, $cI$and dIT_0were not significant. Daily models have higher R^2 than the hourly model because some operational parameters and weather parameters change from hour to hour, but they are constant at a daily time scale. If the hourly model is not able to take the variation into account, it decreases its accuracy. We conclude that the daily model is more accurate.

Katipamula et al. wrote two additional articles (Katipamula et al., 1995 and Katipamula et al., 1998). In those two articles, the same method as in the first article (1994) is used to further evaluate multiple linear regression (MLR) models of building energy use. Katipamula et al. (1995) compared the accuracy of monthly, daily, and hourly predictions and the HOD model of cooling energy consumption for five commercial buildings in Texas. R^2 is not used to evaluate the accuracy of the models. Hourly and daily predictions were modified to monthly predictions in order to compare the predictions with different time resolutions. The MLR model is the same as that in equation 3.16.

Variable	Daily				Hourly			
	Partial R^2 (%)	Model R^2 (%)	C(p)	Prob>F	Partial R^2 (%)	Model R^2 (%)	C(p)	Prob>F
T_o	87.1	87.1	193	0.0001	76.5	71.2	3847	0.0001
T_{dp}^{+}	4.0	91.1	35	0.0001	6.9	83.4	453	0.0001
q_i	0.8	91.9	4	0.0001	0.3	83.7	296	0.0001
q_{sol}	0.0	91.9	5	0.0297	0.6	84.3	4	0.0001

Table 3.8 Results of stepwise regression for one of the buildings of Texas A&M University (Katipamula et al., 1994)

The operational parameters change from hour to hour, but are constant on a monthly and daily basis. Some weather parameters or internal heat gains can be effectively constant on a monthly or even daily basis. Figure 3.23 shows cooling energy consumption for different time resolutions: monthly, daily, hourly and HOD. More scatter appears with time scale changes from month to hour due to changes of cooling energy consumption, which is not caused by changes in the outdoor dry-bulb temperature. From Figure 3.23 it is evident that the monthly time scale shows the highest goodness of fit. However, by introducing variation at the daily and hourly time scales of the outdoor dry-bulb temperature and other independent variables, which are effectively constant on a monthly time scale, more accurate predictions can be gained.

Table 3.9 presents the results of stepwise regression for a building at Texas A&M University. Weekends (WE) and weekdays (WD) are separated for both the hourly and HOD model. For the HOD model, unoccupied and occupied hours are indicated by *U* and *O*, respectively. The outdoor dry-bulb temperature has the highest contribution for all time resolutions. The change point is not significant at monthly time scale because I and IT_0 are not significant. However, the change point exists at daily and hourly time scales. The dew-point temperature is much more significant on a daily basis than on a monthly basis. This means that variation of air humidity is much more significant on a daily basis than on a monthly basis. Internal heat gains are insignificant on a monthly basis, but they are significant on a daily and hourly basis. This means that internal heat gains are effectively constant from month to month. Internal heat gains are more significant during occupied hours in the HOD model. Also, internal heat gains are more significant for weekdays than for weekends in the hourly model, since during weekends the building is unoccupied. Solar radiation influence is insignificant for all time resolutions.

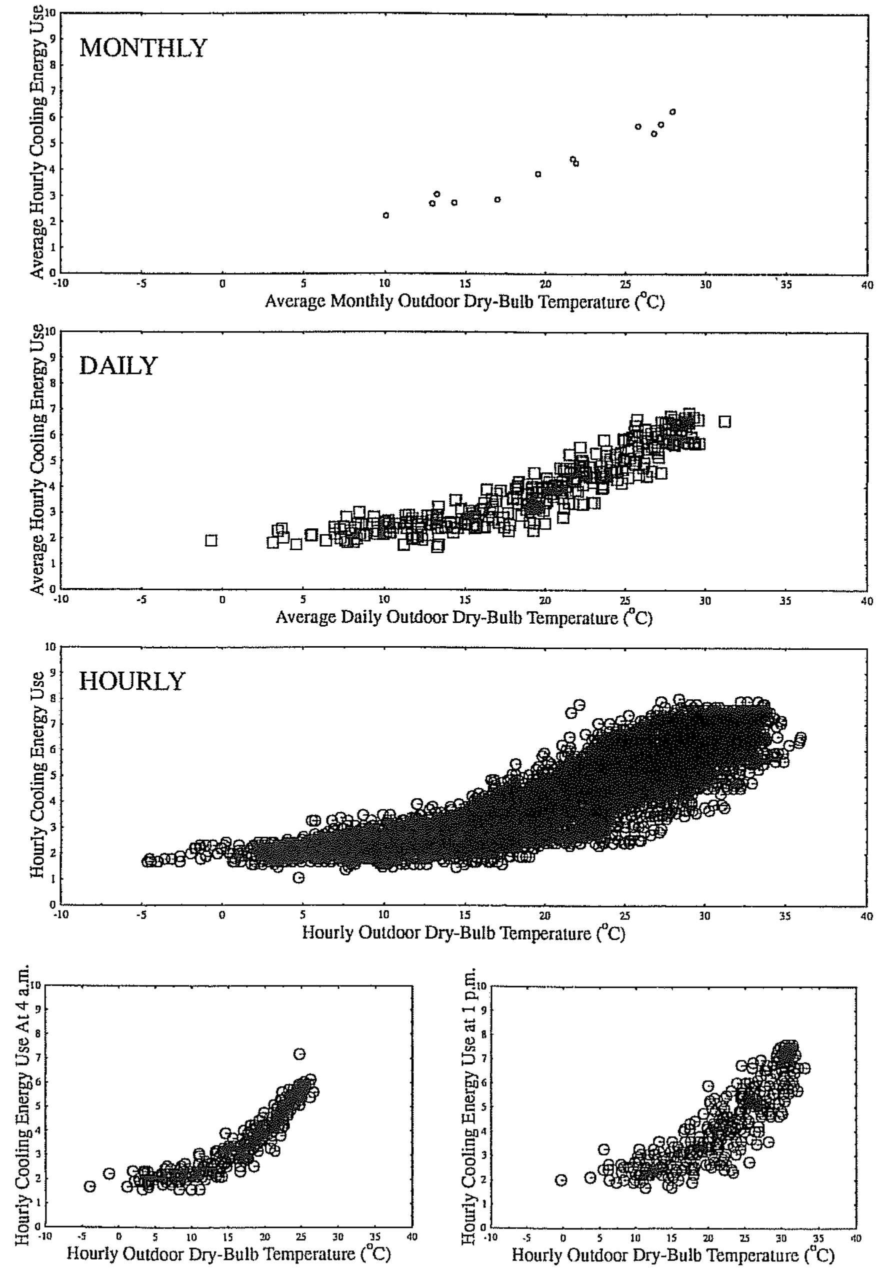


Figure 3.23 Cooling energy consumption for different time resolutions (Katipamula et al., 1995)

Var	Monthly		Daily		Hourly				HOD			
					WD		WE		WD		WE	
	PR^2 (%)	MR^2 (%)	PR^2 (%)	MR^2 (%)	PR^2 (%)	MR^2 (%)	PR^2 (%)	MR^2 (%)	PR^2 U/O† (%)	MR^2 U/O (%)	PR^2 U/O (%)	MR^2 U/O (%)
T_o	93.7	93.7	79.1	79.1	74.5	74.5	9.6	9.6	2.7/65.3	2.7/65.3	2.3/74.3	2.3/74.3
I	0.0	93.7	2.3	81.4	1.7	76.2	1.0	10.6	0.4/ 0.3	3.1/65.6	0.0/ 2.6	2.3/76.9
$I * T_o$	0.0	93.7	0.8	82.2	1.0	77.2	0.4	11.0	1.4/ 4.1	4.5/69.7	0.0/ 0.4	2.3/77.3
T_{dp}^+	3.8	97.5	8.1	90.3	4.3	81.5	73.8	84.8	79.3/ 6.1	83.8/75.8	82.0/12.2	84.3/89.5
q_i	0.0	97.5	2.3	92.6	2.0	83.5	0.1	84.9	0.1/ 2.8	83.9/78.6	0.1/ 0.4	84.4/89.9

Table 3.9 Results of stepwise regression for one of the buildings in Texas (Katipamula et al., 1995)

The R^2 value of the HOD model is higher than the R^2 of the hourly model, and it is the highest for the monthly model; this is expected since daily and hourly models show greater scatter than monthly models (Figure 3.23). However, that does not mean that a monthly model is more accurate, because its R^2 is not calculated for the same number of data points. Through averaging, some information is lost; thus, the daily, hourly and HOD models could give more accurate predictions. In order to compare the predictive ability of each model, hourly and daily predictions were summed to monthly predictions, so they can be compared. Monthly predictions from every model are subtracted from real monthly cooling consumption and those differences are summed into coefficients of variation (CV) and mean bias errors (MBE). Table 3.10 presents those statistics of four models for three buildings. Lower CV values and lower absolute values of MBE imply better predictive ability.

Site	Modeling Period		Indices	Monthly	Daily	Hourly	HOD
	Identification	Prediction					
MSB (DDCV)	Jan. - Dec '92	Jan. - Dec. '93	CV MBE	8.4 -2.2	4.8 -0.6	5.8 -0.7	5.1 -0.9
BUR (VAV)	Jan. - Dec. '92	Jan. - Dec. '93	CV MBE	9.9 -8.2	7.5 -6.5	9.1 -6.4	9.1 -7.7
WIN (VAV)	Jan. - Dec '92	Jan. - Dec. '93	CV MBE	15.3 -12.6	15.2 -12.0	15.7 -10.7	15.5 -11.8

Table 3.10 Comparison of the predictive ability of models with different time resolutions for three buildings (Katipamula et al., 1995)

The daily model has the lowest value of CV, followed by the HOD, hourly and monthly model. There is no clear trend for the MBE statistic. The presented results imply that the daily model is most accurate, followed by the HOD model. This means that HOD model is preferable to the hourly model for modeling hourly heat consumption.

Table 3.11 presents the advantages and disadvantages of models with different time resolutions. Modeling with monthly and daily data requires minimum effort, while the HOD model requires maximum effort. There is no difference in effort for collecting data for the HOD and hourly models, so Katipamula et al. (1995) referred to calculation effort. If the computational tool already exists, there is no significant difference in calculation time, since the present speed of computers requires a couple seconds for calculation. Monthly data can be obtained from monthly utility bills, while other time scales require additional metering. The monthly model requires the longest monitoring period. For daily data, Kissock et al. (1993) have shown that fewer than three months of data are not enough to get accurate predictions of annual energy use. For the hourly and HOD models, there is still no relevant analysis that suggests the necessary monitoring period. The HOD model could require more data than the hourly model, since hourly data are grouped in 24 data sets. It is assumed that three to six months should be enough long monitoring period. Since daily models are more accurate for predicting cooling energy consumption than monthly models, they are more appropriate for savings measurement and verification. Claridge et al. (1994) and Liu et al. (1994) demonstrated that using hourly data is most appropriate for identification of O&M problems. Daily models can spot changes of building energy consumption that are higher than 5%. Hourly and HOD models can be applied for real-time HVAC system control.

	Monthly	Daily	Hourly	HOD
Modeling Effort	Minimum	Minimum	Moderate	Difficult
Metering and Monitoring	None[1]	Required	Required	Required
Data Needed for Robust Modeling	12 months or more	3-6 months or more	3-6 months or more	3-6 months or more
Applicability to Savings Measurements	In some cases	In most cases	All cases	All cases
Prediction Uncertainty	High	Low	Moderate	Low
O&M Opportunities Detection	Limited	Possible	Appropriate	Most appropriate
Dynamic Control	No	Possible	Yes	Best

Table 3.11 Advantages and disadvantages of models with different time resolutions (Katipamula et al. 1998)

Although the analyses presented by Katipamula et al. (1994, 1995 and 1998) are conducted for cooling energy consumption, their conclusions can be applied for space heating and ventilation heating consumption. The analysis concept in those articles is used in this thesis to evaluate daily and hourly modeling of space heating and ventilation heating consumption.

The Great Energy Predictor Shootout II (Haberl et al. 1996) was organized to evaluate the accuracy of predictions with different inverse modeling methods. The MLR method (Katipamula 1996) was close behind winner. The competition assignment was to model hourly cooling and heating energy consumption and electricity consumption. Katipamula (1996) used the HOD grouping to model cooling and heating energy consumption, since was proved to be superior to the hourly grouping in earlier studies. The R^2 values for weekends and unoccupied hours were higher than the R^2 for occupied hours for heating energy consumption. Katipamula marked that the model underpredicted heating energy consumption for high outdoor temperatures and overpredicted for low outdoor temperatures. Katipamula suggested that the accuracy of model can be improved by separating winter from summer.

4 Method of building energy performance analysis based on utilizing monitoring data

4.1 Basic concepts used in the proposed method

The building energy performance analysis method proposed in this thesis is based on the following ideas:

- Using linear regression to model building heat consumption by regressing weather influences as independent variables;
- Recognizing control regimes and relevant monitoring periods with unchanged performance of an HVAC system by reviewing 3-D plots and analyzing linear regression coefficients; and
- Detection of O&M problems through an overview of monitoring history

The method is implemented through a graphical user interface (GUI) tool developed in Matlab. The basic idea is to model heat consumption based on linear regression and to compare the modeled heat consumption with actual heat consumption in order to find periods with malfunctions or HVAC system changes in functioning during a monitoring history.

The result of the first and second phases of the proposed method is a LR model of heat consumption. Detection of O&M problems is achieved by inspecting normalized heat consumption (equation 3.14). Traditionally, residual plots are used to detect outliers. Other plots used for analysis of HVAC system performance require a high level of user expertise. Haberl and Komor (1990a) used hourly data to recognize operation faults in commercial building HVAC systems. In this article, periods with malfunctions were recognized by inspecting differences between real and predicted heat consumption. The differences were presented in 3-D plots according to days and hours. Those plots are easy to understand because they organize data according to time. That enables to determine when fault occurred.

The third phase of proposed method is based on this technique. Instead the difference between real and predicted heat consumption, their ratio (NHC) is used. Since building heat consumption changes with changes in outdoor weather parameters, deviations in real heat consumption from the expected value (modeled prediction) are better presented through their ratio. The tool, which is developed in Matlab, enables implementation of the proposed method. The following results can be gained through use of the program:

- Control regimes of HVAC system, when they were changed during the monitoring period and the present settings;
- Detection of O&M problems by comparing predicted and real heat consumption;
- Savings measurement and verification by comparing predictions of heat consumption gained from models corresponding to pre-retrofit and post-retrofit operations;
- The program user can get an idea of how to implement energy conservation measures.

The GUI tool developed in Matlab enables fast analysis of building energy performance. The whole analysis procedure involves (1) extraction of data, data filtering and saving the data on the computer; (2) recognizing control regimes and relevant monitoring period for modeling; (3) modeling heat consumption through different data resolutions; and (4) analysis of results based on inspection of diagrams.

4.2 Tool for modeling and analysis of building heat consumption

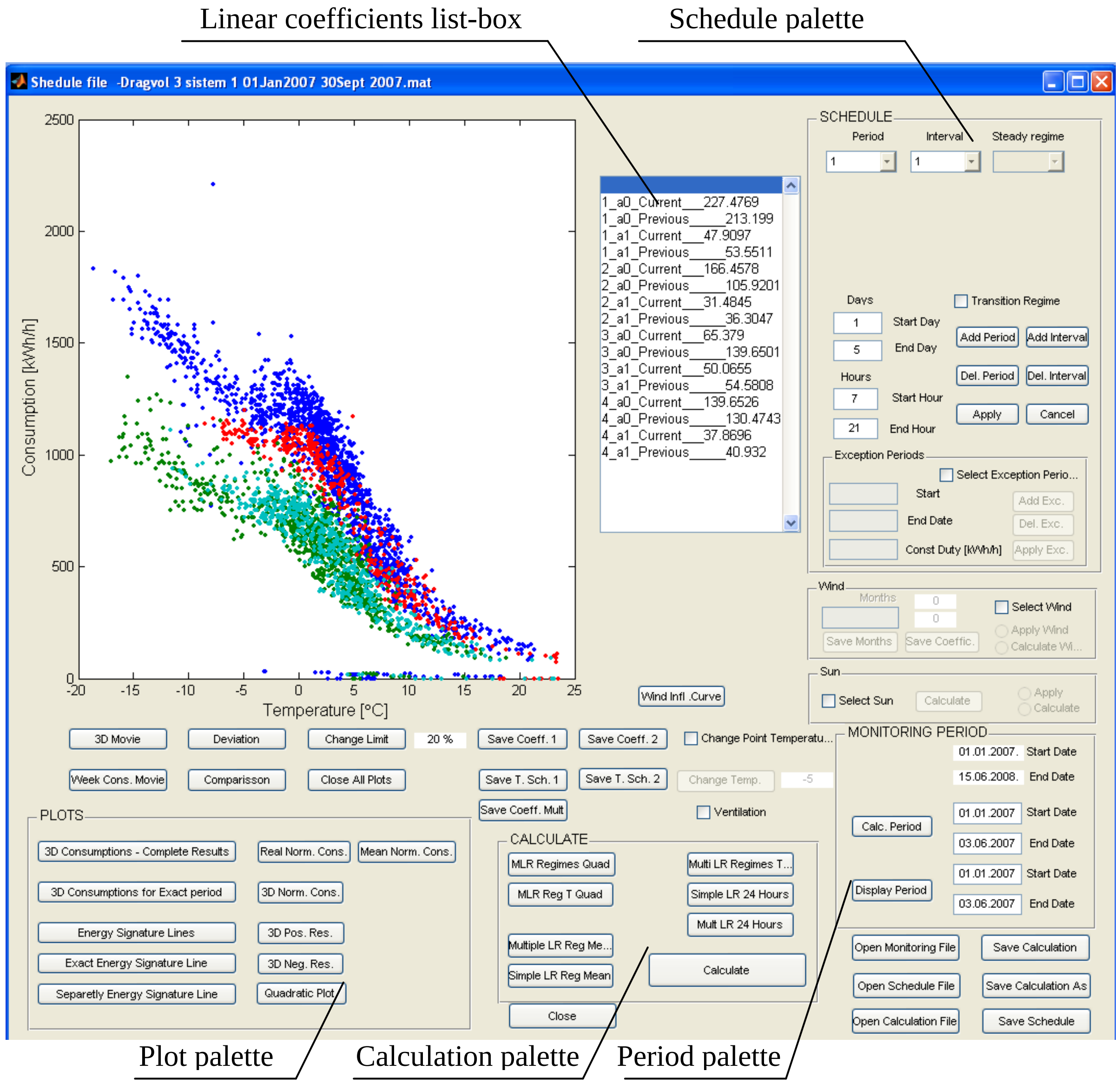


Figure 4.1 Main window of the GUI tool

The main window of the GUI tool is presented in Figure 4.1. Dots in the plot of the main window represent hourly heat consumption for corresponding temperatures in the analyzed monitoring period. Dots are presented in different colors depending on their control regime. Some basic conclusions can be made by inspecting the different colored groups of dots. For example, the system seems to have reduced energy consumption under -5°C, due to reduction of air intake of the ventilation system. If some dots are placed outside of their group, the user should check if the regime time schedule is properly determined.

Coefficients that determine the energy signature lines are in a linear coefficients list-box (Figure 4.2). The energy signature lines are determined through simple linear regression based on regressing outdoor air temperature. There are two coefficients, a_0 and $a_{1,}$ for each regime; a_0 is the base level consumption and a_1 is the slope term, similar to α and β in equation 3.7. There are two values for each of these coefficients. The first is the *current* and the second is *previous*. The current value is determined in the present calculation. The previous value is determined in the calculation prior to the current calculation. If the monitoring period for which the calculation is conducted changes, it is possible to compare the coefficients gained for different periods. Coefficient changes can be a consequence of HVAC performance deterioration. This linear coefficients list-box can be used as a tool to detect faults in the HVAC system operation.

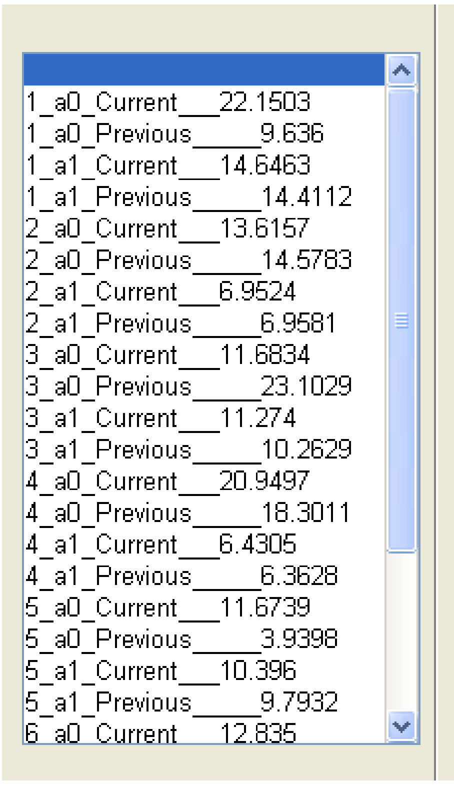


Figure 4.2 Linear coefficients list-box

Control regimes are created by using the 'Schedule Palette' (Figure 4.3). A regime is determined by the hours and days of the week when it is used. The days are determined by numbers; for example, Monday is 1. Every control regime is determined in the popup-menu 'Period'. Every time interval belonging to the control regime is determined by its number in the popup-menu 'Interval'. The schedule overview is enabled by the popup-menu 'Period' and 'Interval'. Control regimes can be added and deleted by pressing 'Added Period' and 'Deleted Period' buttons. Time intervals belonging to the control regime can be added and deleted by pressing 'Added Interval' and 'Deleted Interval' buttons.

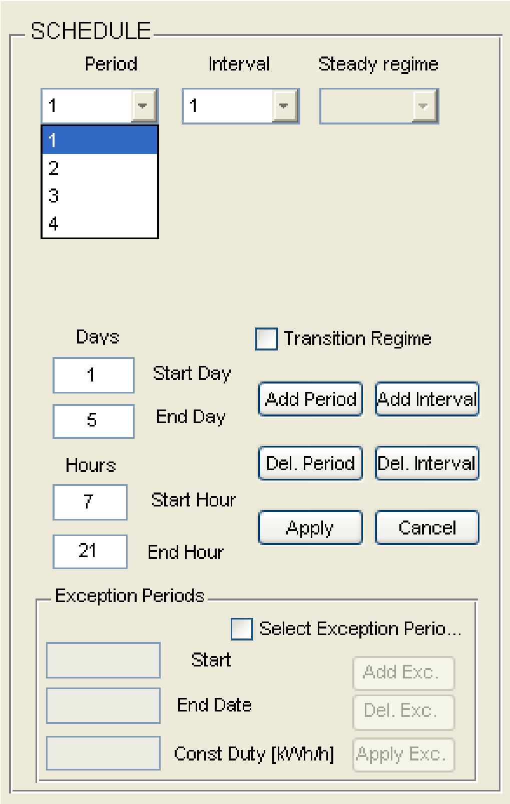


Figure 4.3 Schedule palette

'Exception periods' palette is also in the 'Schedule Palette' (Figure 4.4). It enables days that are suspected to have faulty operation to be excluded from calculation. Start and end days of exception periods are entered in the edit-text boxes. More periods can be excluded by pressing the 'Add Exc.' button. Constant duties will be assigned to these periods, which are entered in the edit-text box 'Const Duty'.

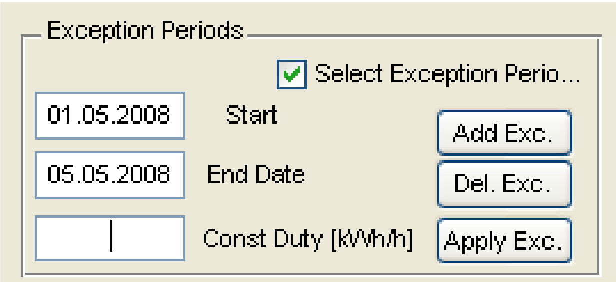


Figure 4.4 Exception periods palette

Selection of monitoring period which is used in calculation is enabled by the 'Monitoring Period' palette (Figure 4.5). Two dates in the upper part of the palette determine the monitoring period for which data exists. Those dates cannot be changed, since they are written automatically after opening a file with monitoring data. Two dates in the middle determine the monitoring period that will be used for calculation. The two dates on the bottom determine the monitoring period that is displayed in different plots. By default the calculation period and display periods are the same. If a user has a special interest in a specific period, the user can get better resolution of plots by changing display period dates.

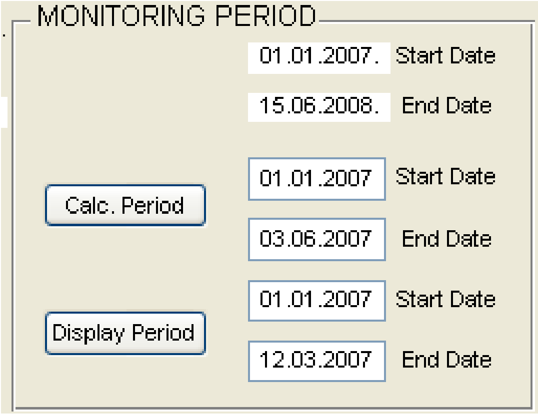


Figure 4.5 Monitoring period palette

The plot palette has eleven buttons to make different 3-D diagrams and plots with energy signature lines (Figure 4.6). 3-D plots presenting heat consumption (Figure 4.7) are obtained by pressing one of two buttons in the left-upper corner of the palette. The difference between ‘3-D Consumptions – Complete Results’ and ‘3-D Consumptions for Exact Period’ is that the first presents heat consumption for the whole period for which calculation is done, while the second presents heat consumption for the period the user defines in the monitoring period palette. Horizontal axes correspond to dates and hours, while vertical axis corresponds to heat consumption (Figure 4.7). Matlab allows 3-D plots to be rotated and zoomed. An hour of special interest can be selected and the value of its heat consumption can be obtained this way. For example, the excessive heat consumption that appeared on the 44-th day of the presented period at $16^{\underline{h}}$ is 2210 kWh/h (Figure 4.7). In all 3-D plots, the horizontal axes are dates and hours. The 3-D consumption plot is useful for initial recognizing HVAC operation faults. From Figure 4.7, it is clear that some values deviate from the typical consumption. Moreover, control regimes are also initially recognized by that plot.

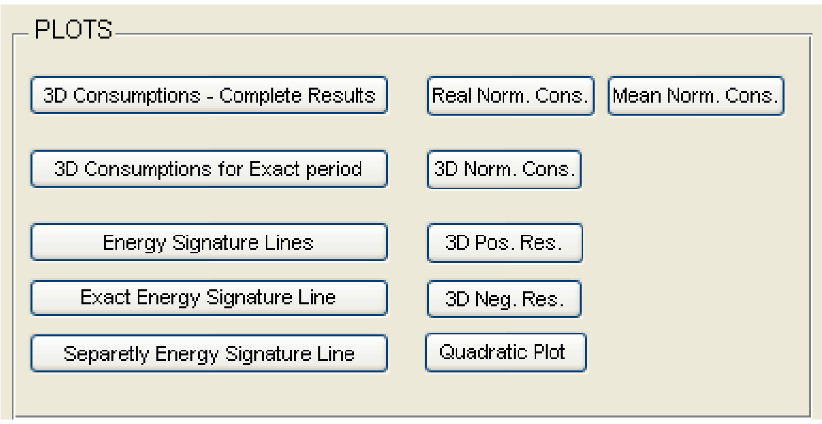


Figure 4.6 Plot palette

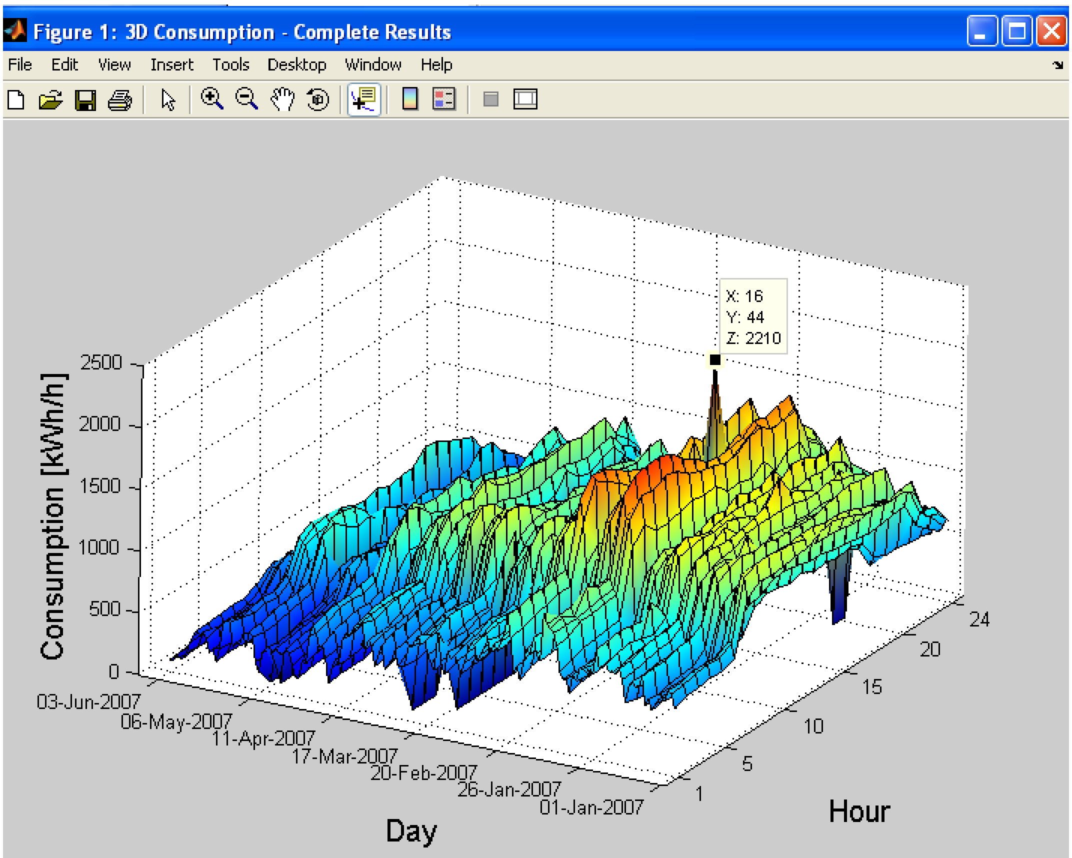


Figure 4.7 Three dimensional plot of heat consumption

'Real Normalized Consumption' and '3-D Normalized Consumption' plots (Figure 4.8) are similar to the '3-D Consumption' plot. They present NHCs on the vertical axis. The difference between 'Real Normalized Consumption' and '3-D Normalized Consumption' plots is that the '3-D Normalized Consumption' plot does not show normalized consumption that exceeds 50%. It is expected that normalized consumption will be over 50% or even larger for some hours. If those values were shown, it would be difficult to recognize deviations smaller than 50% with the color scale used in plots. Color scale also helps deviations be recognized. By pressing '3-D Pos. Res.' and '3-D Neg. Res.', plots with positive and negative NHCs are generated.

By pressing the 'Mean Norm. Cons.' button, a plot presenting the NHC gained from the model using mean values or daily data is generated (Figures 4.9 and 4.10). Figure 4.9 presents normalized consumption for the daily model. Figure 4.10 presents NHCs from the model using mean values grouped by regimes.

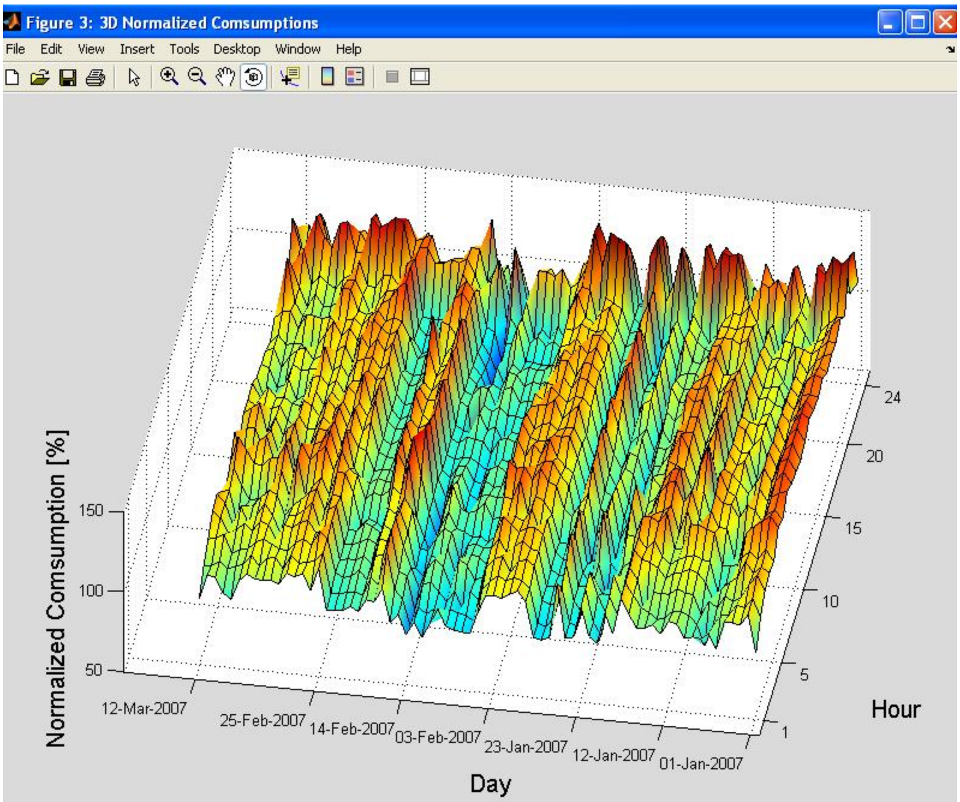


Figure 4.8 Normalized heat consumption plot

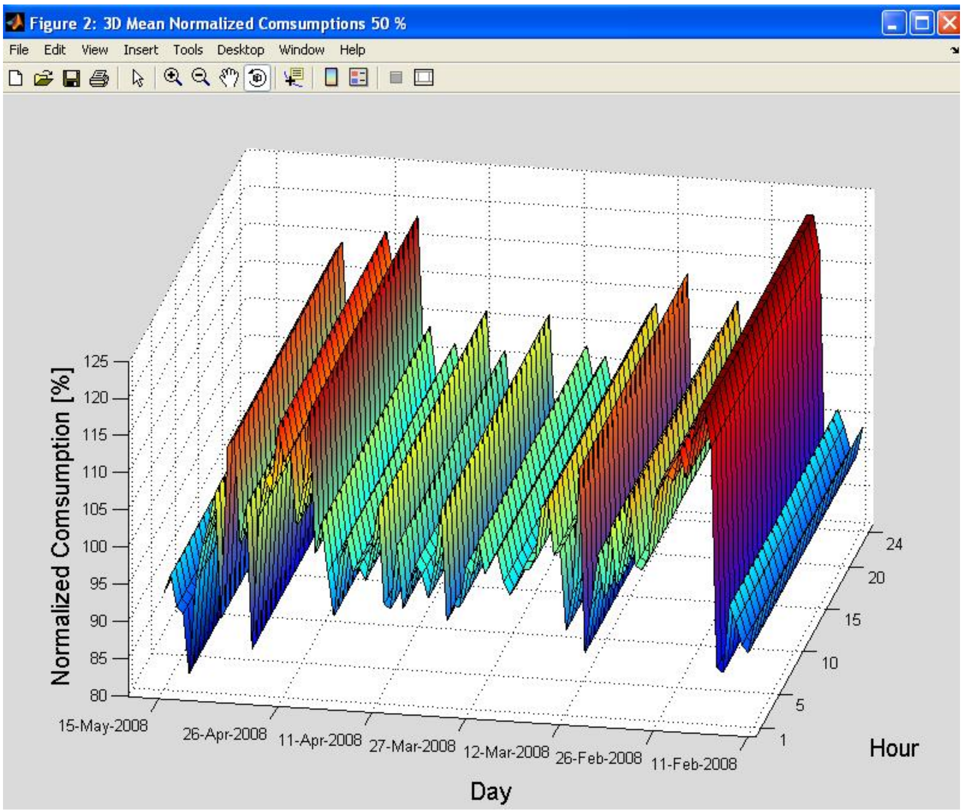


Figure 4.9 Normalized heat consumption plot for calculation with daily data

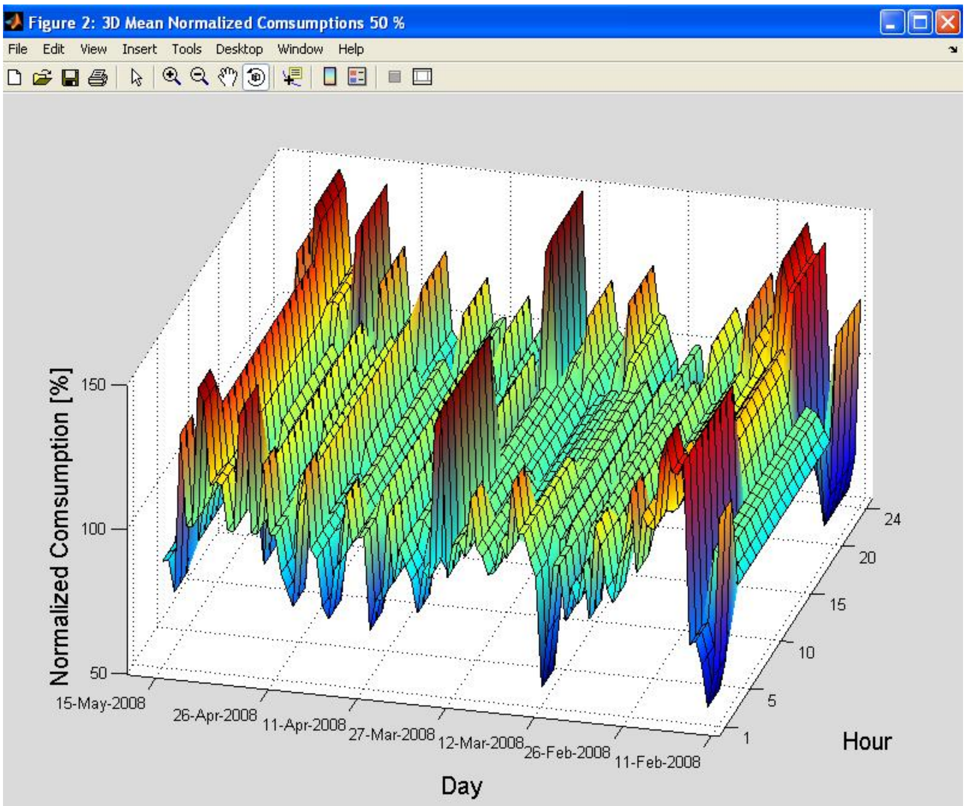


Figure 4.10 Normalized heat consumption plot for calculation with mean values grouped by regime

Energy signature lines for different regimes are obtained by pressing one of two buttons in the lower left corner of the palette. Energy signature lines are a result of simple linear regression. Figure 4.11 presents an energy signature line for one regime of a NTNU campus building. The base level consumption is obtained through the procedure explained in subchapter 3.4. The CPT is 16°C for the presented regime. It can be recognized from the figure that there are two lines that explain the dependence of heat consumption on the outdoor temperature. One line is gained through LR calculation with all points that have temperatures that exceed the CPT. The other line is obtained through LR calculation using the blue points. The first line, defined by all points, is called the *uncorrected energy signature* line. The second line is named the *corrected energy signature* line. This line is gained through linear regression of the heat consumption with deviations from the uncorrected energy signature line that are lower than 20% (blue points). Heat consumption that is within or exceeds the 20% limit is distinguished by different colors. Lines are more separated if there are more dots that deviate from the uncorrected energy signature line. The limit for the deviation of heat consumption from the energy signature lines is 20%. This limit is higher than the recommended limit of day heat consumption deviation from energy signature lines, since hourly heat consumption has more scatter than day heat consumption. The 20% limit can be changed by pressing the ‘Change Limit’ button which opens dialog presented on Figure 4.15. In an ideal case, if all heat consumption is within the 20% limit, the two lines will overlap. Uncorrected and corrected energy signature lines are useful in recognizing if control regimes are correctly defined. Data points that do not belong to the control regime will significantly deviate from others, which will cause the two lines to be more separated.

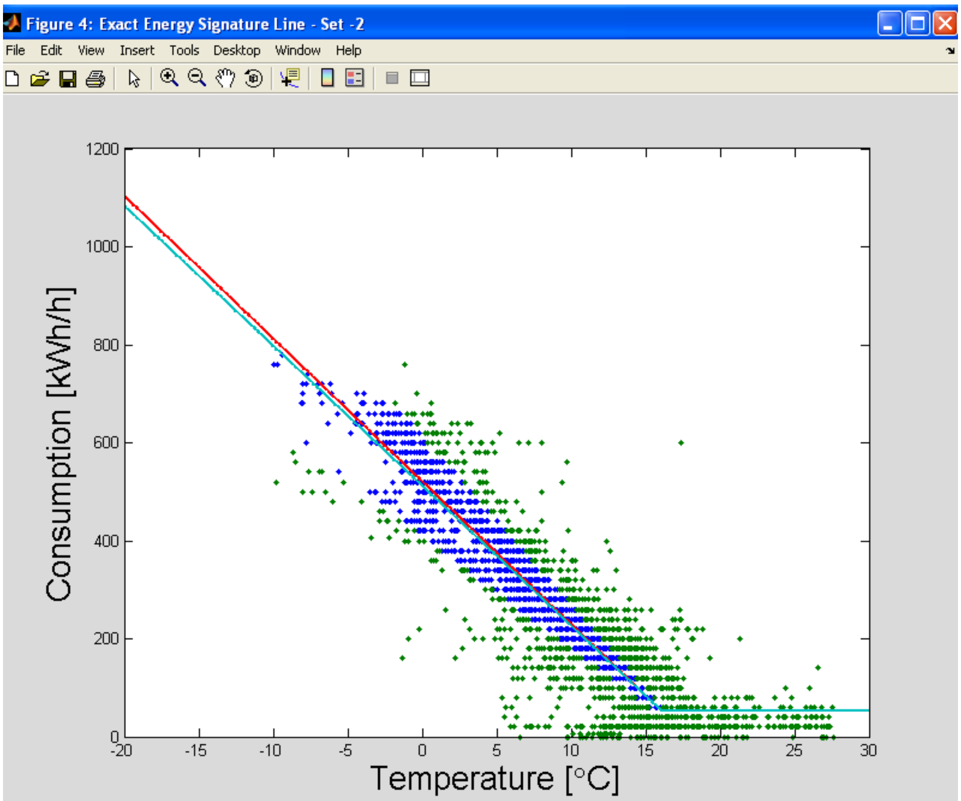
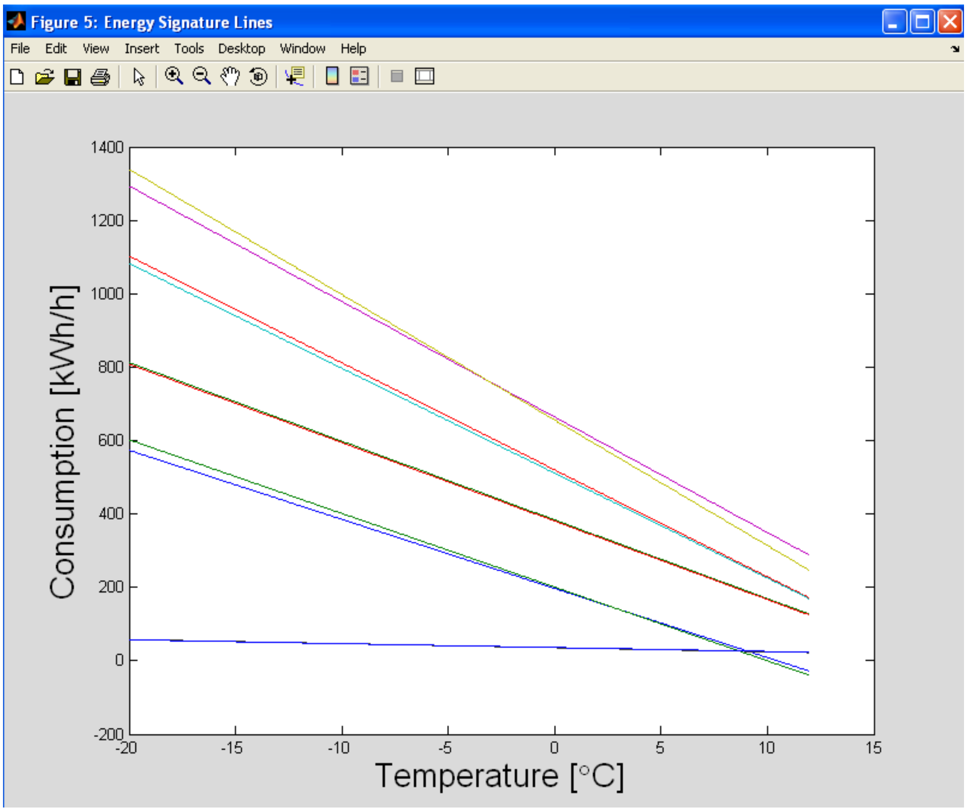


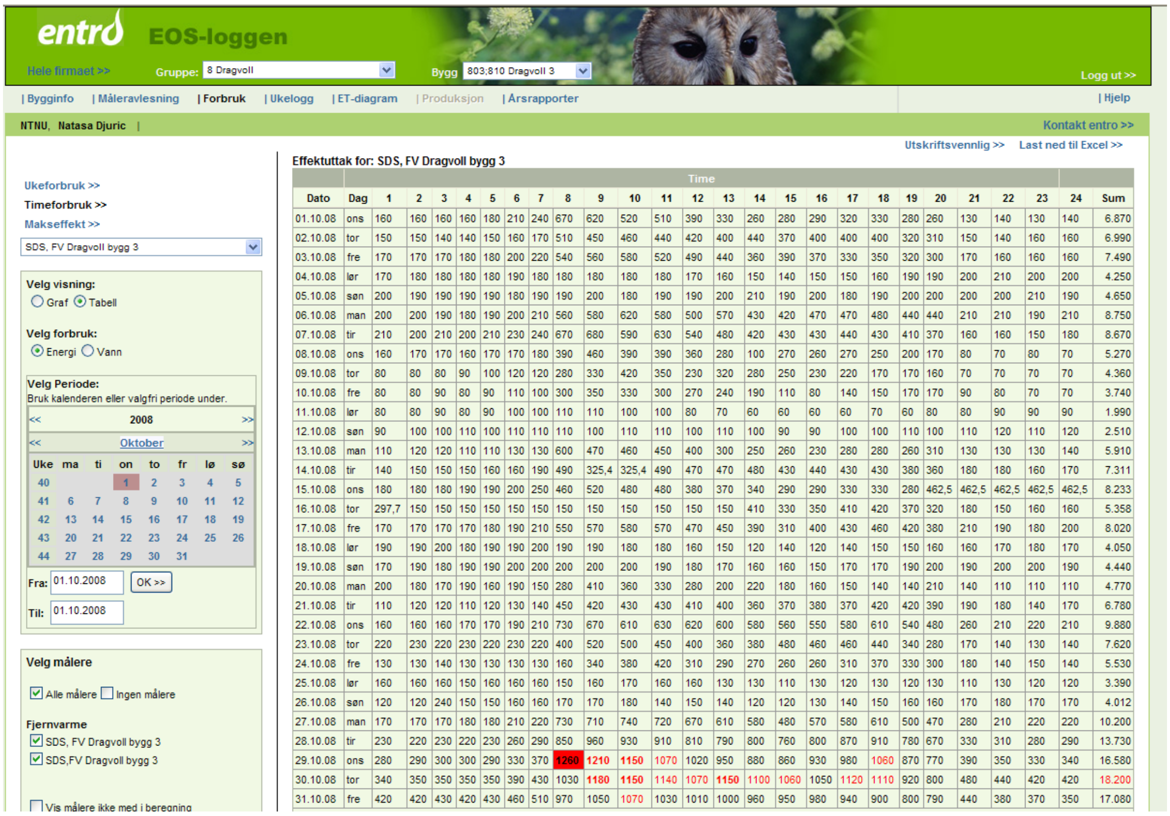
Figure 4.11 Energy signature line



4.12 Energy Signature Lines for five control regimes

Corrected and uncorrected energy signature lines for all regimes are obtained by pressing the ‘Energy Signature Lines’ button (Figure 4.12). There are five pairs of lines that correspond to five control regimes of analyzed building. If some lines are close, which is not the case in the presented figure, the user should consider that the two regimes are not unique and should join them into one.

Hourly monitoring data are mostly presented in tables. Those tables should be filtered first and put in the form that the program requires. That is also the case with the corresponding hourly outdoor temperatures, wind speeds and solar radiations. Hourly heat consumption used in this thesis is taken from the web-site of the Norwegian company Entro AS, which records energy consumption of most NTNU university buildings (Figure 4.13). Meteorological data are taken from the Norwegian meteorological institute web-site. Hourly heat consumption is shown in the table with 24 columns (Figure 4.13). Meteorological data are available in the form of columns from the Norwegian meteorological institute web-site. The developed program is adapted to these table forms, but it should not require much effort to adapt the program to handle other table formats. After filtering, the tables should be copied in the workspace of Matlab as matrixes A, T, W and S, referring to hourly heat consumption, outdoor temperatures, wind speeds and solar radiations, respectively. A is a two-dimensional matrix with dimensions Nx24, where N is the number of days. T, W and S are column matrixes of length N·24. The start and end dates of the monitoring period should be entered in a separate matrix variable called *datum*. This 2x3 matrix consists of six variables that refer to the day, month and year of the start and end of the monitoring period. Five matrixes are saved as a file with a .mat extension. Defining these dates is important, because this is how the program distinguishes days of week.



Effektuttak for: SDS, FV Dragvoll bygg 3

		Time																								
Dato	Dag	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Sum
01.10.08	ons	160	160	160	160	180	210	240	670	620	520	510	390	330	260	280	290	320	330	280	260	130	140	130	140	6.870
02.10.08	tor	150	150	140	140	150	160	170	510	450	460	440	420	400	440	370	400	400	400	320	310	150	140	160	160	6.990
03.10.08	fre	170	170	170	180	180	200	220	540	560	580	520	490	440	360	390	370	330	350	320	300	170	160	160	160	7.490
04.10.08	lør	170	180	180	180	180	190	180	180	180	180	180	170	160	150	140	150	150	160	190	190	200	210	200	200	4.250
05.10.08	søn	200	190	190	190	190	180	190	190	200	180	190	190	200	210	190	200	180	190	200	200	200	200	210	190	4.650
06.10.08	man	200	200	190	180	190	200	210	560	580	620	580	500	570	430	420	470	470	480	440	440	210	210	190	210	8.750
07.10.08	tir	210	200	210	200	210	230	240	670	680	590	630	540	480	420	430	430	440	430	410	370	160	160	150	180	8.670
08.10.08	ons	160	170	170	160	170	170	180	390	460	390	390	360	280	100	270	260	270	250	200	170	80	70	80	70	5.270
09.10.08	tor	80	80	80	90	100	120	120	280	330	420	350	230	320	280	250	230	220	170	170	160	70	70	70	70	4.360
10.10.08	fre	80	80	90	80	90	110	100	300	350	330	300	270	240	190	110	80	140	150	170	170	90	80	70	70	3.740
11.10.08	lør	80	80	90	80	90	100	100	110	110	100	100	80	70	60	60	60	60	70	60	80	80	90	90	90	1.990
12.10.08	søn	90	100	100	110	100	110	110	110	100	110	110	100	110	100	90	90	100	100	110	100	110	120	110	120	2.510
13.10.08	man	110	120	120	110	110	130	130	600	470	460	450	400	300	250	260	230	280	280	260	310	130	130	130	140	5.910
14.10.08	tir	140	150	150	150	160	160	190	490	325,4	325,4	490	470	470	480	430	440	430	430	380	360	180	180	160	170	7.311
15.10.08	ons	180	180	180	190	190	200	250	460	520	480	480	380	370	340	290	290	330	330	280	462,5	462,5	462,5	462,5	462,5	8.233
16.10.08	tor	297,7	150	150	150	150	150	150	150	150	150	150	150	150	410	330	350	410	420	370	320	180	150	160	160	5.358
17.10.08	fre	170	170	170	170	180	190	210	550	570	580	570	470	450	390	310	400	430	460	420	380	210	190	180	200	8.020
18.10.08	lør	190	190	200	180	190	190	200	190	190	180	180	160	150	120	140	120	140	150	150	160	160	170	180	170	4.050
19.10.08	søn	170	190	180	190	190	200	200	200	200	200	190	180	170	160	160	150	170	170	190	200	190	200	200	190	4.440
20.10.08	man	200	180	170	190	160	190	150	280	410	360	330	280	200	220	180	160	150	140	140	210	140	110	110	110	4.770
21.10.08	tir	110	120	120	110	120	130	140	450	420	430	430	410	400	360	370	380	370	420	420	390	190	180	140	170	6.780
22.10.08	ons	160	160	160	170	170	190	210	730	670	610	630	620	600	580	560	550	580	610	540	480	260	210	220	210	9.880
23.10.08	tor	220	230	220	230	220	230	220	400	520	500	450	400	360	380	480	460	460	440	340	280	170	140	130	140	7.620
24.10.08	fre	130	130	140	130	130	130	130	160	340	380	420	310	290	270	260	260	310	370	330	300	180	140	150	140	5.530
25.10.08	lør	160	160	160	150	160	160	160	150	160	170	160	160	130	130	110	130	120	130	120	130	110	130	120	120	3.390
26.10.08	søn	120	120	240	150	150	160	160	170	170	180	140	150	140	120	120	130	140	150	160	160	170	180	170	170	4.012
27.10.08	man	170	170	170	180	180	210	220	730	710	740	720	670	610	580	480	570	580	610	500	470	280	210	220	220	10.200
28.10.08	tir	230	220	230	220	230	260	290	850	960	930	910	810	790	800	760	800	870	910	780	670	330	310	280	290	13.730
29.10.08	ons	280	290	300	300	290	330	370	1260	1210	1150	1070	1020	950	880	860	930	980	1060	870	770	390	350	330	340	16.580
30.10.08	tor	340	350	350	350	350	390	430	1030	1180	1150	1140	1070	1150	1100	1060	1050	1120	1110	920	800	480	440	420	420	18.200
31.10.08	fre	420	420	430	420	430	460	510	970	1050	1070	1030	1010	1000	960	950	980	940	900	800	790	440	380	370	350	17.080

Figure 4.13 Heat consumption of a university building in Trondheim on the Entro web-site

Figure 4.14 presents six buttons in lower right corner of the GUI tool presented in Figure 4.1. The 'Open Monitoring File' button opens the file with five matrixes (A, T, W, S and datum) and displays heat consumption in the point plot presented in Figure 4.1. The beginning and end dates of the monitoring period are written in the GUI's monitoring period palette. After the control regimes are recognized and defined in the schedule palette by the user, it is possible to save the control regime schedule by pressing the 'Save Schedule' button (Figure 4.14). The user can give a name to the schedule and select the directory where the file will be saved. The file containing the schedule can be opened with 'Open Schedule File'. The control regime schedule will be automatically written in the schedule palette. It is possible to save the results gained in the last linear regression calculation by pressing 'Save Calculation As'. If a calculation is already opened, the user can save it in the existing file with the 'Save Calculation' button. Existing calculations can be opened with the 'Open Calculation File' button. All buttons in Figure 4.14 open dialogs similar to the dialog presented in Figure 4.15, where the file to be opened can be selected or the name of the file to be saved can be written.

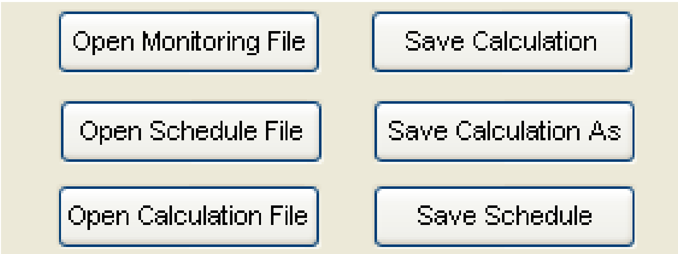


Figure 4.14 GUI buttons of for saving and opening files

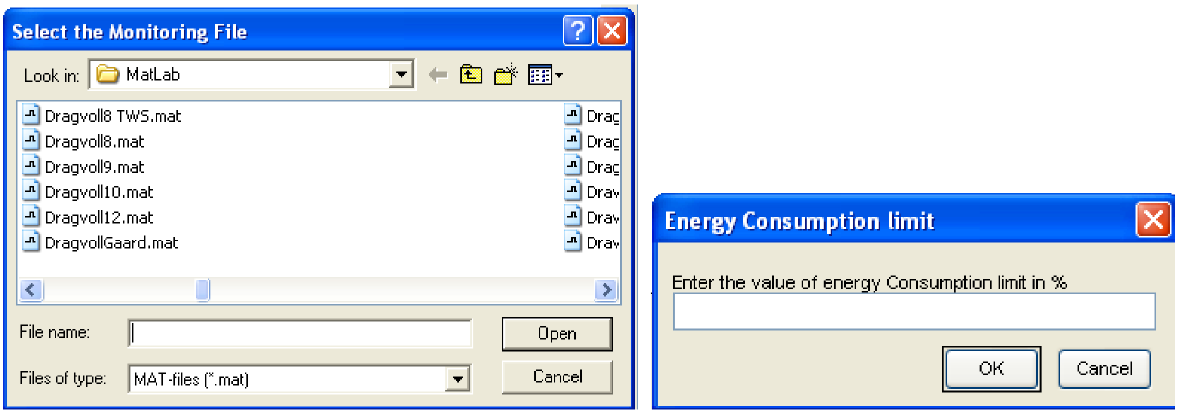


Figure 4.15 Dialog opened by pressing one of the buttons in Figure 4.14 and the dialog box for changing the limits that are used to determine the corrected energy signature line

4.3 Steps of the building energy performance analysis method

The building energy performance analysis method is implemented with the tool for modeling and analyzing building heat consumption that is presented in the previous subchapter. These steps should be followed in building energy performance analysis:

- Identification of control regimes

- Identification of relevant monitoring period
- Identification of HVAC operation malfunctions
- Selecting the correct linear regression model
- Covering nonlinearity in HVAC system operation by different data groupings

4.3.1 Identification of control regimes

After opening the monitoring file, the first step in developing the building heat consumption model is identifying the control regimes by inspecting the 3-D plot of heat consumption (Figure 4.16). Identification of control regimes is important if the models use mean values grouped by regimes or hourly data. For the daily model and HOD model there is no need to recognize the regimes.

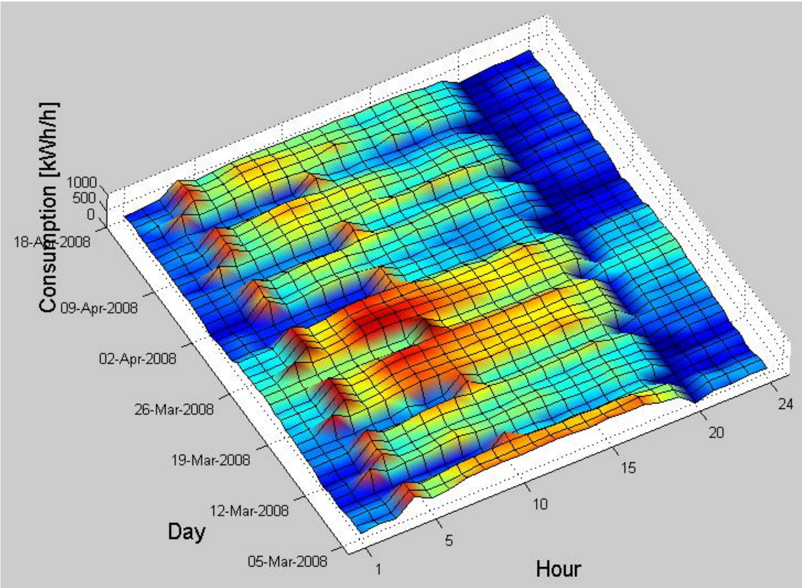


Figure 4.16 Three dimensional plot of heat consumption of a NTNU campus building

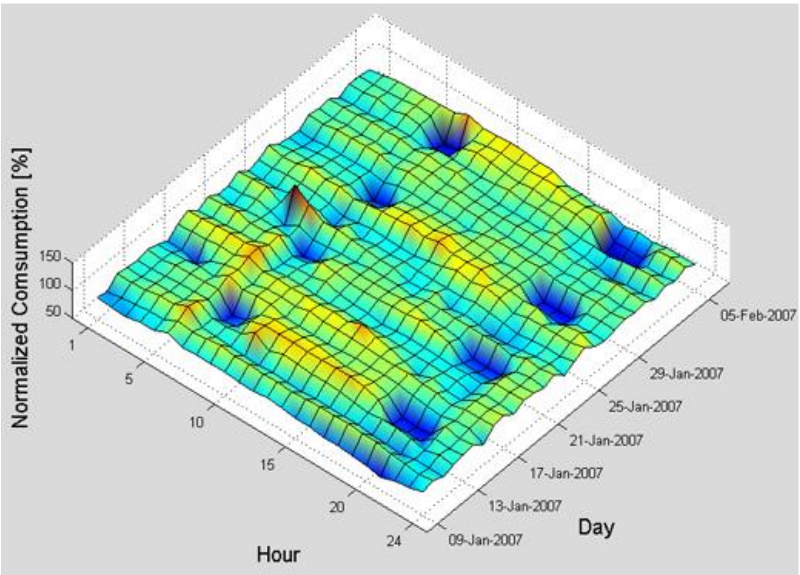


Figure 4.17 Normalized heat consumption plot of a NTNU campus building

It can be recognized in Figure 4.16 that the HVAC system has distinguishable day and night operation. Weekend operation is different from weekday operation. The weekday-day regime lasts from $4^{\underline{h}}$ until $19^{\underline{h}}$, except for Monday when it starts at $3^{\underline{h}}$. During the weekends, the day regime starts at $10^{\underline{h}}$ and lasts until $18^{\underline{h}}$. Peaks appear at the beginning of the day regimes. Regimes are made in the schedule palette. Peaks from Figure 4.16 should be treated as a separate regime lasting for one hour.

The next step is to determine whether or not the regimes are defined properly. If deviations appear systematically in the normalized consumption plot (Figure 4.17), then that is a sign that the regimes are not properly defined. 'Valleys' appear every weekend in Figure 4.17 because the weekend day regime is actually shorter than it was defined. If the weekend-day regime is different from the weekday-day regime, and it is not defined separately, 'valleys' or 'hills' will appear during weekends.

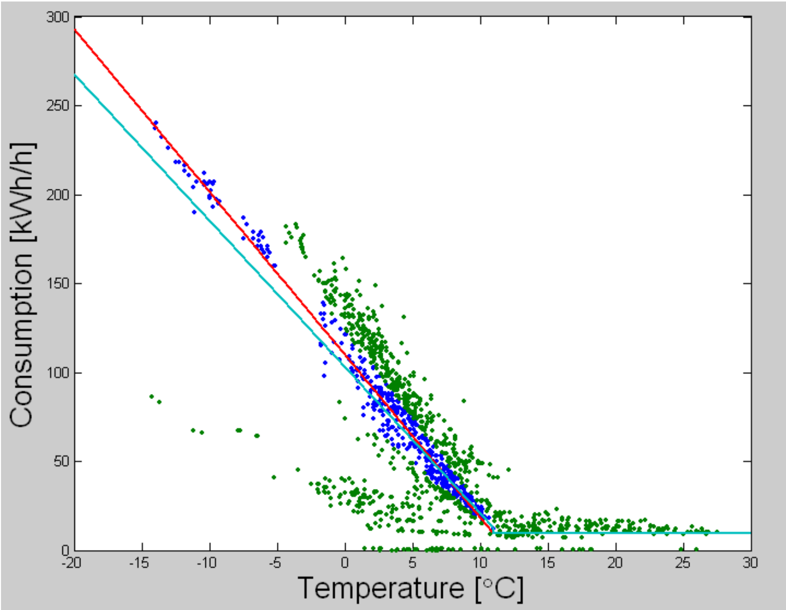


Figure 4.18 Corrected and uncorrected energy signature lines for one control regime of an NTNU campus building; control regime that is not correctly defined

It is also possible to recognize the distinction between regimes by reviewing energy signature lines (Figure 4.12). Corrected and uncorrected energy signature lines can be also used to verify the control regime schedule. If corrected and uncorrected lines are close to each other, such as in Figure 4.19, there are no points that deviate significantly from the energy signature line. It is obvious that the dots in the lower left corner of Figure 4.18 do not belong to the analyzed control regime. If the lines are not close, it is evidence that a regime is not correctly defined.

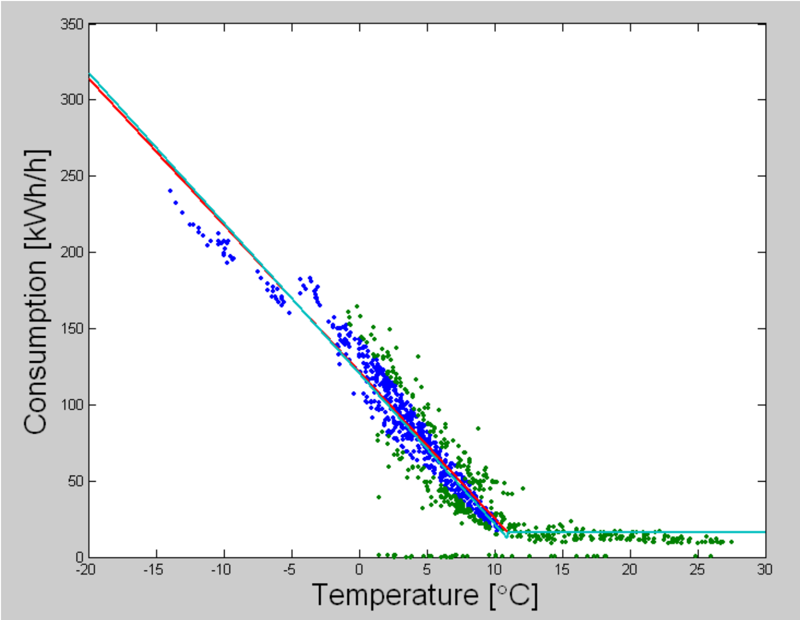


Figure 4.19 Corrected and uncorrected energy signature lines for one control regime of an NTNU campus building; control regime is correctly defined

4.3.2 Identification of relevant monitoring period

Performance of the HVAC system can be changed during the monitoring period. Data points used in the linear regression must originate from a period when control regime settings are the same. It is also possible that HVAC operation changes are a consequence of the installation of new equipment or other retrofits. Information regarding these changes can be obtained from maintenance personal. That is, however, often difficult to accomplish. An easy and reliable way of getting that information is by analyzing an NHC plot (Figure 4.20) or comparing linear regression coefficients for different monitoring periods. Control regimes were changed after February 10, 2008 for heat consumption presented in Figure 4.20. One should use a period with an unchanged system operation to develop a building heat consumption model (periods before or after 10th of February 2008 for normalized heat consumption are presented in Figure 4.20).

In some cases, control regime schedules are not changed, but other settings defining dependency of heat consumption from outdoor parameters may be changed. These changes can be recognized in the normalized consumption plot. In order to confirm them, linear regression coefficients for different monitoring periods should be compared by reviewing a linear coefficients list-box.

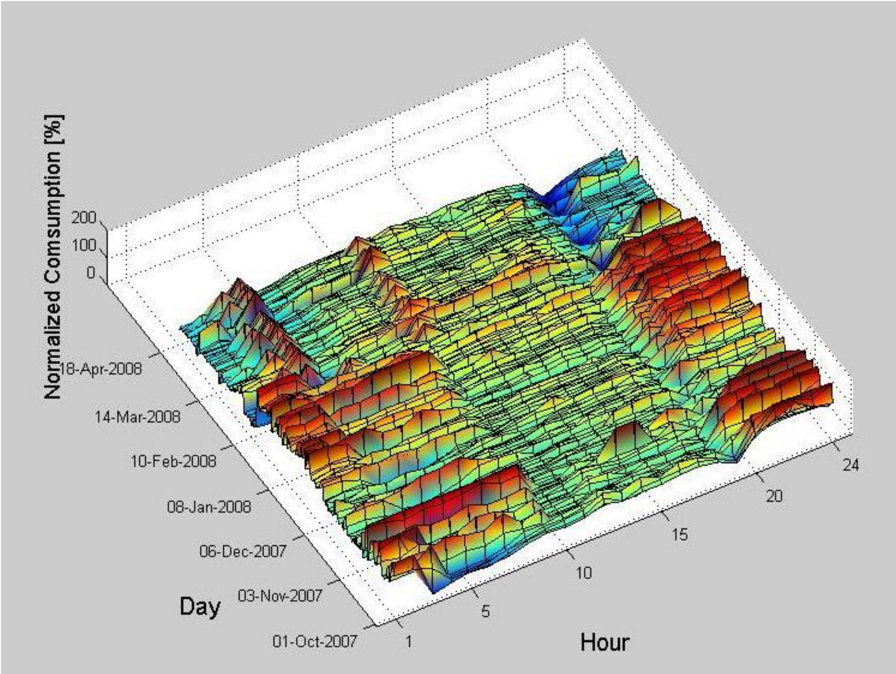


Figure 4.20 Normalized heat consumption plot of an NTNU campus building

If, for some period, NHCs deviate significantly from 100%, that period should be excluded from linear regression by selecting the period in the palette presented in Figure 4.4. The model of heat consumption assumes that the system has operated correctly, so any faulty operation will make the model less accurate.

4.3.3 Identification of malfunctions in HVAC system operation

Analysis of results is done after defining the control regimes and determining the relevant monitoring period. The main result of analysis is identification of malfunctions in HVAC operation through overview of 3-D NHC plots. Ideally, the surface of the plot should look like a horizontal flat surface placed at 100% if the actual heat consumption and predicted heat consumption are equal. This is never case since both performance of HVAC system and the heat consumption model are not perfect. The user should determine reasons for deviations from the flat surface, i.e., if deviations are the result of malfunctions or model inaccuracies. That can be accomplished by controlling 3-D NHC plots gained for different models. The model can be varied by employing MLR models and using different data resolutions. Finally, the model should consider nonlinear heat transfer processes (thermal storage effects) that introduce time delays. Subchapter 3.3 discusses how different data groupings cover different effects. Every data grouping has some advantages and disadvantages. Checking every model by inspecting the 3-D NHC plots should eliminate doubts regarding the correctness of the model.

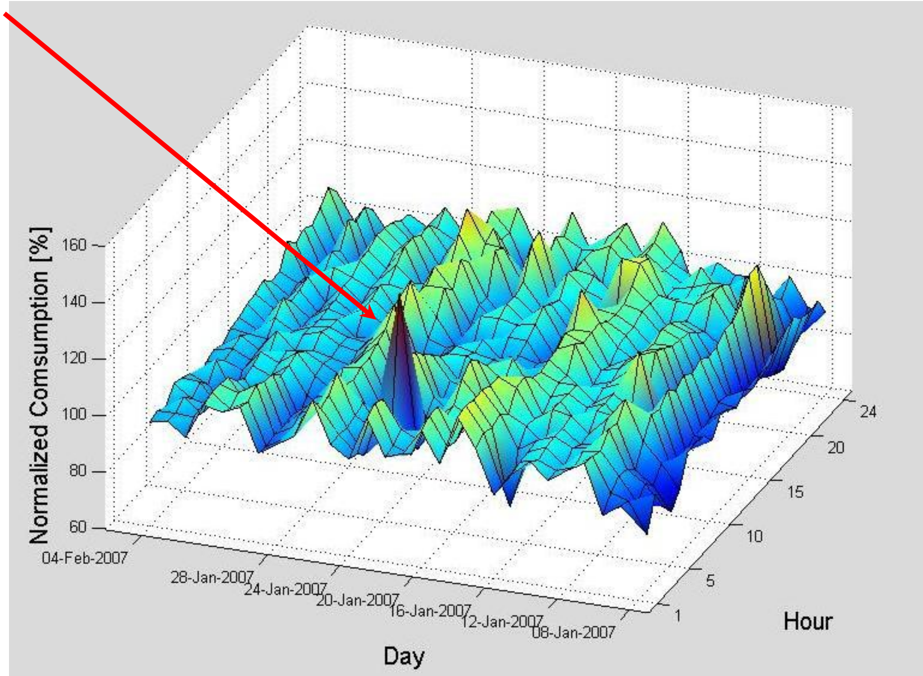


Figure 4.21 Normalized heat consumption plot of an NTNU campus building

If the HVAC system has much higher or lower heat consumption in some period, this can be recognized in 3-D NHC plots as ’hills’ or ’valleys’ that significantly deviate from a ratio value of 100%. This is demonstrated in Figure 4.21. The labeled hour certainly represents fault in the HVAC operation. However, different models should be tested before making a final decision.

4.3.4 Employing multiple linear regression model

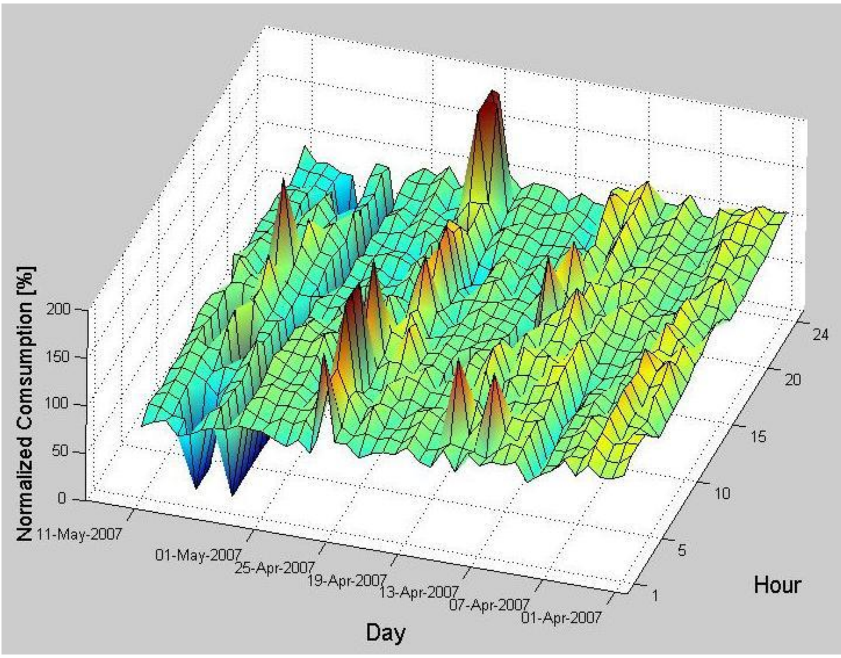


Figure 4.22 Normalized heat consumption plot of an NTNU campus building for a simple linear regression model

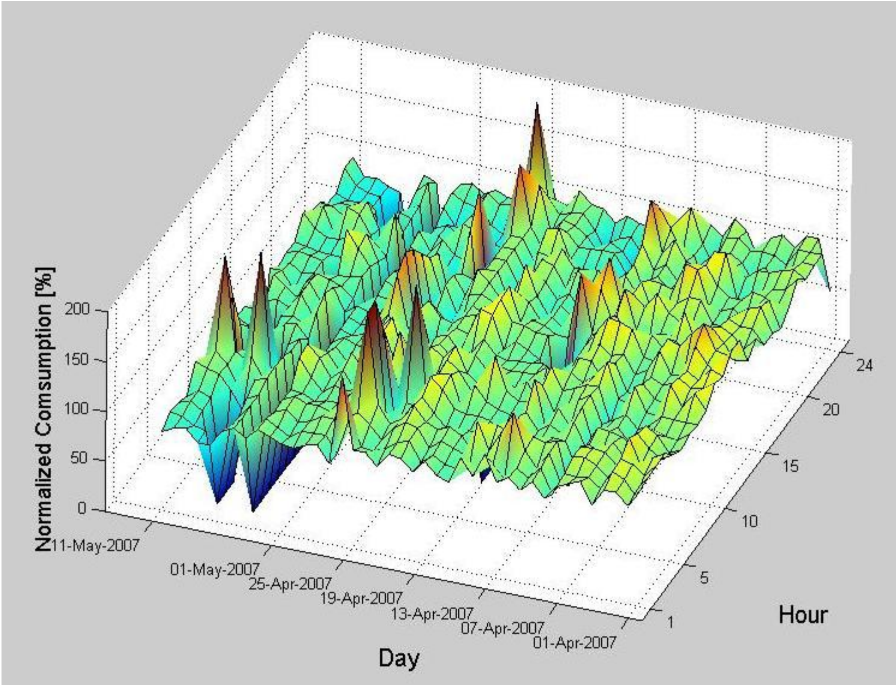


Figure 4.23 Normalized heat consumption plot of a NTNU campus building for a multiple linear regression model

The linear regression model can be defined as either *simple* or *multiple*. The risk of introducing a multiple regression model is that the accuracy of the model can suffer when there are too few data points. Some independent variables of MLR model can be insignificant, so the model should be kept as simple as possible.

Higher NHCs can be recognized for one day in the middle of the presented period in Figure 4.22. Prediction is gained through simple LR with outdoor temperature as the only independent variable. Figure 4.23 presents NHC plot for the same building and same period with predictions gained from the MLR model. Most of the deviations that appear in Figure 4.22 do not appear for the same day in Figure 4.23. That means that the deviations are not a consequence of system operation faults, but a result of inaccuracies in the simple linear regression model.

4.3.5 Covering nonlinearity in HVAC system operation by different data grouping

Different data groupings should cover inaccuracies of LR model, which are a consequence of different phenomena that introduce time delays (subchapter 3.3). Two examples will demonstrate how different data groupings should be used to accurately assess HVAC system performance.

Figure 4.24 presents heat consumption of an NTNU campus building. We recognize that after $21^{\underline{h}}$, heat consumption gradually decreases until midnight. This could be because heat consumption corresponds to more than one aggregate in the HVAC system. It seems that aggregates have different time settings that define decreased night operation. During the morning (between $8^{\underline{h}}$ and $12^{\underline{h}}$), at the beginning of day control regime, higher heat consumption appears compared to the rest of a day. This may be because temperatures are lower in the mornings than during the afternoon. The other reason could be that the building walls must warm up after the night temperature set-back. Figure 4.25 presents NHCs gained from the model with hourly data grouped by control regimes. This data grouping could not cover the gradual decrease of heat consumption from 21$^{\underline{h}}$ to 24$^{\underline{h}}$, so deviations of NHCs appear in that period. It can be also recognized that NHCs are higher during the morning (between 8$^{\underline{h}}$ and 12$^{\underline{h}}$).

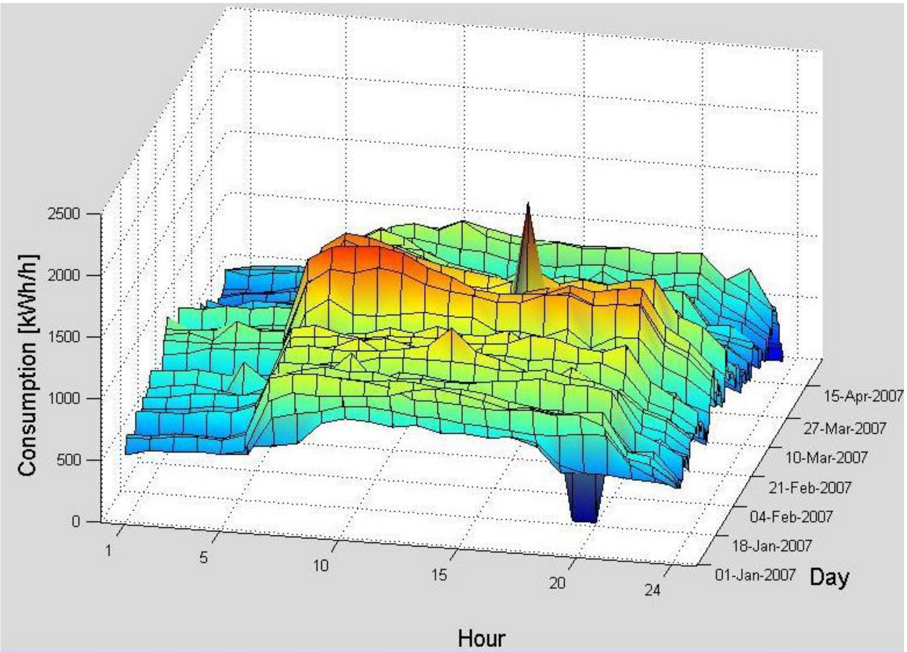


Figure 4.24 Heat consumption plot of a NTNU campus building

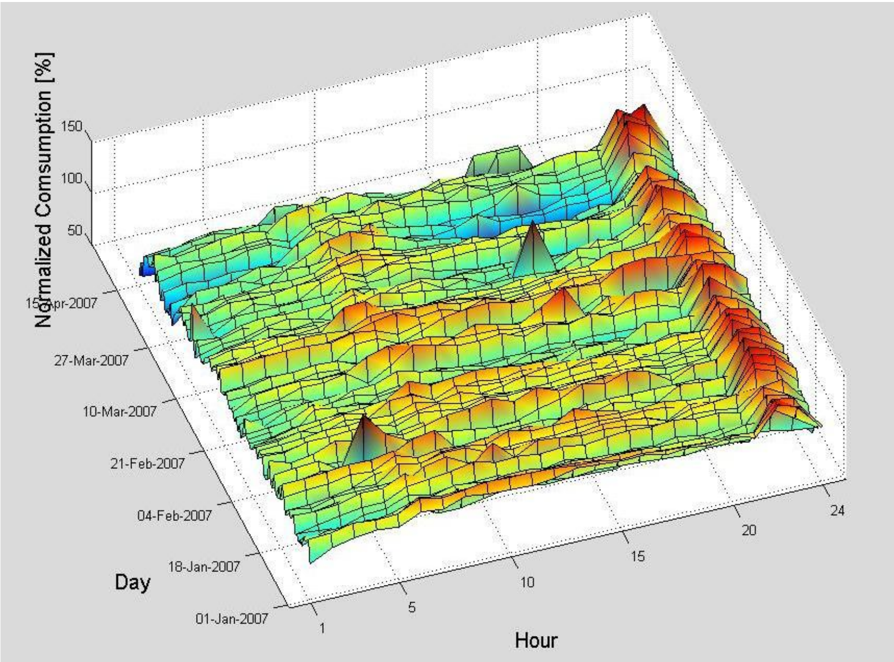


Figure 4.25 Normalized heat consumption plot of an NTNU campus building generated from the model with hourly data grouped by control regimes

Figure 4.26 presents NHCs from the same NTNU campus building gained from the HOD model. Night NHC deviations and higher NHCs during mornings disappeared in this figure. It can be concluded that the HOD grouping covered the effect of the morning warm up, while hourly data did not cover those effects.

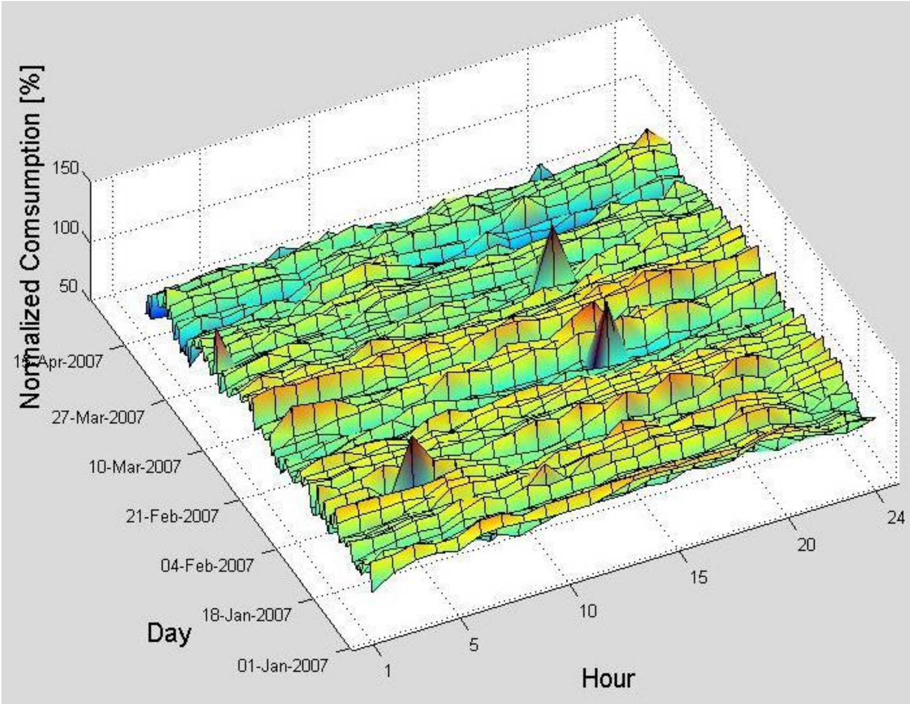


Figure 4.26 Normalized heat consumption plot of an NTNU campus building gained from HOD data

The second example will demonstrate grouping with mean values grouped by regimes. This way of grouping should result in smaller NHC deviations than models using hourly grouping. However, deviations (faults in HVAC operation) sometimes appear on an hourly basis, and models using mean values or daily data cannot show them.

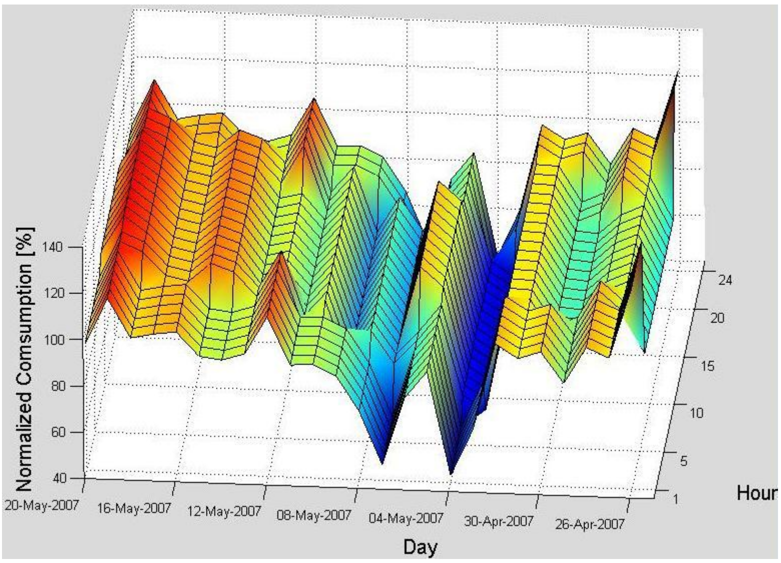


Figure 4.27 Normalized heat consumption plot of an NTNU campus building gained from the model with mean values grouped by regimes

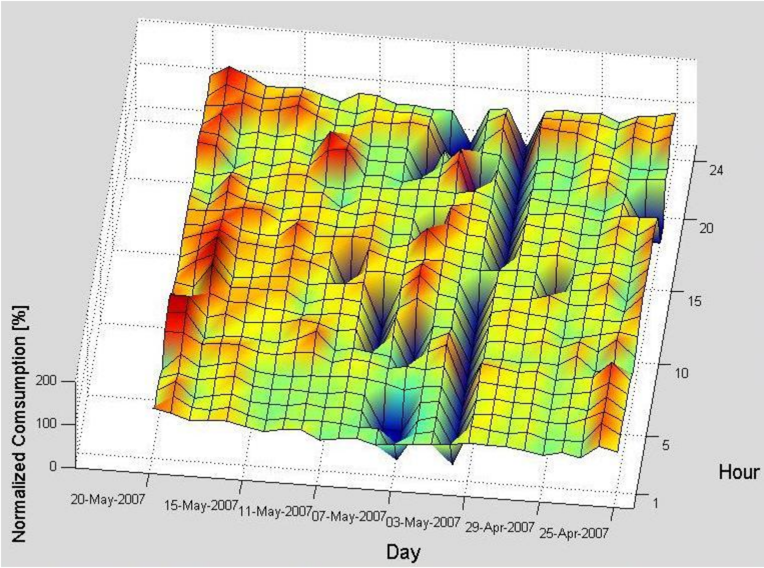


Figure 4.28 Normalized heat consumption plot of an NTNU campus building gained from the model with hourly data grouped by control regimes

Figure 4.27 shows NHCs of an NTNU campus building obtained from the model with mean values grouped by regimes. Heat consumption was lower than predicted by the model on May 3, 2007 and May 4, 2007. Heat consumption was also lower during the night regime on May 7, 2007. NHC deviations are not so great other days. Figure 4.28 presents NHCs for the same building gained from the model with hourly data grouped by control regimes. This figure explains what happened on May 3 and 4. The system started to work with reduced operation on May 3, 2007 at $14^{\underline{h}}$. This problem lasted until $14^{\underline{h}}$ next day. Reduced operation can also be identified during the night between May 6 and 7. However, we recognize that reduced operations also appeared during other days, which we could not identify in Figure 4.27.

4.4 Savings measurement and verification

Figure 4.29 Buttons of the tool for modeling and analyzing building heat consumption used for savings measurement and verification

Tool for modeling and analysis of building heat consumption enables evaluation of savings measurement by comparing predictions of heat consumption that are gained from models corresponding to pre-retrofit and post-retrofit operations. LR calculations are conducted for monitoring periods before and after the retrofit in order to obtain LR coefficients that characterize pre-retrofit and post-retrofit operation. The coefficients are saved after every linear regression calculation. The ‘Save Coeff. 1’ button saves LR coefficients for the pre-retrofit monitoring period. ‘Save Coeff. 2’ saves LR coefficients for the post-retrofit monitoring period. Since control regime schedules can be changed during retrofit, independent variables for which LR coefficients will be applied have to be grouped according to the control regimes schedules. ‘Save T. Sch. 1’ and ‘Save T. Sch. 2’ save independent variables grouped according to schedules in the pre-retrofit and post-retrofit operations, respectively. After that, the user can press the ‘Comparison’ button to get the ratio of heat consumption calculated with LR coefficients gained from post-retrofit and pre-retrofit operation. Energy savings are accomplished if the ratio is lower than 100%.

4.5 Linear regression calculation functions in the tool for modeling and analyzing building heat consumption

Simple or multiple linear regression calculation with different data resolutions are conducted by pressing one of the seven buttons in the ‘CALCULATE’ palette (Figure 4.30). Calculations are conducted by pressing the following buttons:

- ‘Calculate’ - simple linear regression with hourly data grouped by regimes. This function is not used for modeling heat consumption, but to determine uncorrected and corrected energy signature lines, which are used to determine the control regime schedule.
- ‘Simple LR Regimes’ - simple linear regression with hourly data grouped by regimes.
- ‘Multi LR Regimes’ - multiple linear regression with hourly data grouped by regimes.
- ‘Simple LR 24 Hours’ - simple linear regression with HOD grouping.
- ‘Mult LR 24 Hours’ - multiple linear regression with HOD grouping.
- ‘Simple LR Reg Mean’ - simple linear regression with mean values (also used for calculation with daily data).
- ‘Multiple LR Reg Mean’ - multiple linear regression with mean values (also used for calculation with daily data).

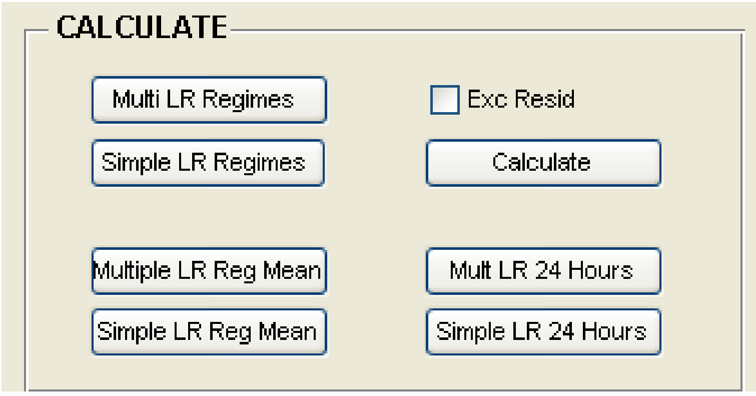


Figure 4.30 Buttons in the ‘CALCULATE’ palette of the tool for modeling and analyzing building heat consumption

Calculations for every function assigned to one of seven buttons in the 'CALCULATE' palette are carried out for the monitoring period defined in the monitoring period palette (Figure 4.5). All functions use the special function that determines the base level consumption and change point temperature. The function follows the algorithm presented in Kissock et al. (2003). Simple linear regression with outdoor air temperature as the independent variable is used to determine the BLC and CPT. All functions eliminate data points from the linear regression with temperatures greater than the change point.

Only function the 'Calculate' uses a limit to determine outliers. A discussion regarding uncorrected and corrected energy signature lines is in subchapter 4.2. Other functions use R-student residuals to determine outliers and eliminate them from calculation. A flow diagram of a general algorithm used for all seven functions is presented in Figure 4.31. The algorithm consists of the three steps presented in Figures 4.32, 4.33 and 4.34. Details and deviations from the presented algorithms for each of the seven functions will be explained after presenting the algorithms in Figures 4.31 - 4.34.

The first step in the flow diagram presented on Figure 4.32 is data loading. Data are loaded from a file with a .mat extension. Details about saving monitoring data and meteorological data are presented in chapter 4.2. The file includes a matrix 'datum' that defines the beginning and end of the monitoring period as well as heat consumption and meteorological data.

The calculation period is defined with a separate function. This function takes the dates of the beginning and the end of the calculation period and shortens them so that the period begins with Monday and ends with Sunday. This is important because regimes are defined by week days, so the calculation period must fit the regimes.

Transformation of monitoring data to four matrixes with 24 columns enables the program to handle all kind of matrixes with heat consumption data and meteorological data. Each row of the matrixes corresponds to a single day. The first member of each matrix gained after transformation corresponds to $1^{\underline{h}}$ at Monday, while the last member of each matrix corresponds to midnight between Sunday and Monday.

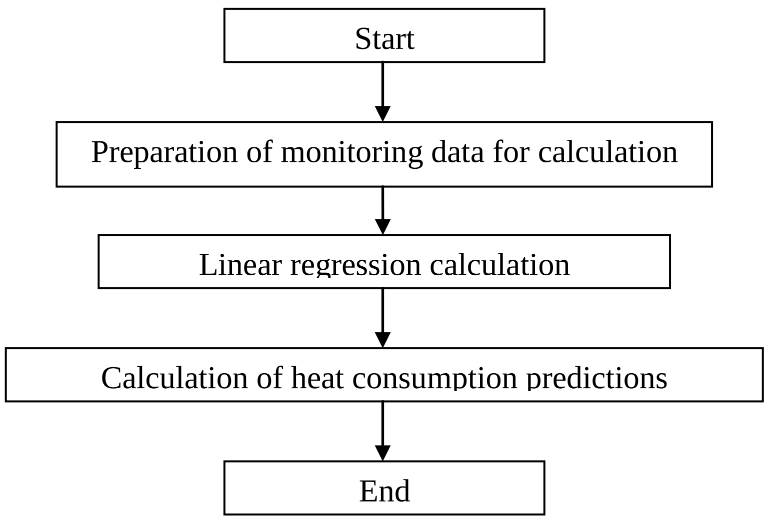


Figure 4.31 Flow diagram of general algorithm

The last step in preparing the monitoring data for calculation is to copy data from four matrixes gained in the previous step into a set of column matrixes. The first column matrix of a set corresponds to heat consumption monitoring data, and the other three to outdoor air temperature, sun radiation and wind speed. A Matlab function performing linear regression demands that dependent and independent variables are in the form of column matrixes. One set of column matrixes has two column matrixes for simple LR, or four matrixes for multiple LR. In the following text and flow charts, four column matrixes will be mentioned, assuming that only two column matrixes exist in the case of simple linear regression, instead of four. Each set of column matrixes corresponds to the control regime in the case of calculations with the hourly vales grouped by regimes or calculation with mean vales grouped by regimes. For HOD calculation, there are 48 sets of column matrixes. To calculate with daily data, there are two sets that correspond to weekday and weekend operation. Before sorting data into sets of column matrixes, it is necessary to calculate the mean values of the monitoring data from the hourly data for calculations with daily data, or calculate the mean values grouped by regimes. Linear regressions are conducted in the next step of the general algorithm. Data are now sorted and prepared for linear regression.

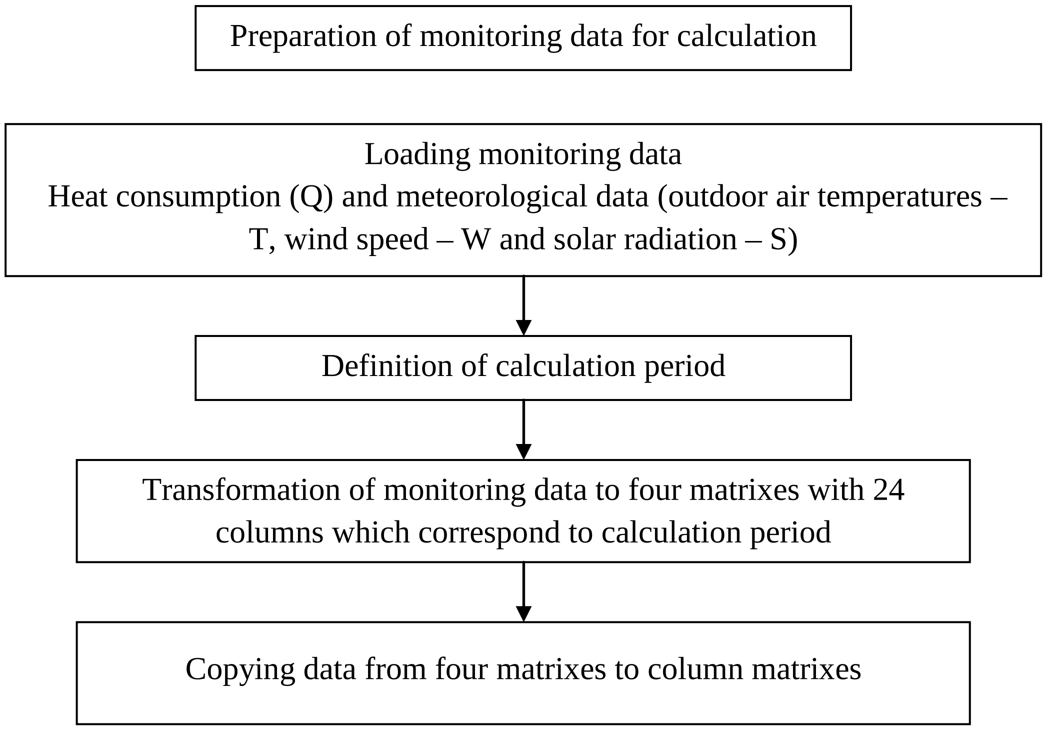


Figure 4.32 Flow diagram of the preparation of monitoring data for calculation

Figure 4.33 presents a flow diagram for the linear regression calculation step. The whole procedure is repeated as many times as the number of sets of column matrixes, so *n* represents the number of column matrix sets.

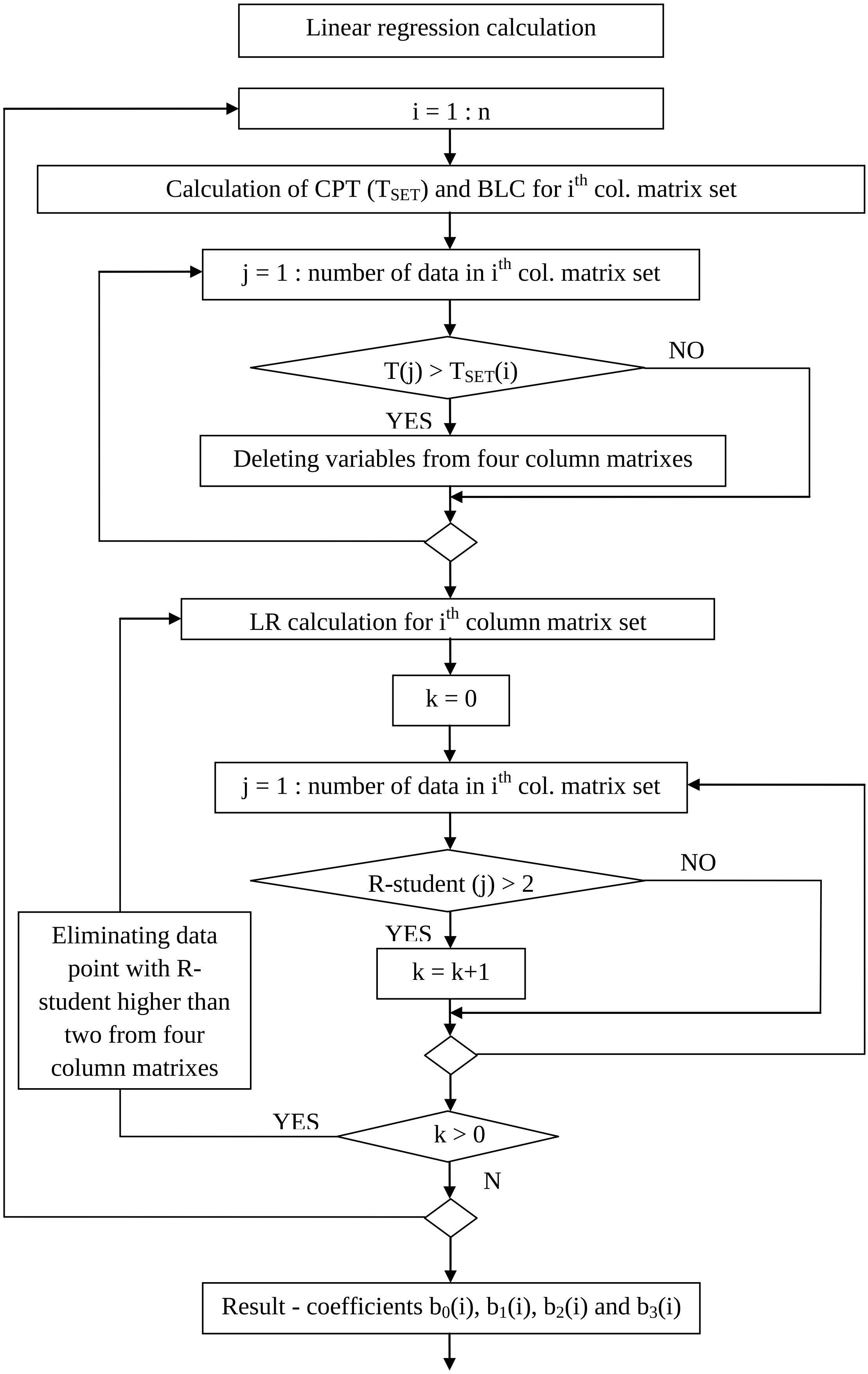


Figure 4.33 Flow diagram for the linear regression calculation step

CPT and BLC are changed from regime to regime, or from weekday to weekend operation. Accordingly, CPT and BLC calculations are performed; they correspond to regimes for calculations with hourly data and calculations with mean values grouped by regimes. Calculations with daily data and the HOD grouping use CPTs and BLCs that correspond to weekdays and weekends. The CPT is lower than the indoor temperature of the building because of heat gains that change from unoccupied to occupied periods. The BLC is a consequence of using hot tap water, so it changes from unoccupied to occupied periods. Unoccupied and occupied periods correspond to regimes. This means that calculation of CPT and BLC according to regimes should be correct. Change of operation from weekdays to weekends also corresponds to changes from unoccupied to occupied periods. It would be more proper to follow daily changes of CPT and BLC in the HOD model by calculating those parameters for every hour of weekday and weekend operation. However, that calculation could be inaccurate, since there may be too few data points for calculation. As a result, CPT and BLC are calculated for weekends and weekdays for the HOD model.

CPTs and BLCs are determined with simple LR calculation with outdoor air temperature as the only independent variable. Since the CPT is lower than the indoor temperature of the building because of solar radiation, among other heat gains, it is logical to calculate CPT with multiple linear regression involving solar radiation. This would mean that CPT would be dependent on solar radiation. However, such a procedure does not exist in the literature.

If the outdoor temperature is greater than CPT, then that data point is eliminated from calculation by deleting it from four column matrixes. Instead of this procedure, an indicator variable I (equation 3.16) could be used to separate data below and over CPT. Since LR model implementation with an indicator variable is not possible with the ‘regress’ function in Matlab, the data have to be separated over and below change point. The LR calculation is performed after eliminating data points that exceed the change point.

The ‘CALCULATE’ pallet (Figure 4.30) includes the check box ‘Exc Resid’. If it is checked, the program eliminates outliers. It is checked if the R-student statistics for every data point are higher than 2 after the linear regression calculation. If there are such points, linear regression is repeated with the data set that does not contain outliers until all outliers are eliminated. Results of the LR calculation step are linear regression coefficients that are used in the next step to define heat consumption predictions.

Figure 4.34 presents a flow diagram for the calculation of heat consumption predictions. It is checked for every data point if the outdoor air temperature is lower than CPT, so a prediction is calculated from coefficients of linear regression multiplied by independent variables or it is equal to BLC. Finally, NHCs are calculated as a ratio of real heat consumption and predicted heat consumption. The specification of each of the seven functions will be discussed now.

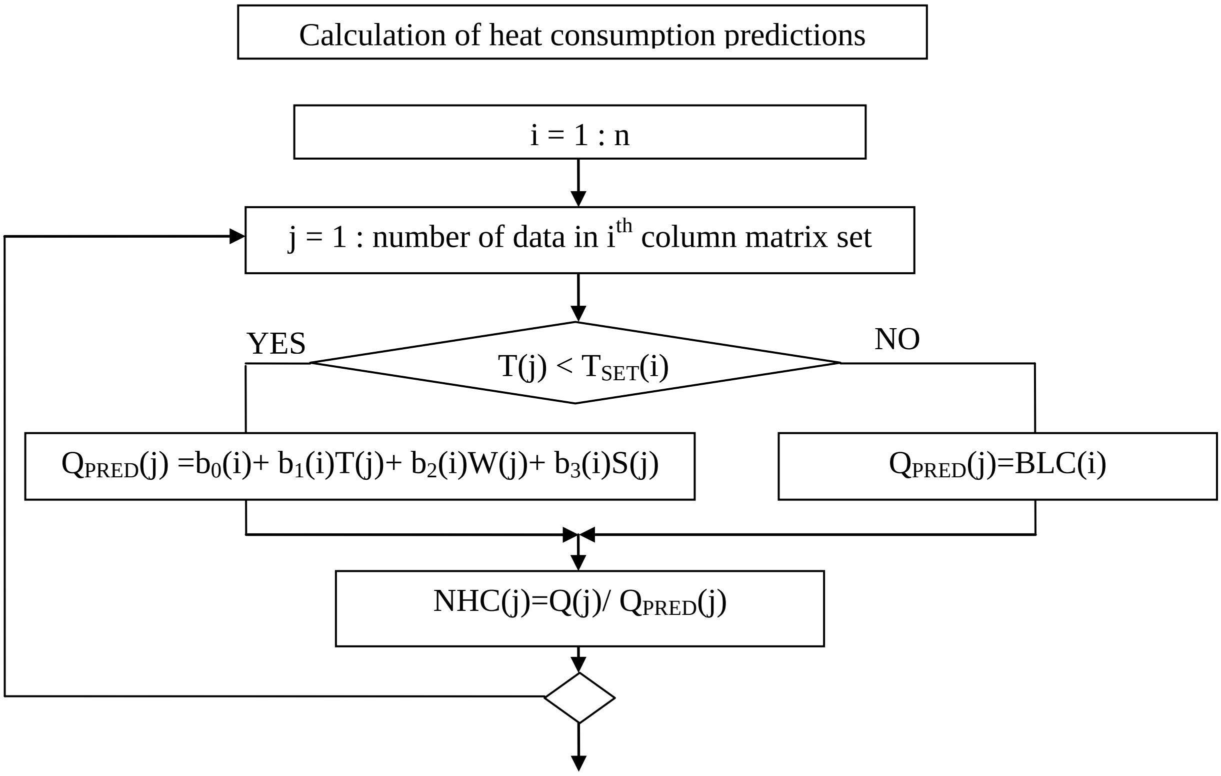


Figure 4.34 Flow diagram for the calculation of heat consumption predictions step

Calculate

This function conducts simple linear regression with hourly data grouped by regimes, (Table 3.1). The same data set is used as in the linear regression of the function 'Simple LR Regimes'. The function 'Calculate' is not used to model heat consumption predictions, but to recognize control regimes by reviewing uncorrected and corrected energy signature lines (subchapter 4.3.1). It is the only function that uses a limit to determine outliers in the linear regression calculation step. The function follows algorithms presented in Figures 4.32 and 4.34. The linear regression calculation step is different from the algorithm shown in Figure 4.33. The first linear regression calculation determines the uncorrected energy signature line. This calculation is done with the function that determines BLC and CPT. The generated energy signature line represents heat consumption prediction, which is then used to decide if actual heat consumption are within the set limit (20% is the default value which can be changed). The corrected energy signature line is determined through linear regression of data points within the limit.

Simple LR Regimes

This function conducts simple linear regression calculation with hourly data grouped by regimes. The function fully follows the presented algorithm except that, instead of four column matrixes, only two column matrixes are used.

Multi LR Regimes

Multiple linear regression is performed with this function with hourly data grouped by regimes. All functions that involve multiple linear regression perform the procedure for determining the wind independent variable. Discussion about the wind independent variable is presented in subchapter 3.6.1. Three different formulas are used to define the wind independent variable:

$$W_{INDEPENDENT\ VARIABLE} = w \cdot (T_{IN} - T_{OUT}) \tag{4.1}$$

$$W_{INDEPENDENT\ VARIABLE} = w^2 \cdot (T_{IN} - T_{OUT}) \tag{4.2}$$

$$W_{INDEPENDENT\ VARIABLE} = \sqrt{w} \cdot (T_{IN} - T_{OUT}) \tag{4.3}$$

where:

w - wind speed in m/s

T_{IN} – indoor air temperature (20°C is used for all calculations)

T_{OUT} – outdoor air temperature

Since data points with temperatures over CPT are not used in linear regression, the independent variable defining the wind influence is always positive. It is possible to introduce other wind speed power in equations 4.1 – 4.3, except 1, 2 or 0.5. It is assumed that three presented cases will cover the various phenomena.

Three linear regression calculations are conducted with three different wind influence independent variables defined by one of three equations 4.1 – 4.3. The coefficient of determination (R^2) is defined for every linear regression calculation. The model with the highest R^2 value is selected. The coefficient of determination is the main criteria for evaluating the goodness of fit in linear regression calculations and selecting a proper linear regression model (Walpole 2007). It demonstrates the extent of the variation of the dependent variable explained by the model. The equation for coefficient of determination is:

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{4.4}$$

where:

$SST = \sum_{i=1}^{n}(y_i - \bar{y})^2 = SSR + SSE = \sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2 + \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ - total sum of squares;

SSR – regression sum of squares; It represents explained variation;

SSE – error sum of squares; It represents unexplained variation;

$\hat{y}_i$ – prediction gained from linear regression for the i^{th} data point;

$\bar{y}$ - mean value of dependent variable;

y_i - dependent variable for the i^{th} data point.

The numerator in equation 4.4 represents the variation of the dependent variable that is explained by the model, while the denominator is the overall variation. Walpole (2007) also defines an adjusted coefficient of determination (R^2_{adj}), which is more appropriate for comparing models with different numbers of independent variables than R^2. This coefficient is R^2 adjusted for degrees of freedom, i.e., for number of independent variables and number of data points. Since models involving different wind power have the same number of degrees of freedom, it is not necessary to use R^2_{adj}. Thus, using R^2 is adequate.

After determining the power of the wind influence independent variable, the next step is eliminating the residuals. The selected wind influence independent variable is used to predict heat consumption. Determining the wind influence is conducted for the column matrix set. This is logical because the column matrix sets correspond to unoccupied and occupied hours, when the windows are opened by occupants. The procedure for determining the power of wind influence independent variable is conducted in every function with multiple linear regression that involves wind speed.

Simple LR 24 Hours

This function conducts simple linear regression with the HOD data grouping. Calculations of BLC and CPT in this function and the function ‘Mult LR 24 Hours’ is done for data grouped in weekend and weekdays, i.e. not for every hour. Calculations could be done separately for every hour, but due to the risk that too few data points would be involved in the calculations this is not done in this thesis.

Mult LR 24 Hours

The only difference between this and the previous function is that ‘Mult LR 24 Hours’ uses multiple linear regressions. The procedure for determining wind independent variable is done for every hour. If the occupants open the windows in the morning when they come to work, that can be recognized by a change in the power for the wind independent variable or by a change in the value of the linear regression coefficient corresponding to wind influence. A change in the direction of the sun in combination with the building orientation can be covered by this model. If linear regression coefficients corresponding to sun radiation have higher values during the morning, then the building has an eastern orientation. A western orientation should cause higher regression coefficient values during the afternoon.

Simple LR Reg Mean

This function performs simple linear regression with mean values and daily data. Mean values of hourly data are calculated in preparation of the monitoring data for the calculation step (Figure 4.32). It is necessary to eliminate hourly data points that correspond to temperatures over CPT from calculation of mean values, since during a period corresponding to one regime, or during a day, the temperature may rise above the CPT. Mean values are calculated for data points with temperatures lower than CPT. CPTs and BLCs are calculated for each regime for calculation with mean values grouped by regimes. For calculation with daily data, CPTs and BLCs are calculated for weekdays and weekends. There is no need to check if temperatures are over the CPT in the linear regression calculation step (Figure 4.33) as in other functions, since this is checked already in preparation of monitoring data for calculation step. Regarding the calculation of heat consumption predictions step (Figure 4.34), if all temperatures during the period corresponding to a control regime or day are greater than the CPT, a prediction of heat consumption is equal to BLC. For the opposite case, heat consumption predictions are calculated from linear regression coefficients.

Multiple LR Reg Mean

All features explained for the previous function apply to this function. The only difference is that multiple LR is conducted instead of simple LR.

5. Evaluation of proposed method

The building energy performance analysis method proposed in this thesis will be estimated qualitatively and quantitatively. Qualitative evaluation will identify O&M problems of space heating and ventilation system of NTNU campus buildings using the proposed method. This will be presented in chapter 6. Quantitative analysis will evaluate different features implemented in the heat consumption model. The following model features are implemented in order to refine model:

- Simple and multiple linear regression modeling
- Different data resolution implemented in linear regression calculation
- Excluding outliers

In addition to these features, quantitative analysis will analyze the monitoring sample duration necessary to get a representative model.

5.1 Evaluation of simple and multiple linear regression models

Introducing multiple linear regression should increase the goodness of fit. This can be checked if R^2 for models gained through single and multiple linear regressions are compared. This represents stepwise regression. Results of modeling for a number of analyzed buildings will be presented for each data grouping.

Experiment results are analyzed by the mean value and variance if experiment parameters are fixed during the experiment. Linear regression must be used for experiments whose parameters that determine the outcome of the experiment are not fixed. In this case, the mean value and variance do not give the necessary information, since results vary with changes of parameters, i.e. independent variables. R^2 is introduced in order to evaluate variance. Adjusted coefficient of determination R^2_{adj} has to be used in order to compare LR calculation results conducted with data sets with different numbers of independent variables and different numbers of data points. Excluding outliers causes the number of data points involved to vary. Including more independent variables in multiple regression model is also a reason to use R^2_{adj}. R^2 is expressed in equation 4.4. R^2_{adj} is:

$$R^2_{adj} = 1 - \frac{SSE/(n-k-1)}{SST/(n-1)} \tag{5.1}$$

where:

SST – total sum of squares

SSE – error sum of squares

n – number of data points

k – number of independent variables

There is no significant difference between R^2_{adj} and R^2 if k is much smaller than n and n is fixed value. Since k is equal to three and n is number of data points gained from monitoring intervals longer than three months, n is significantly higher than k. This means that the difference between R^2_{adj} and R^2 is insignificant. In the remaining text, R^2 will be discussed, although R^2_{adj} was calculated.

Linear regressions are conducted for each column matrix set. R^2, SST and SSE are calculated by summing differences expressed in equation 4.4 for data points belonging to column matrix sets. Evaluation of the improvement by introducing multiple linear regression models will be done for four data groupings: hourly data, HOD, mean values and daily. Linear regression calculations for each data grouping are performed for the same set of data points. The model evaluation is based on the analysis of coefficients of determination, sequential sum of squares and linear regression coefficients. Subchapter 5.2 compares results of LR for different data groupings. Coefficients of variation are used to determine which data grouping gives the most precise heat consumption prediction. Results of modeling ventilation heat consumption are presented separately. Part of the NTNU University campus (Dragvoll) has electric heating, so that district heating is used for ventilation heating and preparation of hot tap water. Measurements for other buildings correspond to mixed heat consumption of space heating and ventilation system. Since the same LR model is used for both systems, it was possible to simultaneously model heat consumption for both systems with one LR formulation.

5.1.1 Hourly data grouped by regimes

Hourly data grouped by regimes, are presented in Table 3.1. A sequential sum of squares evaluates how much variation is attributed to an individual variable (Walpole 2007):

$$R(\beta_3|\ \beta_1, \beta_2)=SSR- R(\beta_1, \beta_2) \tag{5.2}$$

where:

$R(\beta_3|\ \beta_1, \beta_2)$ – sequential sum of squares for independent variable x_3

SSR - regression sum of squares gained from calculating involving all three independent variables

$R(\beta_1, \beta_2)$ – regression sum of squares for calculation involving x_1 and x_2

If an independent variable, e.g. x_3, does not contribute significantly to the overall variation, the sequential sum of squares for x_3 ($R(\beta_3|\ \beta_1, \beta_2)$) will be lower than the sequential sum of squares for other variables.

R^2 and the sequential sums of squares (SSS) will be calculated separately for each regime (column matrix set). Since the mean value of the dependent variable that would be calculated for all data has no meaning because system performance changes through control regimes, calculations of R^2 for all data is meaningless. In order to get an overall estimator of the calculation, the overall adjusted coefficient of determination $R^2_{overall}$ is calculated by summing deviations from mean values corresponding to separate column matrix sets:

$$R^2_{\text{ovearall}} = 1 - \frac{(\sum_{j=1}^{n\_r}\sum_{i=1}^{n\_j}(y_i-\hat{y}_i)^2)/(n\_ovearall-k-1)}{(\sum_{j=1}^{n\_r}\sum_{i=1}^{n\_j}(y_i-\bar{y}_j)^2)/(n\_ovearall-1)} \tag{5.3}$$

where:

$\bar{y}_j$ - mean value of the dependent variable for the j^th column matrix set

n_r – number of column matrix sets

n_j - number of data points in j^th column matrix set

$n_{overall} = \sum_{j=1}^{n\_r} n\_j$ - number of all data points

k – number of independent variables

The same equation is also used for other groupings. This enables goodness of fit to be compared for different data groupings. Sequential sums of squares are calculated separately for every column matrix set.

Correction of $R^2_{overall}$ for number of degrees of freedom is insignificant since $n_{overall}$ is far greater than k. This means that the difference between overall adjusted coefficient of determination and overall coefficient of determination is insignificant. Overall coefficient of determination is obtained from equation similar to equation 5.3 that does not include correction for degrees of freedom. In the remaining text, overall coefficient of determination will be discussed, although overall adjusted coefficient of determination was calculated.

5.1.1.1 Ventilation system

The results of linear regression for the NTNU campus building Dragvoll 3 are presented in Tables 5.1 - 5.7. This building is selected as representative for stepwise regression since it has significant solar gains. The results presented in Tables 5.1 - 5.4 were obtained from calculations not implementing excluding outliers, while the results presented in Tables 5.5 - 5.7 are obtained from calculations implementing excluding outliers. There are four regimes in operation for the Dragvoll 3 ventilation system. The linear coefficient β_1 for the control regime Monday-Friday $8^{\underline{h}}$-$20^{\underline{h}}$ is higher than the other β_1 coefficients in Tables 5.1 and 5.2. The other β_1 coefficients have similar value, which means that both weekend control regimes and night weekday control regimes are the same. However, a distinction between days and nights allows the influence of the sun to be analyzed for the weekend day regime. The signs of linear coefficient β_3 in Table 5.2 are negative, which means that the sun causes decreased heat consumption. Coefficient β_3 has a lower value for weekend day regime. This may be because of a computational fault due to the small number of data points for this control regime.

	β_0	β_1 (Temperature)
Weekday $8^{\underline{h}}$ -$20^{\underline{h}}$	14.62	61.58
Weekday night	16.18	26.00
Weekend $8^{\underline{h}}$ -$20^{\underline{h}}$	8.95	25.86
Weekend night	4.59	23.45

Table 5.1 LR coefficients of simple linear regression for calculation without excluding outliers

β_1 and β_0 for the weekday day regime changed significantly when introducing the multiple LR model. Other LR coefficients did not change significantly. Table 5.4 presents sequential sums of squares. It demonstrates that the contribution of solar gains is significant for the weekday day regime. β_1 and β_0 for simple linear regressions comprise those influences. Multiple LR changed β_1 and β_0 by separating the influences.

	β_0	β_1 (Temperature)	β_2 (Wind)	β_3 (Sun)
Weekday $8^{\underline{h}}$-$20^{\underline{h}}$	120.61	54.91	0.5422	-0.1392
Weekday night	4.66	24.35	0.7267	-0.1864
Weekend $8^{\underline{h}}$-$20^{\underline{h}}$	26.77	23.60	0.5059	-0.0433
Weekend night	2.20	20.59	0.8419	-0.2004

Table 5.2 LR coefficients of multiple linear regression for calculation without excluding outliers

The coefficients of determination in Table 5.3 are low. R^2s in other literature sources are higher than 70%. This may be because the LR model could not fully capture significant solar radiation due to time delays that result from the thermal storage effect. It is expected that excluding outliers will increase R^2. The R^2 values of multiple LR for all control regimes, as well as $R^2_{overall}$, are higher than for simple LR. It is concluded that multiple linear regression have increased the goodness of fit. Weekends have a higher R^2 than weekdays, which can be explained by variations due to building occupancy.

		Weekday $8^{\underline{h}}$ -$20^{\underline{h}}$	Weekday night	Weekend $8^{\underline{h}}$ -$20^{\underline{h}}$	Weekend night
Simple	R^2	64.52 %	59.59 %	77.71 %	74.23 %
	$R^2_{overall}$	65.26 %			
Multiple	R^2	67.19 %	61.93 %	79.85 %	77.39 %
	$R^2_{overall}$	67.92 %			

Table 5.3 Coefficients of determination for four regimes of NTNU's building Dragvoll 3, obtained through simple and multiple linear regression for calculation without excluding outliers

Sequential sum of squares is a measure of the improvement of introducing single influences into the model. SSS in Table 5.4 shows, as expected, that outdoor temperature has the greatest influence on building heat consumption for all regimes. SSS for day control regimes that correspond to the influence of the sun has higher values than those corresponding to wind. This shows that the sun contributes more to changing building heat consumption than wind during the day. The sun even contributes during hours before $8^{\underline{h}}$ and after $20^{\underline{h}}$ because the days are long in the spring in Norway. However, SSS for the sun is much lower than for other influences for night regimes.

Control regime	Weekday $8^{\underline{h}}$ -$20^{\underline{h}}$	Weekday night	Weekend $8^{\underline{h}}$ -$20^{\underline{h}}$	Weekend night
SSS Temperature	74 637 000	12 875 000	7 773 500	4 924 000
SSS Wind	362 500	524 180	133 470	279 870
SSS Sun	4 716 500	95 838	181 840	72 221

Table 5.4 Sequential sums of squares for four regimes of NTNU's building Dragvoll 3 for calculation without excluding outliers

Tables 5.5 and 5.7 present results for calculation implementing excluding outliers. LR coefficients presented in Table 5.5 demonstrate changes from those presented in Table 5.2. The most significant change appeared with β_3 for the weekday day regime. It seems that excluding outliers has removed data points from calculation when sun influence was dominant. This may be because the model did not capture sun influence in the first calculation when all data points were included. Due to the time delay of the sun influence, hourly heat consumption does not correspond fully to hourly solar radiations. That is why β_3 can be underestimated in the initial calculation. When determining the outliers, data points with high solar influence were not adequately represented by the model, so they were recognized as outliers even though they may not be outliers. The SSS corresponding to the sun influence during the weekday day control regime (table 5.7) has a much lower value than in Table 5.4. This proves that data points with high sun influence were recognized as outliers and excluded. Analysis of excluding outliers will be presented in subchapter 5.3.

	β_0	β_1 (Temperature)	β_2 (Wind)	β_3 (Sun)
Weekday $8^{\underline{h}}$ -$20^{\underline{h}}$	-48.673	68.846	0.8990	-0.0494
Weekday night	6.8346	22.762	0.7374	-0.1202
Weekend $8^{\underline{h}}$ -$20^{\underline{h}}$	-25.826	29.819	0.1728	-0.0184
Weekend night	-39.043	24.315	0.8001	-0.1810

Table 5.5 Coefficients of multiple linear regression for calculation with excluding outliers

R^2 presented in Table 5.6 is higher than R^2 in Table 5.3, as expected. However, this does not mean that the calculation involving procedure of excluding outliers gave a more accurate prediction of the building HC. The difference between the simple and multiple LR is not as significant in Table 5.6 because solar influence is neglected.

		Weekday $8^{\underline{h}}$ -$20^{\underline{h}}$	Weekday night	Weekend $8^{\underline{h}}$ -$20^{\underline{h}}$	Weekend night
Simple	R^2	89.76 %	78.37 %	91.38 %	87.19 %
	$R^2_{overall}$	88.77 %			
Multiple	R^2	89.58 %	78.85 %	91.38 %	88.79 %
	$R^2_{overall}$	88.84 %			

Table 5.6 Coefficients of determination for four regimes of NTNU's building Dragvoll 3 obtained with simple and multiple linear regression for calculation with excluding outliers

Control regime	Weekday $8^{\underline{h}}$ -$20^{\underline{h}}$	Weekday night	Weekend $8^{\underline{h}}$ -$20^{\underline{h}}$	Weekend night
SSS Temperature	89 577 000	9 454 400	8 158 900	4 535 400
SSS Wind	837 250	469 640	14 059	225 010
SSS Sun	467 090	38 753	22 204	41 950

Table 5.7 Sequential sums of squares for four regimes of NTNU's building Dragvoll 3 for calculation with excluding outliers

To conclude, the model did not cope properly with solar influence. More reliable results seem to be gained with linear regression without excluding outliers. Introducing multiple LR increased the goodness of fit. Results of the LR with hourly data for four additional ventilation systems are presented in Appendix A.2. Dragvoll Idrettsbygg and Dragvoll 8 buildings have the highest $R^2_{overall}$ of all buildings with ventilation systems (Tables 0.27 and 0.31). Two day regimes for both of these buildings have β_1 coefficient values, so regimes are not changed from weekdays to weekends (Tables 0.26 and 0.30). Introducing MLR did not significantly improve the R^2 for two day regimes (Tables 0.27 and 0.31). SSS for wind and solar influences are not significant (Tables 0.28 and 0.32). β_0 and β_1 did not change when introducing multiple LR model for two day regimes. R^2 for the weekend has a higher value than for weekdays, due to lower occupancy of the Dragvoll Idrettsbygg building (Table 0.27). β_3 for the weekday day regime is positive for Dragvoll Idrettsbygg building and for Dragvoll 8 building for the weekend day regime (Tables 0.26 and 0.30). This is not important because solar radiation is not significant for these two buildings.

SSSs corresponding to wind and solar radiation influence for the Dragvoll 2 building are significantly lower than the SSS for outdoor temperature (Table 0.38). $R^2_{overall}$ did not improve significantly by introducing the MLR model (Table 0.37). LR coefficients β_1 shows that there is no difference between weekend and weekday day regimes (Table 0.36). All night regimes belong to one control regime. The weekday day regime has much lower R^2 than other regimes, probably due to occupancy (Table 0.37).

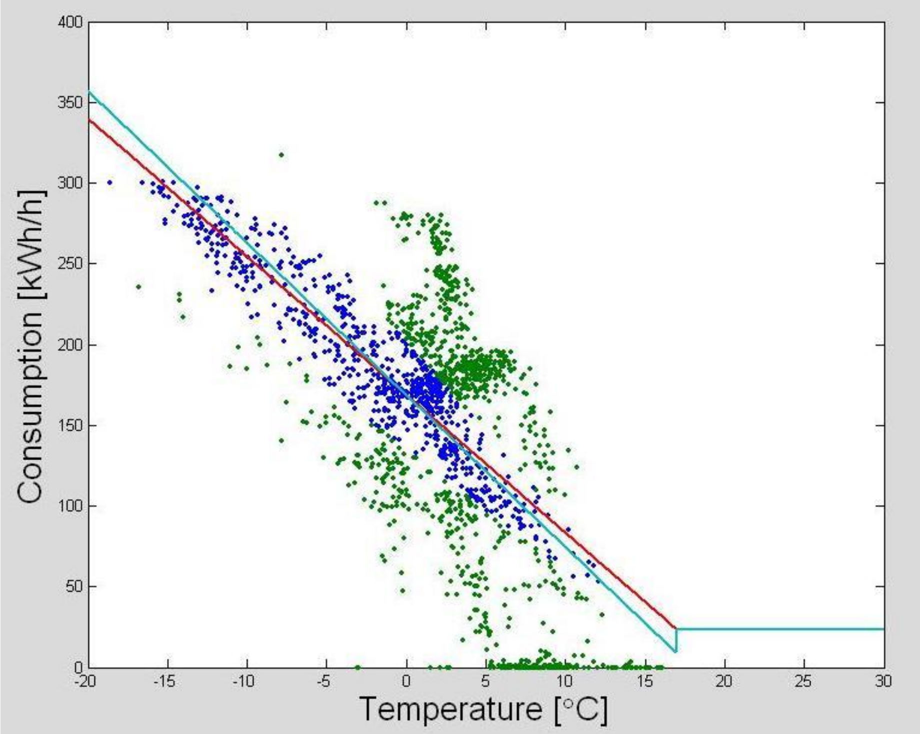


Figure 5.1 Hourly heat consumption of Dragvoll 9 for the day regime

Coefficients of determination for Dragvoll 9 building are poor (Table 0.34). Hourly heat consumption of the day control regime for this building is presented in Figure 5.1. There are obviously many variations that are not explained by changes in outdoor temperature. Although R^2 increased when introducing multiple LR, the improvements are not significant. To conclude, the models did not capture variations introduced by other influences (solar radiation or occupancy).

5.1.1.2 Space heating system

Appendix A.1 presents LR calculation results for six buildings with mixed heat consumption of space heating and ventilation system.

Building Sentral Bygg 1 has the same control regimes during nights and weekends. R^2 did not improve much by introducing the multiple linear regression model (Table 0.3). The SSS corresponding to sun influence has low values compared with SSSs for other influences (Table 0.4). That means that HC is not influenced much by the sun, so a positive value of coefficient β_3 for the weekday day control regime is an insignificant computational fault (Table 0.2). Wind influence is more significant (Table 0.4), so improvement of R^2 is a result of introducing wind influence into the MLR model. All β_1 coefficients are lower for MLR than for the SLR model as a consequence of introducing wind influence into the LR model (Tables 0.1 and 0.2).

Wind influence is insignificant for the Sydområdet NHL Forskning building (Table 0.8). The improved R^2 is a result of introducing solar radiation into the LR model. R^2 is higher for day than for night operation (Table 0.7).

R^2 for the Gamle-fysikk and Berg buildings is not significantly changed by introducing the MLR model (Tables 0.11 and 0.15). Both wind and solar radiation influences have approximately equal contributions to HC variation of those buildings (Tables 0.12 and 0.16).

β_3 for day control regime is positive for the Gløshaugen Idrettsbygg building (Table 0.18). Since large SSS is attributed to solar radiation for this control regime (Table 0.20), the MLR model did not address sun influence correctly.

There is no difference between day and night operations for the Varmetekniske laboratoriet building (LR coefficients in Tables 0.21 and 0.22). Influences other than the outdoor temperature were not significant (Table 0.24).

For most of the buildings, the R^2 is higher for night than for day, owing to lower HC variation due to internal heat gains. R^2 has increased for all buildings by employing the MLR model. However, it cannot be concluded that the MLR model is significantly more accurate than the SLR model for this way of grouping data. A similar analysis for other data groupings will be presented for the same buildings.

5.1.2 HOD grouping

Appendix B presents results for modeling building HC with the HOD grouping.

5.1.2.1 Ventilation system

A complete set of tables is presented for the Dragvoll 3 building in Appendix B.2, while for the remaining four buildings, tables of special interest will be analyzed.

Coefficient β_1 shows a difference between regimes for the Dragvoll 3 building (Tables 0.57 and 0.58). It is evident that the weekday day regime lasts from $8^{\underline{h}}$ - $20^{\underline{h}}$. The control regime is unchanged during weekend days. Coefficient β_3 is negative or equal to zero for every hour. Coefficient β_2 is negative for $8^{\underline{h}}$ - $12^{\underline{h}}$ during weekdays. The SSS for solar influence are much higher compared to the SSS for wind during this period of the day (Table 0.60). We conclude that the negative β_2 (calculation fault) did not significantly influence accuracy. Introducing multiple linear regression model increased overall R^2 from 68.60 % to 74.43 %, i.e. 5.83 % (Table 0.59). In the case with hourly data, this coefficient increased from 65.26 % to 67.92 %, i.e. 2.66 % (Table 5.3), so the HOD grouping addressed solar influence more appropriately. Solar influence is more dominant than wind influence, according to SSS (Table 0.60), so improvement can be attributed to introducing solar radiation into the MLR model. SSS for solar radiation and outdoor air temperature influences for day regimes ($8^{\underline{h}}$ - $20^{\underline{h}}$) are values of the same order (Table 0.61), which was not the case with calculation with hourly data (Table 5.4). The SSS for this regime is 11 875 829. For the same regime, the SSS obtained through calculation with hourly data was 4 716 500. The HOD grouping coped better with solar influence than the calculation with hourly data.

Coefficients β_0 and β_1 are changed by introducing the MLR model for weekdays between $8^{\underline{h}}$ and $20^{\underline{h}}$ (Table 0.57). Solar and wind influences were not as important for the other hours (Table 0.60), so those coefficients are not significantly changed by introducing the MLR model.

Coefficient β_3 is higher during the morning than during the afternoon (Table 0.57). If the LR coefficient is higher, that means that the dependent variable, i.e., building heat consumption, is more sensitive to changes in the corresponding independent variable. The building is probably oriented to the east, so morning sun has more influence than afternoon sun. The SSS have higher values for $9^{\underline{h}}$, $10^{\underline{h}}$, $16^{\underline{h}}$ and $17^{\underline{h}}$ than for the rest of day (Table 0.60). This is a consequence of a lower sun elevation angle for those hours.

Unoccupied hours have generally higher R^2 than occupied hours, which means that building occupancy introduced unexplained variations in building HC (Table 0.59). Improvement of overall R^2 gained by introducing MLR model is not as significant for calculation with excluding outliers, from 88.46% to 90.66%, i.e., 2.19% (Table 0.62). For calculations with hourly data, this coefficient increased from 88.77% to 88.84%, i.e., 0.07% which is negligible (Table 5.6). Excluding outliers completely excluded sun influence in calculation with hourly data, because data points with significant solar influence were recognized as outliers because the model did not initially explain solar influence correctly. The SSS for solar radiation are much lower for calculation with excluding outliers (Table 0.63), but it seems that many fewer data points with high solar radiation were excluded than in the calculation with hourly data. That means that, initially, in calculation without excluding outliers, solar influence was better modeled. However, the HOD model did not fully consider variations due to solar radiation, since the SSS for a weekday day regime ($8^{\underline{h}}$ - $20^{\underline{h}}$) is 3 185 496 (Table 0.63), which is much lower than the 11 875 829 gained for calculation without excluding outliers (Table 0.61).

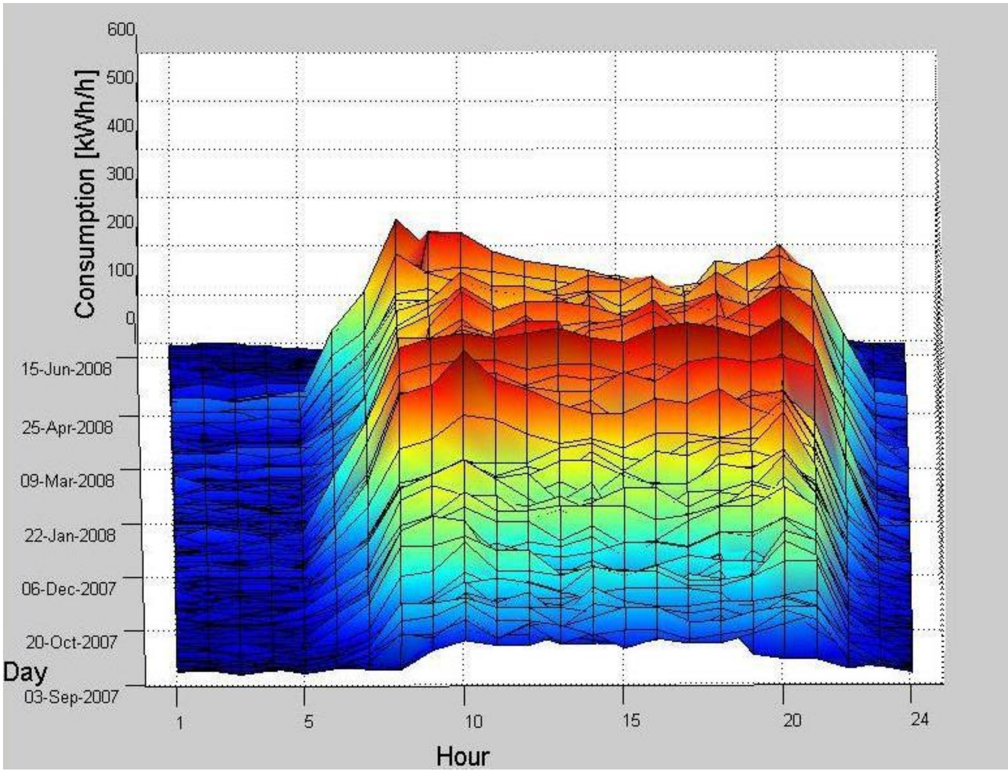


Figure 5.2 Hourly heat consumption of Dragvoll Idrettsbygg building

The overall R^2 for the Dragvoll Idrettsbygg building for simple linear regression is 88.79% (Table 0.65), which is much higher than for calculating with hourly data (70.72%). This improvement is a consequence of inadequate covering of morning and evening transition regimes by the model with hourly data. Transition regimes can be recognized in Figure 5.2.

R^2 values are higher for days than for nights as a consequence of transition regimes, and they are higher for weekends than for weekdays due to occupancy (Table 0.65). The β_3 coefficient is positive for some hours in Dragvoll Idrettsbygg (Table 0.64). However, the SSS corresponding to sun influence is insignificant (Table 0.66), so this does not cause serious inaccuracy of heat consumption predictions.

The overall R^2 improved for Dragvoll 8 from 84.28% for the SLR calculation to 86.15% for the MLR calculation, i.e., 1.87% (Table 0.67). For calculation with hourly data, the improvement was from 82.91% to 84.22%, i.e., 1.31%. That means that the HOD model copes better with wind and solar radiation influences. The SSS for wind and solar radiation influences are low (Table 0.68).

The SLR calculations gave close $R^2_{overall}$ for the HOD calculation and calculation with hourly data for the Dragvoll 2 building (Tables 0.75 and 0.37), so the HOD model did not consider occupancy better than the model with hourly data. Improvement in the overall R^2 is gained by introducing the MLR model for the HOD calculation (Table 0.75). There were no significant improvements for calculation with hourly data (Table 0.37), so LR with the HOD grouping coped better with solar and wind influences. Excluding outliers did not decrease SSS for solar influence (Tables 0.77 and 0.78) as with the Dragvoll 3 building. The R^2 values are lower from $8^{\underline{h}}$ to $16^{\underline{h}}$ for weekdays than for the other hours (Table 0.75). This university building has many auditoriums, so occupancy could introduce many unexplained variations during occupied period.

LR with HOD grouping better coped with solar influence than calculation with hourly data for Dragvoll 9 building. The SSS for solar influence shows that the improvement is mainly a result of including solar radiation in the model. Excluding outliers did not significantly decrease the SSS for solar influence.

5.1.2.2 Space heating system

LR coefficients β_0 and β_1 show changes with different control regimes. The Sentral Bygg 1 building has a weekday day regime lasting from $7^{\underline{h}}$ to $19^{\underline{h}}$ (Table 0.39). It was earlier concluded that the sun influence is not significant and that wind influence has some significance for this building, according to the SSSs gained for calculation with hourly data. According to the SSS presented in (Tables 0.41 and 0.42), the sun influence is more significant than the wind because its SSS is higher for most hours during a weekday day. It seems that the sun influence is better captured with the HOD grouping than in calculations with hourly data. However, the SSS for sun influence is much lower than the SSS for outdoor air temperature influence, so improvement of R^2 by introducing the MLR model is just 2.12%, from 77.06% to 79.18% (Table 0.40). R^2 values are from 80% to 90% for the EC building in Katipamula (1996). R^2 are much worse for the BUS building. Most R^2 values for the Sentral Bygg 1 building are also between 80% and 90%. The SSS for calculation with excluding outliers shows smaller values for sun influence (Table 0.43), so it can be concluded that excluding outliers diminishes the influence of the sun.

Sydområdet NHL Forskning building also has insignificant sun influence according to the SSS corresponding to sun influence gained for calculation with the hourly data. The SSS for solar radiation is much higher for the HOD calculation (Table 0.45). The R^2 value improvement by introducing the MLR model (Table 0.44) is also greater than for calculations with hourly data. However, calculation with excluding outliers decreased the SSS for solar radiation (Table 0.47) and decreased R^2 improvement by introducing the MLR model (Table 0.46), so calculation without excluding outliers did not fully consider solar radiation.

The HOD calculation captured better wind and solar influences than calculation with hourly data for the Gamle-fysikk building, since the SSS for wind and solar influence are significantly larger (Table 0.49). Excluding outliers did not decrease the SSS for wind and solar radiation (Table 0.51) or decrease the R^2 improvement by introducing the MLR model (Table 0.50), so calculation without excluding outliers fully covered both influences. The SSS is higher for solar radiation than for wind influence.

Gløshaugen Idrettsbygg has a significant SSS corresponding to sun influence for calculation with hourly data grouped by regimes. A positive coefficient has appeared in this case for the β_3 coefficient for the day regime. For calculation with the HOD grouping, the β_3 coefficient was again positive (Table 0.53). However, the SSS corresponding to sun influence is not significantly large in this calculation, so the sun does not influence the building heat consumption (Table 0.55). For calculation with hourly data, the overall R^2 for simple linear regression is 72.75%. For the same calculation with HOD grouping overall coefficient of determination is 79.93% (Table 0.54). Reason for this difference is that calculation with HOD grouping better covers effects of heat accumulation or other influences introducing time-delay for outdoor air temperature.

R^2 improvement by introducing MLR model is not significant for Berg and Varmetekniske laboratoriet buildings (Table 0.52 and 0.56), so wind and solar radiation did not significantly influence heat consumption.

It can be concluded that LR with an HOD grouping better covers the wind and sun influences on building heat consumption than linear regression with hourly data, according to results for five buildings with a ventilation system and six with mixed ventilation and space heating systems. The R^2 values had greater increases with the HOD calculations when the MLR model is engaged. Sequential sums of squares corresponding to wind and sun influences also had higher values for calculations with the HOD grouping.

HOD calculations produced higher R^2 values for almost all buildings than the hourly calculations. The R^2 value was analyzed in this part of thesis to evaluate how different data groupings coped with different influences. Higher R^2 does not mean that a LR model better predicts heat consumption. A comparison of predictions gained through calculations with four groupings will be presented later through analysis of mean bias errors and coefficients of variation.

5.1.3 Mean values grouped by regimes

Appendix C presents results for modeling heat consumption with mean values. In order to compare the goodness of fit of the calculations with different data grouping, it is necessary to adapt the overall coefficient of determination $R^2_{overall}$ (equation 5.3). Mean heat consumption belonging to a regime (Table 3.2) is:

$$y_i = \frac{\sum_{k=1}^{n\_h} y\_h_k}{n\_h} \tag{5.4}$$

y_h_k – hourly value of the dependent variable n_h – number of hours belonging to the j^{th} regime during a day

Overall adjusted coefficient of determination is calculated in this case according to the equation:

$$R^2_{ovearall} = 1 - \frac{(\sum_{j=1}^{n\_r}(\sum_{i=1}^{n\_j}(y_i-\hat{y}_i)^2)\cdot n\_h))/(n\_ovearall-k-1)}{(\sum_{j=1}^{nr}(\sum_{i=1}^{nj}(y_i-\bar{y}_j)^2)\cdot n\_h))/(n\_ovearall-1)} \quad (5.5)$$

$\hat{y}_i$ – prediction of dependent variable

$\bar{y}_j$ - mean value of dependent variable for the j^{th} regime

n_h – number of hours belonging to the j^{th} regime during a day

n_r – number of regimes

n_j - number of data points in the j^{th} regime

$n_{overall} = \sum_{j=1}^{n\_r} n\_j \cdot n\_h$ - number of all hourly data points

k – number of independent variables

The difference between equation 5.3 and 5.5 is that in equation 5.5 the sum of deviations of dependent variables from predicted values of dependent variable and mean values of dependent variable are multiplied by the number of hours belonging to the j^{th} regime during a day - n_h. This was to adjust the overall adjusted coefficient of determination calculated for mean values to hours. Thus, it is possible to compare $R^2_{overall}$ for mean values and hourly values.

5.1.3.1 Ventilation system

For Dragvoll 3, the overall R^2 improved from 73.16% to 83.26%, i.e., 10.10% (Table 0.87). For calculations with hourly data and the HOD grouping, the improvement was 2.66% and 5.83%, respectively. The SLR calculation with the HOD grouping had an R^2 value of 68.60%, which is significantly lower than 73.16% with mean values. This is because of variation introduced by internal gains, since the thermal storage effect should not influence ventilation heat consumption. The SSS corresponding to the sun has the same order as the SSS corresponding to outdoor air temperature (Table 0.90). For the weekday day regime ($8^{\underline{h}}$ - $20^{\underline{h}}$), the SSS for solar influence is 21 620 300. For the same regime in the calculation with the HOD grouping, the SSS was 11 875 829, while for calculation with hourly data it was 4 716 500. Calculation with mean values has captured the solar influence better than both the HOD and hourly calculations. However, the sum of squares for solar influence for calculation with excluding outliers decreased to 7 031 310 (Table 0.91). This shows that this way of grouping also has a problem capturing solar influence. The β_0 and β_1 coefficients changed for all regimes by introducing the MLR model (Table 0.89). For the night regime, solar radiation was also influential because of the long days during the spring and summer (Table 0.90).

For other buildings with ventilation systems, $R^2_{overall}$ values are higher for the SLR calculations with mean values than for the SLR calculations with two previously presented data groupings. Dragvoll Idrettsbygg has $R^2_{overall}$ equal to 95.69% (Table 0.92) which is much higher than 88.79 % gained for the HOD grouping calculation. Since the thermal storage effect should not influence ventilation heat consumption, the R^2 improvement is a consequence of averaging variation introduced by internal heat gains.

$R^2_{overall}$ improved for Dragvoll 8 from 89.87% for the SLR calculation to 92.01% for the MLR calculation, i.e., for 2.14% (Table 0.93). For calculation with the hourly and HOD data, improvements were 1.31% and 1.87%, respectively. That means that the model with mean values better considers the influence of wind and solar radiation than the HOD and hourly model.

$R^2_{overall}$ obtained from the SLR calculation for Dragvoll 2 is 78.84% (Table 0.97). The SLR for models with hourly and HOD data produced $R^2_{overall}$ equal to 66.22% and 66.00%, respectively. This proves that the calculation with mean values better considered variation due to occupancy. The R^2 value for the weekday day regime is lower than for other regimes due to occupancy. The SSS values for solar radiation influence (Table 0.98) are lower than for the HOD calculation.

Dragvoll 9 had significant solar influence in the HOD calculation. The R^2 improvement when introducing the MLR model for calculation with mean values is 6.76% (Table 0.94), which is a greater improvement than for the other data groupings. $R^2_{overall}$ is 64.37% for calculation with the MLR model. For the same type of calculation with hourly data and the HOD grouping, $R^2_{overall}$ is 50.45% and 54.35%, respectively. The SSS for solar influence (Table 0.95) is also higher than for other groupings, which proves that this grouping best takes solar influence into account. Excluding outliers did not decrease the SSS for solar influence (Table 0.96). During the night, the ventilation is turned off, so low values of R^2 are not significant (Table 0.94).

Calculation with the HOD grouping did not produce significantly lower values of SSS for solar influence than calculation with mean values. This shows that the HOD grouping considers solar influence well, and that this data grouping is preferable if hourly predictions should be produced for buildings with significant solar gains.

5.1.3.2 Space heating system

$R^2_{overall}$ improved for Sentral Bygg 1 from 90.27% for the SLR calculation to 93.28% for the MLR calculation, i.e., 3.01% (Table 0.80). $R^2_{overall}$ improvement for the HOD model is 2.12 %. The SSS is much higher for solar radiation than for wind influence (Table 0.81). Calculation with mean values better considers solar influence because the mean values average the thermal storage effect for solar radiation. R^2 for the SLR calculation with the HOD grouping is much lower than the corresponding value for calculation with mean values as a consequence of averaging thermal storage effects. The difference between those R^2 values is 13.21%. Since improvement by introducing the MLR model is much lower, it can be concluded that most unexplained variations in the HOD model are not a result of wind or solar radiation, but the thermal storage effect. Excluding outliers reduced the SSS for solar radiation (Table 0.82). This shows that this data grouping did not fully captured solar radiation for this building.

$R^2_{overall}$ improved for Sydområdet NHL Forskning from 91.58% for the SLR calculation to 92.73% for the MLR calculation, i.e., 1.15% (Table 0.83). For calculation with the HOD grouping improvements was from 86.62% to 87.66%, i.e., 1.04%. The model with mean values did not cope significantly better with wind and solar radiation, but coped much better with the thermal storage effect, since R^2 for SLR calculation is much higher. Solar and wind influences are not significant for this building.

R^2 improvement by introducing MLR model is not significant for Berg, Gløshaugen Idrettsbygg, Varmetekniske laboratoriet and Gamle Fysikk, so wind and solar radiation did not significantly influence heat consumption. R^2 for the SLR calculation with the HOD grouping are 87.46%, 79.93%, 89.95% and 86.85%, respectively, for these buildings. R^2 for the SLR calculation with mean values are 94.38%, 86.34%, 93.71% and 94.38%, respectively. These improvements are the result of averaging the thermal storage effect.

Improvements by introducing the multiple linear regression model are greater for calculations with this way of grouping than for calculations with hourly and HOD data. However, predictions gained by this calculation do not give information about hourly heat consumption, so faults happening on an hourly basis are hidden.

5.1.4 Daily grouping

Calculation of overall R^2 for daily data follows equation 5.5. Mean values of dependent variable are not calculated for regimes, but for weekdays and weekends, so n_h used in equations 3.4 and 3.5 is 24, n_r is 2 and n_j is the number of weekdays and weekend days.

It is expected that calculations with mean values should give better results than calculation with daily data due to variations introduced by regimes that are averaged in the daily model. Calculations with mean values use independent variables that exactly match the corresponding heat consumption. Calculations with daily data use values of independent variables that are mixtures of values corresponding to different control regimes. For example, extremely low temperature during night will decrease the daily mean temperature, but low night temperatures will less influence daily heat consumption if the HVAC system operates with reduced heat consumption during the night. Thus, calculations with mean values should produce more accurate predictions than calculations with daily data. The advantage of daily calculations over calculations with other groupings is that the effects of thermal storage should be better covered with calculations with data that are averaged over a longer time interval.

A function that performs calculation with mean values in the tool developed in Matlab is used for calculation based on daily data. Two types of days (weekdays and weekends) are defined instead of regimes in the tool. Appendix D presents the results of LR calculations with daily data.

5.1.4.1 Ventilation system

$R^2_{overall}$ improved for the Dragvoll 3 building from 76.08% for the SLR calculation to 86.56% for the MLR calculation, i.e. 10.48% (Table 0.108). For calculation with mean values, the overall R^2 improved from 73.16% to 83.26%, i.e. 10.10%, so daily calculation covered more variation due to solar influence.

Calculations with daily data produced similar results to calculations with mean values for Dragvoll Idrettsbygg.

The SLR calculation for Dragvoll 8 produced $R^2_{overall}$ equal to 90.59% (Table 0.112). $R^2_{overall}$ for the SLR calculation with mean data is 89.87%. These results show that the daily data averaged more variation due to occupancy than mean values grouped by regimes.

$R^2_{overall}$ is 56.02% for SLR calculation for Dragvoll 9 and 64.86% for the MLR calculation (Table 0.113). For the calculation with mean values, SLR model gave $R^2_{overall}$ equal to 57.61%, while the MLR model gave 64.37%. Both data groupings gave similar R^2s and similar values of solar radiation SSS. Excluding outliers did not decrease the solar radiation SSS (Tables 0.114 and 0.115).

$R^2_{overall}$ is 83.30% for the SLR calculation for Dragvoll 2 and 84.69% for the MLR calculation (Table 0.116). For the calculation with mean values, the SLR model gave $R^2_{overall}$ equal to 78.84%, while the MLR model gave 80.21%. Slight improvements were achieved to $R^2_{overall}$ by introducing the MLR model. The SSS for solar influence are similar for these models. The main improvement accomplished with daily model is better coverage of occupancy variation, since SLR gave better results.

Calculations with daily data and mean values produced similar results for five analyzed buildings. Both models are equally capable to cover all analyzed variations.

5.1.4.2 Space heating system

$R^2_{overall}$ improved for Sentral Bygg 1 from 91.96% gained for SLR calculation to 95.24% for MLR calculation, i.e. 3.27% (Table 0.101). The $R^2_{overall}$ improvement for calculation with mean values is 3.01% (from 90.27% to 93.28%). R^2 for the SLR calculation with daily data is higher than the corresponding value for calculation with mean values. This means that the daily data better averaged thermal storage effects. Calculation with mean values gives a similar SSS for solar influence as calculation with daily data (Table 0.102). Since R^2 improvement by introducing the MLR model is almost same, both models cope similarly with solar radiation influence. Excluding outliers reduces weekday solar radiation SSS to 50% (Table 0.103). The SSS for outdoor air temperature is not reduced by excluding outliers. This means that this grouping did not fully consider solar radiation influence for this building.

$R^2_{overall}$ improved for Sydområdet NHL Forskning from 93.37% for the SLR calculation to 94.64% for the MLR calculation, i.e., 1.27% (Table 0.104). For calculation with mean values, improvement was from 91.58% to 92.73%, i.e., 1.15%. The major difference between models is that the daily data better averages the thermal storage effect, which can be concluded from the higher R^2 for the SLR calculation. There is no difference in covering other influences between those two models.

The calculations with daily data produced slightly higher R^2 values than calculations with mean values for Gamle Fysikk, Gløshaugen Idrettsbygg and Varmetekniske laboratoriet. For these buildings, influences other than outdoor temperature are not significant, so major improvement is gained by averaging thermal storage effects. R^2 has similar values for weekends and weekdays.

5.1.5 Evaluation of selecting independent variables for wind influence

Selection of wind independent variable is discussed in subchapter 3.6.1. The wind independent variable in equation 3.7 is the product of the wind speed element W^* and the difference between the indoor air temperature and outdoor air temperature (T_{IN}-T). Indoor air temperature is considered to be constant. Different powers of wind speed W, $W^{1/2}$ and W^2 are analyzed. Three linear regression calculations with different wind speed elements were conducted and coefficients of determination were compared in order to find which expression of wind speed fits the best. This way of selecting linear regression model is recommended in Walpole (2007).

In the W^2 case, the results of linear regression were not stable in some calculations. Since variation of wind speed is high (0 m/s to 10 m/s is normal variation for Trondheim), variation of W^2 is even higher, which suggests that, in some cases, $B_2 \cdot W^2 \cdot (T_{IN}\text{-}T)$ can surpass contributions of other independent variables. Two cases of wind independent variables, $W^{1/2} \cdot (T_{IN}\text{-}T)$ and $W \cdot (T_{IN}\text{-}T)$, are assumed to cover the heat demand for natural ventilation properly and were used in analysis.

For all analyzed buildings, the wind was not a significant influence, so introducing the wind independent variable into equation 3.7 did not significantly improved the goodness of fit. If sums of squares for wind influence are significant, this would signify poor quality of building windows. It is expected that daily patterns of opening windows can be recognized through change of power of wind in calculation with HOD grouping. For most of the buildings, both powers of wind speed (1 and ½) appeared after 48 linear regressions as a choice which gives the best goodness of fit. It cannot be claimed that one of them is significantly better to represent the influence of the wind. A clear pattern that can be explained by opening windows appeared for the Gamle kjemi building. This pattern can be also recognized for Berg building. Powers appearing in the wind independent variable giving best goodness of fit are presented in Appendix B.3 (Table 0.79). Gamle kjemi has a clear pattern that can be recognized during hours in which the building is occupied. With Berg, it can be recognized that the power changed $5^{\underline{h}}$ during weekdays. The procedure of selecting power of wind is performed for calculations with all groupings.

5.2 Comparison of monitoring data resolution

Data with lower resolution (mean values and daily data) average variations that are unexplained by hourly and HOD model. As a result, models with lower data resolutions produce higher R^2s. However, part of the information is lost due to averaging. Thus, models with higher data resolutions can give more accurate predictions. Katipamula et al. (1995 and 1998) have demonstrated that, although lower data resolutions (monthly data) produce higher R^2, daily and HOD data produced lower CV and MBE, i.e., more accurate predictions. Subchapter 5.2.1 will compare R^2 values for different data resolutions in order to evaluate the capability of different data groupings for covering different influences determining the heat consumption of space heating and ventilation systems. The extent of contributions from different influences determining heat consumption will be evaluated by comparing R^2 values obtained from calculations with different data grouping and by comparing sequential sums of squares.

Since R^2 values are not obtained from calculations with daily and mean values from hourly data, as is the case for HOD and hourly data, R^2s cannot be compared in order to evaluate how different data groupings cover variation of heat consumption. Subchapter 5.2.2 will compare MBEs in order to evaluate predicting ability of calculations with different data resolutions. CVs are used to evaluate ability of model to cover variation.

5.2.1 Comparison of R^2 values for different monitoring data resolutions

Appendix E presents a comparison of overall $R^2_{overall}$ values for calculations with different data resolutions. The SSS is presented for buildings with significant solar radiation.

R^2 values for SLR calculations show how data groupings cover thermal storage effects due to change of outdoor temperature and heat gains due to occupancy. Data groupings with lower resolutions (mean values and daily data) average those effects. HOD grouping follows daily patterns of thermal storage and building occupancy.

The difference between $R^2_{overall}$ for MLR and SLR calculations (improvement by introducing MLR model) shows how data groupings coped with solar and wind influence. Solar radiation thermal storage effect is also covered by averaging by lower resolution data and by determining the daily pattern of thermal storage through HOD grouping. Greater improvement achieved by introducing the MLR model and higher SSS corresponding to solar radiation show that some data grouping better copes with solar radiation thermal storage effect.

5.2.1.1 Space heating system

Comparisons of $R^2_{overall}$ for four ways of grouping data are presented in Appendix E.1. Calculations with daily data gave the highest values of $R^2_{overall}$ for both SLR and MLR calculations in most cases. Calculation with daily data and calculations with mean values gave similar results. Calculations with the HOD grouping gave higher $R^2_{overall}$ than calculations with hourly data for all buildings, except for building Sentral bygg 1 (Table 0.119). Since $R^2_{overall}$ values for calculations with hourly and HOD data are calculated with hourly data (mean values in calculation of R^2 for hourly data are calculated for periods corresponding to regimes; mean values for HOD data in calculation of R^2 are calculated for each hour of day), it can be concluded that the HOD grouping better covered variation of heat consumption of space heating systems. This conclusion will be proved through analysis of CVs. Calculations with hourly data and HOD grouping gave lower R^2s than calculation with mean values and daily data.

The better goodness of fit for SLR calculations is because groupings with lower data resolutions cope better with time-delays that are a result of the thermal storage effect due to outdoor temperature change. Calculations with hourly data gave the lowest $R^2_{overall}$ for SLR calculations. Appendix E.1 shows differences between $R^2_{overall}$ for SLR calculations with hourly data and other data groupings. The HOD grouping covered part of the variation due to the thermal storage effect. Differences are positive for all buildings except for Sentral bygg 1 building (Table 0.119). SLR calculations with the HOD grouping for Gløshaugen Idrettsbygg gave significantly higher $R^2_{overall}$ than calculation with hourly data (Table 0.128) as a result of covering transition regimes. However, calculations with daily data and mean values have much higher differences, so they covered the thermal storage effect due to change of outdoor temperature to higher extent than HOD grouping. Daily data covered the best of all grouping thermal storage effects since differences between SLR $R^2_{overall}$ for this grouping and hourly grouping are highest. The differences are slightly lower for calculations with mean values, so this grouping is close to daily data in covering thermal storage effects due to changes in outdoor temperature.

	Weekdays day	Weekend day
Varmetekniske laboratorier	94.00 %	93.13 %
Elektro B	94.03 %	95.83 %
Materialtekniske laboratorier	81.72 %	83.63 %
Produktdesign	89.78 %	80.66 %
Metallurgi	94.05 %	91.61 %
Oppredning gruvedrift	94.33 %	94.80 %
Verkstedtekniske laboratorier	91.05 %	91.33 %
Marinteknisk senter Tyholt	98.19 %	98.34 %

Table 5.8 Coefficients of determination for calculation with mean values grouped by regimes for eight NTNU buildings with monitored space heating system

Improvement of $R^2_{overall}$ gained by introducing MLR model is a measure how model copes with wind and solar influence. Only Sentral Bygg 1 has significant influences other than outdoor temperature (Table 0.119). Solar radiation influence is more significant for this building than wind influence. Improvements gained by introducing MLR model are presented for all data groupings. Calculations with hourly data have the lowest improvement since these calculations are least capable of covering the thermal storage effect due to solar radiation. HOD grouping is far better than the hourly data in this sense. HOD model can better cover change of sun position during day for buildings with dominant orientation than hourly data. SSS shows contributions from solar radiation to heat consumption. Daily data and mean values gave the highest SSS for solar radiation and the greatest improvements in $R^2_{overall}$. SSS shows that MLR calculations with mean values have explained even more variations of heat consumption due to solar influence than calculations with daily data. It can be concluded that those two groupings are equally capable of covering thermal storage effects due to solar radiation.

The hourly model is the worst regarding covering both thermal storage effects. Daily data are the best in this sense. Differences between $R^2_{overall}$ for SLR calculations with daily data and $R^2_{overall}$ for SLR calculations with hourly data are significantly higher for all buildings than improvements gained by introducing MLR model for calculations with daily data. This demonstrates that unexplained variations of hourly model (difference between 100% and R^2) are more consequence of thermal storage effect due to change of outdoor temperature than solar radiation or wind influences. Since for all buildings (except Gløshaugen Idrettsbygg) the $R^2_{overall}$ for MLR daily model is close to 95%, there are 5% more unexplained variations. Even if all 5% could be attributed to solar radiation or wind influence, they would not overcome the differences between $R^2_{overall}$ for SLR calculations with daily data and hourly data that are a result of covering the thermal storage effect due to changes in outdoor temperature.

The SSS for wind presented in Appendix A.1, B.1, C.1 and D.1 shows that this influence was not significant for any of buildings. It is not observed significant difference between R^2s obtained for weekdays and weekends, so it seems that occupancy did not significantly influence the heat consumption of space heating system of six analyzed buildings. Moreover, R^2s for SLR calculations with daily data are lower for weekends than for weekdays for all six buildings (Tables 0.101, 0.104, 0.105, 0.106 and 0.107). Change of control regimes makes it difficult to recognize difference between occupied and unoccupied periods through comparing R^2s, since control regimes follow occupancy. If space heating system would operate without night temperature set back, occupancy would be more recognizable. Differences between R^2 for SLR calculations with daily data and hourly data could be consequence of averaging occupancy. However, analysis did not show significant influence of occupancy, so it could be concluded that thermal storage effect is main reason for differences between R^2s for SLR calculation. It will be demonstrated in chapter 6 how thermal storage postpones change of heat consumption. It will be demonstrated that changes of outdoor temperature are not followed by corresponding changes of normalized heat consumption, which is a consequence of thermal storage effect. Weekdays and weekend day regimes are the same for eight buildings presented in Table 5.8. It is possible for them to compare R^2 values in order to evaluate influence of building occupancy. There are no significant differences between R^2 values, so occupancy did not influence significantly heat consumption. R^2 was significantly greater for weekday day regime than for weekend day regime for Produktdesign building. Presented results show that there is no significant influence of building occupancy on heat consumption of analyzed space heating system.

5.2.1.2 Ventilation system

Comparisons of $R^2_{overall}$ for four ways of grouping data are presented in Appendix E.2. SLR calculations with HOD grouping gave higher $R^2_{overall}$ than SLR calculations with hourly data for all buildings except for Dragvoll 2 building (Table 0.145). $R^2_{overall}$ is much higher for SLR HOD calculation for Dragvoll Idrettsbygg building (Table 0.138) due to transition regimes (Figure 5.2). MLR HOD calculations gave higher $R^2_{overall}$ for all buildings. It can be concluded that HOD data better covered variations in heat consumption of ventilation heating than did hourly data. Calculations with daily data gave higher $R^2_{overall}$ values than did calculations with mean values for most buildings for SLR calculations, and for all buildings with MLR calculation.

Wind did not have a significant influence on any of the five buildings, and this can be seen in tables with SSS values in Appendix A.2, B.2, C.2 and D.2. Dragvoll 3 and Dragvoll 9 buildings have significant influence of solar radiation. Solar influence was not significant for the Dragvoll 8, Dragvoll 2 or Dragvoll Idrettsbygg buildings.

Improvements of $R^2_{overall}$ gained through employing the MLR model are close for calculations made with daily data and calculations with mean values for two buildings with significant solar influence (Tables 0.135 and 0.142). Other way to evaluate improvement gained through introducing MLR model is to compare SSS. Appendix E.2 presents SSS for those two buildings (Tables 0.136 and 0.143). Calculations with hourly data gave five to ten times lower SSS for solar radiation influence than calculations with daily data. This shows that calculations with hourly data cannot cope successfully with solar influence because hourly heat consumption does not correspond to sun radiation due to time-delays between sun radiation and its influence on heat consumption. Calculations with HOD grouping gave much higher values of SSS for solar radiation influence than calculations with hourly data. Calculation with HOD grouping seems to be able to explain significant amount of variation of heat consumption as a consequence of sun influence. Calculations with mean values grouped by regimes produced SSS higher than calculations with daily data. However, those values are close to each other, suggesting both models address solar radiation equally well.

		Weekdays day	Weekend day
Dragvoll 2	01.01.’07 - 10.06.’07	76.85 %	86.26 %
	01.01.’07 - 01.04.’07	58.03 %	69.85 %
Dragvoll Idrettsbygg	03.09.’07 - 15.06.’08	95.84 %	97.33 %
	07.01.’08 - 15.06.’08	95.57 %	98.06 %

Table 5.9 Coefficients of determination for calculation with mean values grouped by regimes for two NTNU buildings with monitored ventilation system

Appendix E.2 presents differences between $R^2_{overall}$ for SLR calculations with hourly data and other data groupings. The hourly model could not cover transition regimes for the Dragvoll Idrettsbygg building, and the HOD model had a much higher $R^2_{overall}$ than did the hourly model (Table 0.138). Calculations with daily data and calculations with mean values grouped by regimes gave a higher $R^2_{overall}$ for SLR calculations than did the HOD calculations. This increase in the $R^2_{overall}$ was attributed for the space heating system to the thermal storage effect, due to changes in outdoor temperatures. For the ventilation system, thermal storage effect should not be significant. Heat accumulation in walls should influence only heat consumption of space heating system. Temperature on inside wall surface can be low after night temperature set-back. This could influence indoor air temperature and amount of heat delivered by economizer. Daily data and mean values would average this effect. However, those buildings do not operate with night temperature set-back. Analysis of ventilation system similar to analysis of thermal storage effects on space heating system presented in Liu et al. (1995) would explain extent of thermal storage effects on ventilation systems. Occupancy could be a reason why R^2 values for SLR calculations with daily data and mean values are higher than for calculations with HOD grouping. R^2 values are higher for weekends than for weekdays for Dragvoll Idrettsbygg, Dragvoll 2, Dragvoll 3 and Dragvoll 8 (Tables 0.111, 0.116, 0.108 and 0.112). $R^2_{overall}$ is poor for Dragvoll 9, so this building should not be taken into consideration. Systems operate during unoccupied hours with significantly reduced air flow, so it is hard to fully recognize occupancy influence by comparing R^2s for unoccupied and occupied periods. Inspection of ventilation systems normalized heat consumption did not show time delay to changes of outdoor temperature, so thermal storage effect should not be significant for ventilation systems. This will be presented in chapter 6. Weekdays and weekend day regimes are the same for two buildings presented in Table 5.9. Dragvoll Idrettsbygg is the sport center which is opened through whole week. It is hard to evaluate if building is less occupied during weekends than during weekdays. R^2 values are greater for weekend day regimes than for weekday day regimes. Results, presented in Tables 5.8 and 5.9, shows that internal heat gains more influence ventilation heat consumption than heat consumption of space heating system. Sun heat gains were more significant for the buildings with monitored ventilation systems than for the buildings with monitored mixed space heating and ventilation. Presented results show that sun and internal heat gains are utilized by ventilation system more than by space heating system.

5.2.2 Evaluation of predicting ability of calculations with different data resolutions

Appendix E presents coefficients of variation and mean bias errors for eleven analyzed buildings. MBE evaluates the predicting ability of calculations with different data resolutions. The formulation for MBE is:

$$\mathrm{MBE} = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n \cdot \bar{y}} \tag{5.6}$$

where:

$\hat{y}_i$ - daily prediction of heat consumption (dependent variable)

$\bar{y}$ - mean daily heat consumption

y_i- daily heat consumption

n - number of days

Predictions from the hourly model, HOD model and the mean values model must be calculated on daily basis. If the MBE is low, the prediction of overall heat consumption for the analyzed period is close to the actual value. Heat consumption predictions producing low MBE are suitable for savings measurement and verification.

CV is more important than MBE for the detection of O&M problems, since CV shows how predictions cover variations in heat consumption. CV is a criterion for selecting data grouping that will be used in the detection of O&M problems through comparing modeled and real heat consumption. CV is calculated from the root mean square error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{5.7}$$

CV is:

$$\mathrm{CV} = \frac{\mathrm{RMSE}}{\bar{y}} \tag{5.8}$$

If the CV is low, more variation is covered by the model. R^2 could be used to analyze data variation if all of the data have the same resolutions. Since models with different resolutions are compared, R^2s cannot be used in this sense.

Calculations with lower resolutions are better at covering time delays due to thermal storage effects. Since occupancy is not an independent variable of the MLR model, lower resolutions also capture this effect more effectively. Calculations with higher resolutions introduce more information into the model. The accuracy of predictions gained through calculations with different data resolutions represents a trade-off between those two influences.

MBEs and CVs are compared separately by examining their scores. A score of 1 is attributed to the data grouping with the lowest CV. A score of 4 is attributed to the data grouping with the highest CV. The same procedure is conducted for the evaluation of MBE. Scores corresponding to each grouping are summed for all buildings (separately for CV and MBE) into overall scores. Results are presented separately for six buildings with space heating systems and five buildings with ventilation systems in Appendix E.1 and E.2.

5.2.2.1 Space heating system

Calculations with HOD data and calculations with mean values produced the best overall scores according to Table 0.118. Calculations with daily data produced higher CV for all buildings than calculations with mean values (Tables 0.121, 0.123, 0.125, 0,127, 0.129 and 0.131). This proves the hypothesis that calculations with mean values grouped by regimes produce more accurate predictions than calculations with daily data if the HVAC system operation is changed thorough the control regimes. Moreover, HOD and hourly data produced lower CVs than calculations with daily data. The main reason for poor prediction quality gained through calculations with daily data is that the daily data do not cover variation of control regimes. Earlier analysis (Katipamula et al., 1995 and 1998) showed that daily data produced the lowest CV for HVAC systems that operate without changes through control regimes.

Outdoor temperature has the most significant influence on heat consumption of a space heating system; this is proved earlier through stepwise regression and analysis of sequential sums of squares. Hourly and HOD data groupings introduce more variations of outdoor temperature than do other models. Thermal storage effect deteriorates predictions of calculations with hourly data, so they produced higher CVs than calculations with HOD data and mean values.

Calculations with mean values cover thermal storage effects better than calculations with HOD data; HOD data introduce more variation than mean values grouped by regimes. It seems that the advantages of these two models produced the similar improvement of predictions, and thus gave similar values of CV.

Calculations with hourly data produced the lowest MBEs (Table 0.118); thus, these are the most suitable for savings measurement and verification purposes.

5.2.2.2 Ventilation system

Similar results to those obtained for the space heating systems are gained for the ventilation systems (Appendix E.2). Calculations with HOD data produced the lowest CVs, followed by calculations with mean values (Table 0.132). Daily data produced the highest CVs as a result of averaging control regimes by this model. Advantage of models with daily data and mean values over models with hourly and HOD data is that models with daily data and mean values better cover thermal storage effect due to solar influence and building occupancy. However, models with hourly and HOD data covered more variation due to changes in outdoor temperature, so outdoor temperature was the most important influence in defining the HOD grouping as the best.

Other ranking is obtained when CVs for buildings with significant solar radiation (Dragvoll 3 and 9) are summed (Table 0.134). In this case, hourly data gave the highest CV due to the inability of hourly data to capture thermal storage effect due to solar radiation. Calculations with mean values gave the lowest CV, followed by HOD grouping.

Scores for buildings with insignificant solar influence (Dragvoll 2, Dragvoll 8 and Dragvoll Idrettsbygg) gave the lowest CV for calculations with HOD data, followed by calculations with hourly data (Table 0.133). Thermal storage effect due to changes in outdoor temperature is not significant for the ventilation system (as it is for the space heating system); thus, calculations with mean values did not have any advantage over calculations with hourly and HOD data in this respect. HOD data better covered variation due to building occupancy than did hourly data; thus, calculations with HOD data produced lower CVs than calculations with hourly data.

Calculations with hourly data also produced the lowest MBEs for the ventilation system (Table 0.132).

5.3 Evaluation of model improvement through excluding outliers

Chapter 3.7 explains that R-student residual is statistics that is used in recognition of outliers. The tool developed for the modeling and analysis of building heat consumption have option for excluding outliers during calculations. Usually, calculations are conducted by default without excluding outliers. If the check-box ‘Exc Resid’ is selected, outliers are detected after conducting every LR calculation and are then eliminated from the next calculation, in order to avoid their influence. Chapter 4.5 explains the position of the recognition of outliers in calculation algorithms. The criterion for a data point to be recognized as an outlier is that the R-student residual is higher than two. The condition that should be fulfilled is that none of data points has an R-student residual higher than two. It is possible that the criterion that all R-student residual values should be lower than two can never be reached if the heat consumption is not fully explained by LR model. During a LR calculation, which was conducted with Minitab statistical software, the second calculation (conducted with a set of data without data points recognized as outliers after the first calculation) recognized new outliers. Calculations were repeated with new set of data, but new outliers appeared again. The same problem also appeared during the calculations in this newly developed tool. It was necessary to limit excluding outliers to 15% of the number of data points employed in calculation.

Excluded outliers increased the coefficient of determination, as demonstrated in Appendix A, B, C and D. However, this does not mean that the gained model and predictions of heat consumption will be more accurate if data points that are not outliers are recognized as outliers, due to an inability of model to cover all variations of heat consumption properly.

CVs for calculations without and with excluding outliers were compared. CVs are presented in Appendix F. Three buildings have significant solar influence (Dragvoll 3, Dragvoll 9 and Sentral Bygg 1). Appendix F presents SSS for solar radiation influence for those three buildings gained through calculations without and with excluding outliers (Tables 0.154, 0.158 and 0.147). It seems that excluding outliers can cause model performance to decrease even worse for data points with dominant sun influence. Excluding outliers decreased the SSS for solar radiation for the Dragvoll 3 and Sentral Bygg 1 buildings (Tables

0.154 and 0.147), since the LR model does not fully cover solar radiation and data points with higher solar radiations are excluded. Excluding outliers did not decrease the SSS for solar radiation influence for Dragvoll 9 building (Table 0.158). CVs for calculations made after outliers were excluded are higher than CVs for calculations made without excluding outliers for those three buildings, suggesting the model is less accurate for calculations with excluded outliers (Tables 0.148, 0.155 and 0.159).

CVs for the other eight buildings are mostly lower for calculations not performing excluding residuals than for calculations performing excluding residuals (Appendix F), so excluding residuals cause the model accuracy to deteriorate. For 44 calculations (11 buildings multiplied by four models), CVs are for 15 calculations performing excluding residuals lower than CVs for calculations not performing excluding residuals.

It is possible that 15%, as a limit of the number of data points that can be excluded as outliers, is too high. The program could exclude just points that are obvious outliers if a lower limit were used. Outliers can also be excluded manually.

5.4 Evaluation of monitoring sample duration

Kissock et al. (1993) claimed that, for the precise prediction of building heat consumption based on daily data, three to six months of monitoring history is required. No analysis determined the required length of monitoring period for hourly data. Other authors have assumed that the same time period is sufficient for precise modeling. Changes of the control regimes have appeared for almost all analyzed NTNU buildings on a yearly basis. For more than two years of monitoring history, most of the buildings had two or more changes of control regimes. This proves an interest in determining the shortest monitoring period that can generate reliable results.

CVs computed for six and three month periods are compared with CVs obtained from predictions for the same periods calculated from LR coefficients gained from calculations with a year period (CV_Appl in Appendix G). CVs and CV_Appl's are compared in order to compare the accuracy of models gained by linear regression of data for different monitoring period durations. If predictions of overall heat consumption were compared, that would neglect variation of data from mean heat consumption. Thus, CVs were calculated. CVs and CV_Appl's were calculated for two six-month periods and three three-month periods for three analyzed buildings with space heating system (Appendix G.1). CVs and CV_Appl's were calculated for three six-month periods and four three-month periods for ventilation heat consumption of Dragvoll Idrettsbygg building (Table 0.166). Control regimes were changed during periods shorter than a year for the other buildings were ventilation heat consumption was monitored. CV_Appl's are calculated for two more buildings with LR coefficients gained from calculations with six-month periods. Results are presented in Tables 0.167 and 0.168.

Change points calculated for winter are lower than the change points calculated for a one-year period (Table 5.10). Thus, applying LR coefficients gained for six and three month periods over a one-year period can give higher CVs. If the LR coefficients from winter would be applied on year data, obtained prediction of yearly heat consumption would be inaccurate. Since the focus of this thesis is not predicting overall heat consumption, but is developing a LR model that will accurately describe heat consumption variation, CV comparisons were not made over the one-year period. The heating season in Norway lasts from September to May, which means that there are plenty of data for modeling building heat consumption. CVs are calculated and presented for four ways of grouping data in Appendix G.

	Weekday	Weekend
01.01.2007 – 02.12.2007	15	15
01.01.2007 – 01.04.2007	10	11

Table 5.10 Change point temperature for weekdays and weekends for the Sentral Bygg 1 building

Calculations over a three-month period for three buildings with space heating produced the lowest CV values for period 01.01.2007 – 01.04.2007 which corresponds to lower outdoor temperatures (Tables 0.162, 0.163 and 0.164). Higher CVs for periods corresponding to higher outdoor temperatures is consequence of thermal storage effect which is more significant for higher outdoor temperatures (discussed in subchapter 3.3.1.1). CVs are also lowest for the same period for buildings where ventilation heating was monitored. Modeling with a three month monitoring period with lower outdoor temperatures can be more effective than modeling with six months or a one-year monitoring period.

CVs are in most cases lower than CV_Appl's, both for three and six month periods. Appendix G includes Tables 0.161 and 0.165 that present percentages of calculations that produced a lower CV than the corresponding CV_Appl. Three months proved to be long enough to produce sufficient accurate LR coefficients for all four ways of grouping data, since the presented percentages are high (higher than 50%). The CVs are lower than the CV_Appl's, even for the period 02.04.2007 - 01.07.2007 (Tables 0.162, 0.163, 0.164 and 0.166). For many data points, the outdoor temperatures are higher than the change point temperatures for this period, so the LR calculation was effectively performed with less than three months of monitoring data, which demonstrates that even time periods shorter than three months can produce reliable predictions of heat consumption. Six months of data produced CVs that were, in most cases, lower than the CV_Appl's, suggesting that modeling should be conducted with six month data instead of with year data.

CVs for daily data are mainly higher than for other data groupings, which prove the conclusions from the previous subchapters.

5.5 Improvement of the building daily heat consumption model through introducing daily change in outdoor air temperature as an independent variable of the linear regression model

One of the most significant reasons for the inaccuracy of the discussed heat consumption model is due to the time delay which is a consequence of thermal storage. Walls represent barriers between a building and its surrounding. Heat transfer between the indoor air and the inner surface of a wall defines the amount of heat delivered by a space heating system. A change in outdoor temperature does not immediately change the building heat demand due to heat accumulation in the walls. Thus, change in outdoor air temperature will be introduced in the model of building heat consumption through a time-lagged variable.

Figure 5.3 is a three dimensional presentation of outdoor air temperatures for Trondheim. It can be seen that temperature increased greatly on the October 26. Temperatures increased again during the evening of the October 27 and the morning of the October 28. Also, on the October 31, the temperature increased during the afternoon. Presented models of hourly heat consumption do not account for changes in outdoor temperature. Although the outside air temperature increases, the space heating system continues to deliver an unchanged amount of heat to the building, because walls are still cold. Thus, the actual heat consumption is higher than the value predicted by the model that is gained through linear regression calculations with hourly outdoor temperatures. Figure 5.4 presents ratios of actual and modeled heat consumption, i.e., normalized heat consumption, of one of the buildings of NTNU campus. Hourly increases of temperatures during October 26, 27, 28 and 31 are not followed by a decrease in building heat consumption, because the walls were still cold, thus demanding a higher amount of heat than predicted by the model. It is possible to develop a model that will also account for changes in outdoor temperatures. However, it is not possible to know how much energy is necessary in order to heat the internal walls. The longer a period of cold weather has lasted prior to the analyzed day, the longer it will take for the walls to warm. Also, it is hard to represent the change in temperature from hour to hour; the temperature can increase suddenly (in just a few hours) or over a longer period of time. For these reasons, changes in outdoor temperature will not be involved in the model of hourly heat consumption (hourly and HOD model). A sudden fall in temperature causes the same problems when modeling building heat consumption. In this case, the actual heat consumption will be lower than that predicted due to the cooling of the walls.

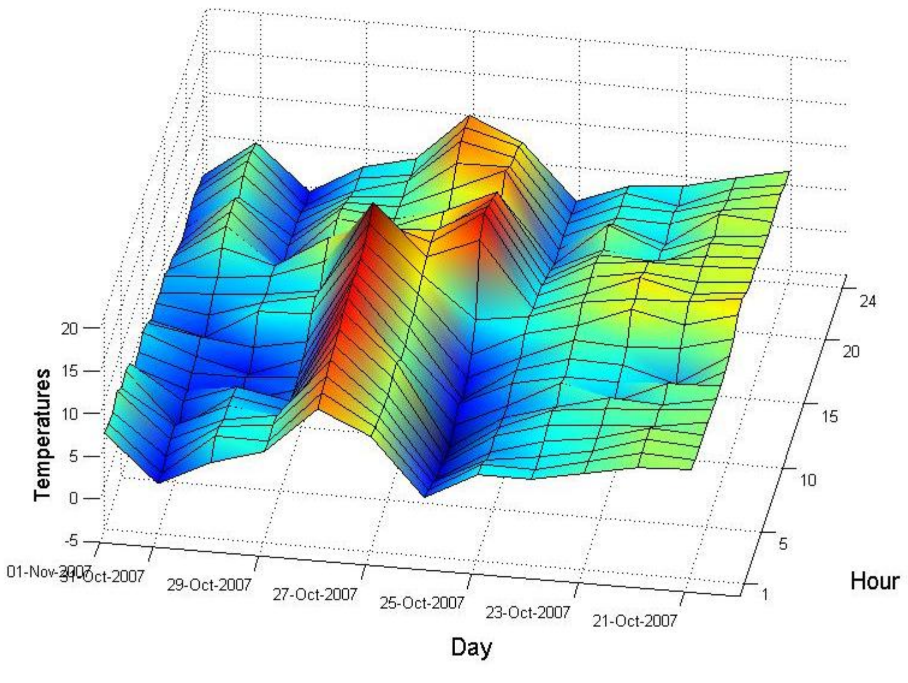


Figure 5.3 Hourly outdoor air temperatures for period October 21, 2007 – November 1, 2007 in Trondheim

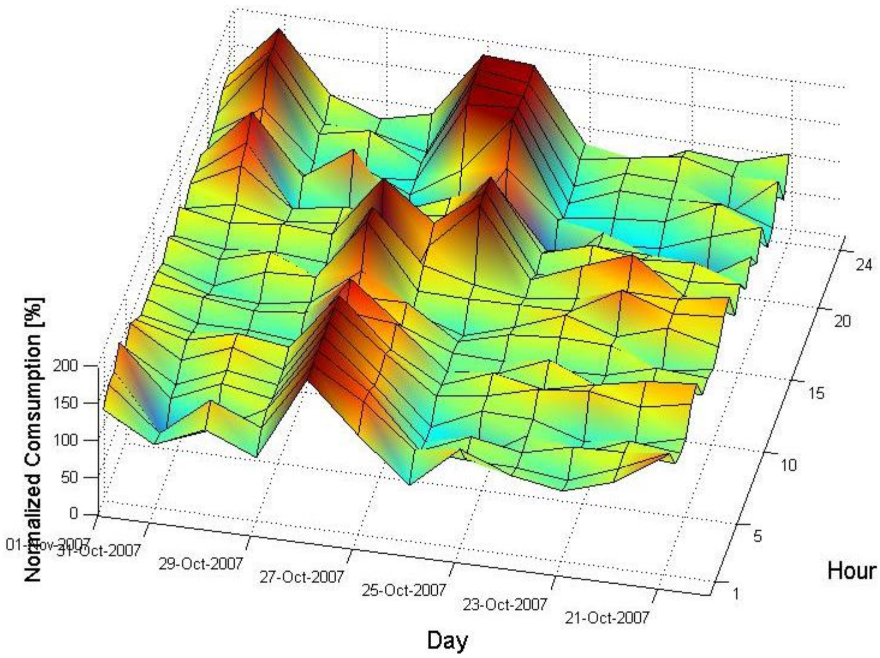


Figure 5.4 Normalized hourly heat consumption of Gamle Kjemi building for period October 21, 2007 - November 1, 2007

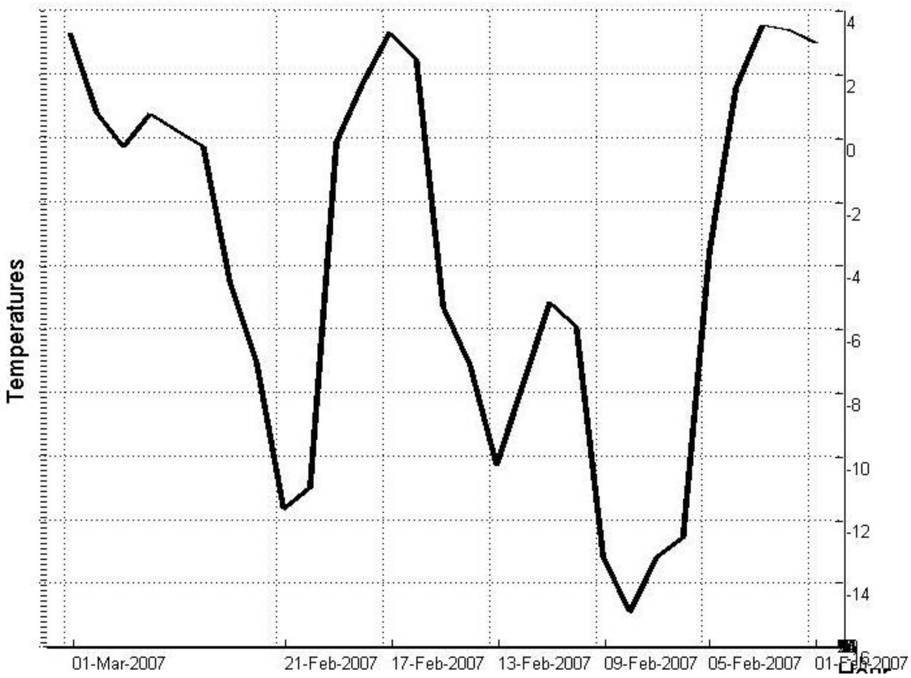


Figure 5.5 Mean daily temperatures during February 2007 in Trondheim

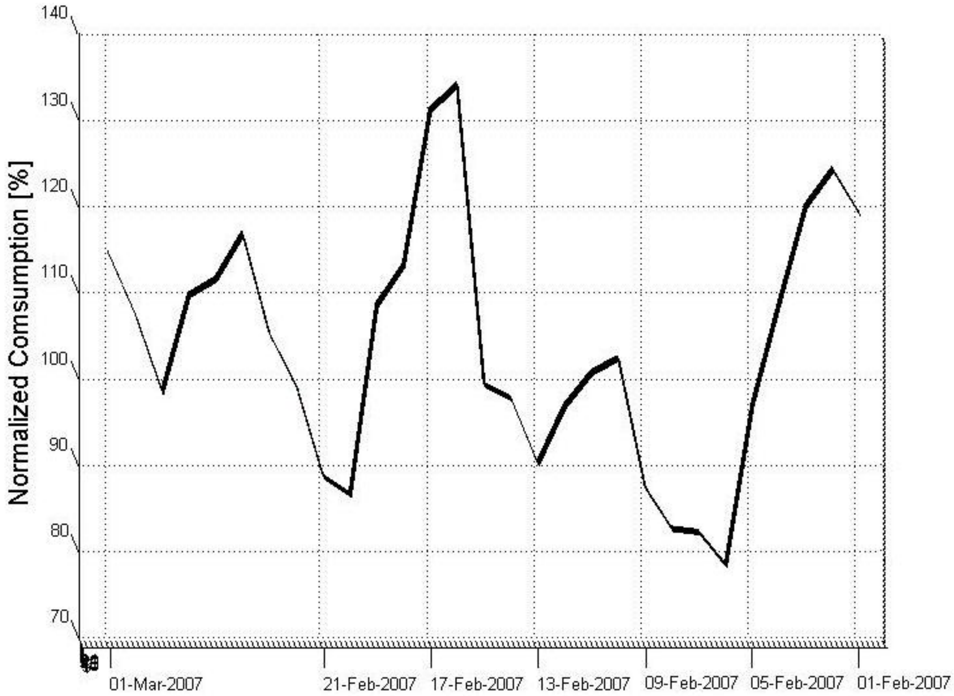


Figure 5.6 Normalized daily heat consumption for the Gamle Kjemi building during February 2007 (Simple linear regression model)

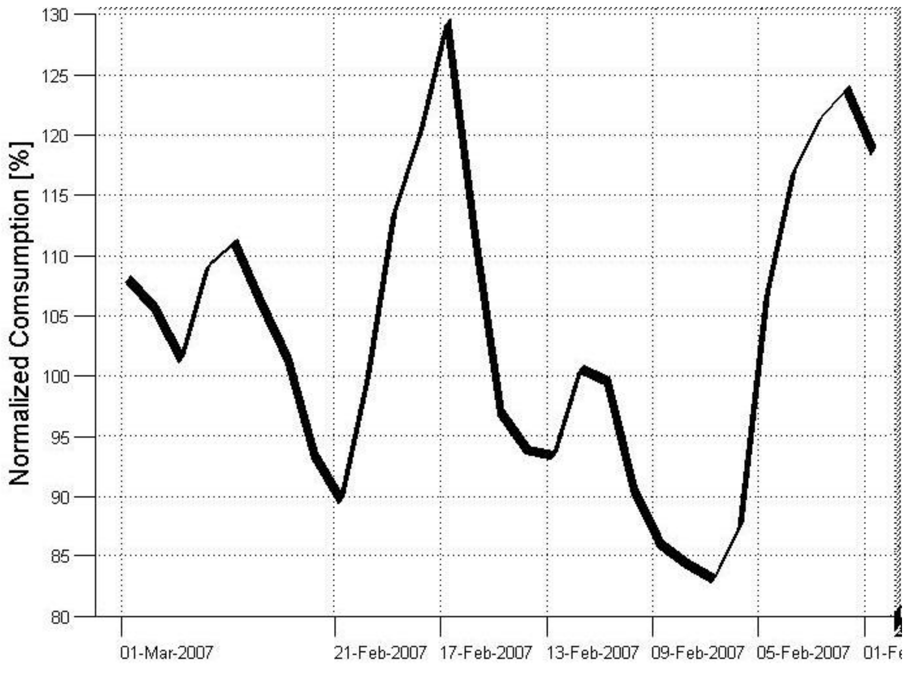


Figure 5.7 Normalized daily heat consumption for the Gamle Kjemi building obtained with a model involving time-lagged variable

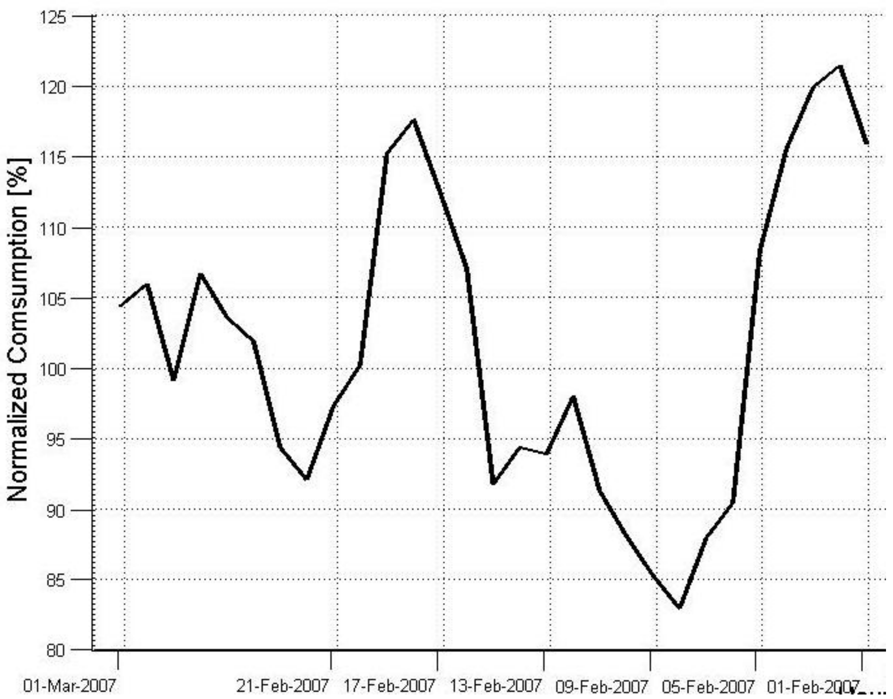


Figure 5.8 Normalized daily heat consumption for the Gamle Kjemi building obtained through model involving two time-lagged variables

The daily model of heat consumption is more appropriate than the model with mean values for introducing the change in outdoor temperature (time-lagged variable) as an independent variable. Changes in outdoor temperatures are represented by the difference between the mean daily temperatures for the actual day and the day before it. The problem that is not solved in this way is that the amount of heat required to warm up or cool down walls after a sudden increase or decrease of outdoor temperature is unknown. However, it is expected that introducing change in outdoor temperature into the model will increase the model's goodness of fit.

Figures 5.5 and 5.6 present the mean daily temperatures and normalized daily heat consumption gained for simple linear regression model for the Gamle Kjemi building during February 2007. It is obvious that changes in normalized daily heat consumption follow changes in outdoor temperatures. For February 6, the temperature decreased from -6°C to -12.5°C, i.e., a change of -6.5°C. Normalized heat consumption also showed this decrease. For 7 February, the temperature fell less than 1°C, but the normalized daily heat consumption was even lower than that for February 6. This was unexpected and suggests that, in this case, the effects of a change in outdoor temperature last for more than one day, i.e., the walls need more than one day to cool down. That is why it can be useful to also introduce into the model the change in outdoor temperature for at least the last two (or even more) days. For 18 February, outdoor temperature decreased but the normalized heat consumption remained over 100%, because the walls were still warming up. Figure 5.7 presents the normalized daily heat consumption for the Gamle Kjemi building obtained with a model using a time-lagged variable. Highest deviations in normalized heat consumption appeared on Figure 5.6 for 6, 16, 20 and 24 of February. Deviations for those days (Figure 5.7) are lower than those on Figure 5.6, so introducing time-lagged variable improved model. Normalized heat consumption in Figure 5.8 is obtained using the model including two time-lagged variables. The first time-lagged variable is the difference between the mean daily temperature and the mean temperature of the previous day. The second time-lagged variable is the difference between the mean daily temperature and the mean temperature two days prior. For 16, 20 and 24 of February, the deviations from 100% in Figure 5.8 are lower than in Figure 5.7. It is important that extreme deviations are minimized so they are not interpreted as faults of HVAC system operation. Models involving changes in daily temperatures cannot fully cover the effects of accumulation. Hourly normalized heat consumption and hourly heat consumption should be checked in order to see if extreme deviations of normalized heat consumption are a consequence of the cooling down or warming up of walls due to outdoor temperature change. The model involving time-lagged variable of outdoor temperature change is:

$$Q = A + B_1 \cdot (T_{SET} - T) + B_2 \cdot W^* \cdot (T_{IN} - T) + B_3 \cdot S + B_4 \cdot \Delta T + B_5 \cdot 2\Delta T \qquad (5.9)$$

where ΔT and $2\Delta T$ are time-lagged variables for one and two day temperature differences respectively.

Table 5.10 gives the coefficients of determination for calculations with twenty NTNU's buildings. Calculations are done with daily data through five types of linear regressions:

- simple linear regression, outdoor air temperature (T) is the only independent variable
- multiple linear regression involving outdoor air temperature (T), solar radiation (S) and wind speed (W)
- multiple linear regression with outdoor temperature (T) and time-lagged variable for one day temperature difference (ΔT)
- multiple linear regression with outdoor temperature (T), time-lagged variables for one day (ΔT) and two days temperature differences ($2\Delta T$)
- multiple linear regression with outdoor temperature, solar radiation, wind speed, time-lagged variables for one and two days temperature differences (T, W, S, ΔT and $2\Delta T$)

It is expected that involving more independent variables should increase the coefficient of determination. Additionally, introducing time-lagged variables should significantly improve the goodness of fit for buildings with a high thermal mass. It can be concluded from Table 5.11 that the coefficients of determination with five independent variables are the highest.

Independent variables of linear regression	T	T, W and S	T and ΔT	T, ΔT and $2\Delta T$	T, W, S, ΔT and $2\Delta T$
Sentral Bygg 1	93.77 %	93.79 %	94.53 %	95.00 %	95.14 %
Sydområdet NHL Forskning bygg	93.37 %	94.64 %	93.88 %	94.08 %	95.12 %
Gamle Fysikk	93.05 %	93.57 %	94.44 %	95.01 %	95.28 %
Berg	95.41 %	96.26 %	95.88 %	96.04 %	96.67 %
Gamle Kjemi	94.50 %	96.14 %	95.83 %	96.61 %	97.58 %

Sentral Bygg 2	93.11 %	93.56 %	93.76 %	94.11 %	94.33 %
Elektro B	96.49 %	96.93 %	97.06 %	97.32 %	97.58 %
Materialtekniske Laboratorier	92.02 %	93.95 %	93.25 %	93.62 %	95.02 %
Produktdesign	92.35 %	93.63 %	92.59 %	93.15 %	94.04 %
Elektro E and F	92.70 %	93.62 %	94.15 %	94.89 %	95.38 %
Metallurgi	93.67 %	95.38 %	94.88 %	95.77 %	96.81 %
Oppredning – gruvedrift	93.31 %	95.69 %	93.96 %	94.58 %	96.39 %
PFI	88.96 %	90.05 %	89.91 %	90.42 %	91.29 %
Verkstedtekniske Laboratorier	89.52 %	94.81 %	90.44 %	91.60 %	95.71 %
Tyholt Marintekniskenter	98.11 %	98.25 %	98.27 %	98.34 %	98.47 %
Dragvoll 3	70.35 %	86.13 %	70.51 %	70.96 %	86.65 %
Dragvoll 8	81.77 %	82.90 %	81.93 %	82.14 %	83.25 %
Dragvoll Idrettssenteret	96.58 %	97.17 %	96.56 %	96.77 %	97.31 %
Dragvoll 2	83.30 %	84.69 %	83.87 %	86.08 %	86.86 %
Dragvoll 9	56.02 %	64.86 %	56.81 %	57.04 %	65.36 %

Table 5.11 Coefficients of determination for five linear regression calculations for twenty NTNU's buildings

Heat consumption of the last five buildings in the table represents only to ventilation heat consumption. In this case, change of outdoor air temperature immediately influenced heat consumption, so the goodness of fit is not expected to improve significantly by introducing the time-lagged variable of temperature change into the model. Improvements are not significant for these five buildings except for Dragvoll 2 building. In the case of ventilation heat consumption, a decrease in outdoor temperature can cause the walls to release heat for some time to the inner space, so that the exhaust air transfers this released heat through the economizer and to the supply air. Although it is expected that the heat released from the walls will influence the consumption of space heating, there could be some decrease of heat consumption for the ventilation system. Appendix H presents two figures of normalized daily heat consumption for Dragvoll Idrettssenteret. Figure 0.2 presents normalized daily heat consumption calculated with outdoor temperature, solar radiation and wind influence as independent variables. Figure 0.3 presents normalized daily heat consumption calculated with outdoor temperature, solar radiation, wind influence and two time-lagged variables. Although deviations from 100% are lower on Figure 0.3, the improvement for this figure is not as significant as the improvement gained for Gamle Kjemi building (space heating system, Figures 5.6 - 5.8). There were significant changes in the mean daily temperature during February 2007 (Figure 0.1). However, normalized daily heat consumption did not track along with those changes as was case with the Gamle Kjemi building. Introducing time-lagged variables significantly improved the R^2 for the Dragvoll 2 building. Appendix H presents the normalized daily heat consumption for calculations without and with time-lagged variables and the corresponding mean daily temperatures (Figures 0.8, 0.9 and 0.10). Significant changes in the mean daily temperature during February 2007 are followed by similar changes in normalized heat consumption. Deviations from 100% are lower for calculations involving time-lagged variables for days with significant changes in outdoor temperatures (Figure 0.10). Normalized hourly heat consumption between January 19, 2007 and February 1, 2007 and corresponding hourly outdoor temperatures are presented in Figures 0.6 and 0.7. Increases in the outdoor temperature during January 25 and of January 30 are followed by increases in the normalized hourly heat consumption as a consequence of the thermal storage effect.

Figure 5.9 presents changes in the outdoor air temperature for Trondheim during February 2007. Normalized hourly heat consumptions for the Dragvoll Idrettssenteret building (only ventilation) and the Gamle Kjemi building (mixed space heating and ventilation) are presented on Figure 5.10 and 5.11, in order to show that heat accumulation has more influence on space heating than it does on ventilation. The influences of sudden temperature changes on normalized heat consumption for the Gamle Kjemi building can be recognized in Figure 5.11. During the morning of February 16, the temperature increased suddenly. Normalized heat consumption in Figure 5.11 was significantly greater than 100% for that same day. Change of temperature is followed by change of normalized heat consumption for the other days for the Gamle Kjemi building. There is no recognizable change in the normalized heat consumption for February 16 in Figure 5.10. Temperature deviations during nights and evenings, which can be recognized on Figure 5.10, are not significant since heat consumption during nights and evenings are quite low. Appendix H presents the similar figures as Figures 5.9 – 5.11 for January 2007 (Figures 0.4, 0.5 and 0.11). During the morning of January 25, the temperature increased suddenly. The normalized heat consumption for the Gamle Kjemi Building was significantly more than 100% for that day. For the Dragvoll Idrettssenteret building, there is no recognizable change in the normalized heat consumption for that day.

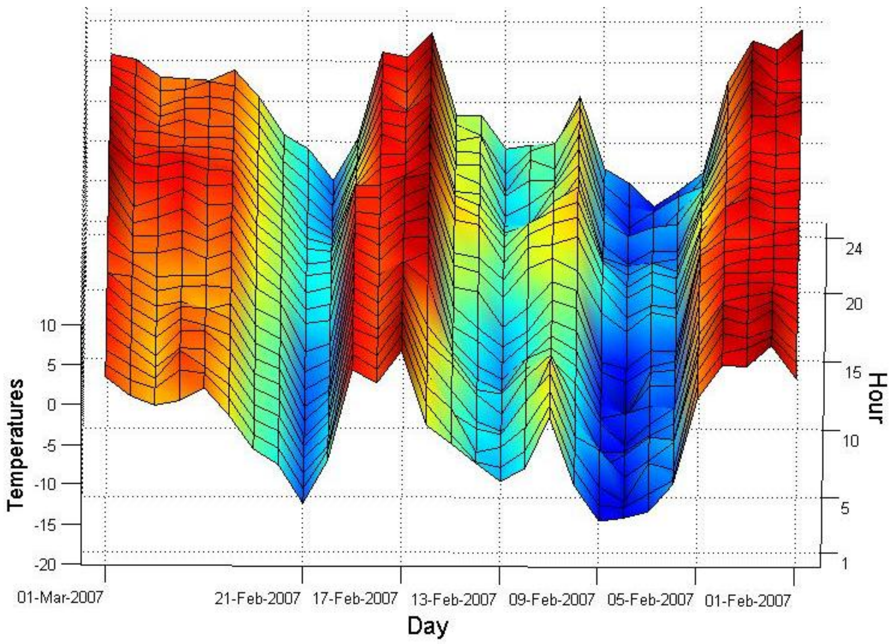


Figure 5.9 Hourly outdoor air temperatures during February 2007 in Trondheim

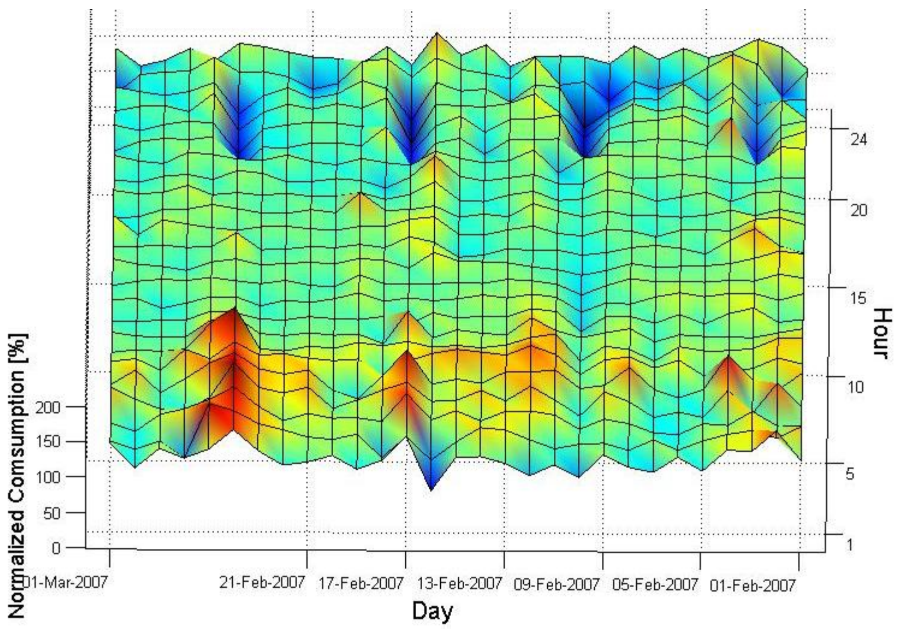


Figure 5.10 Hourly NHC for the Dragvoll Idrettssenteret building during February 2007

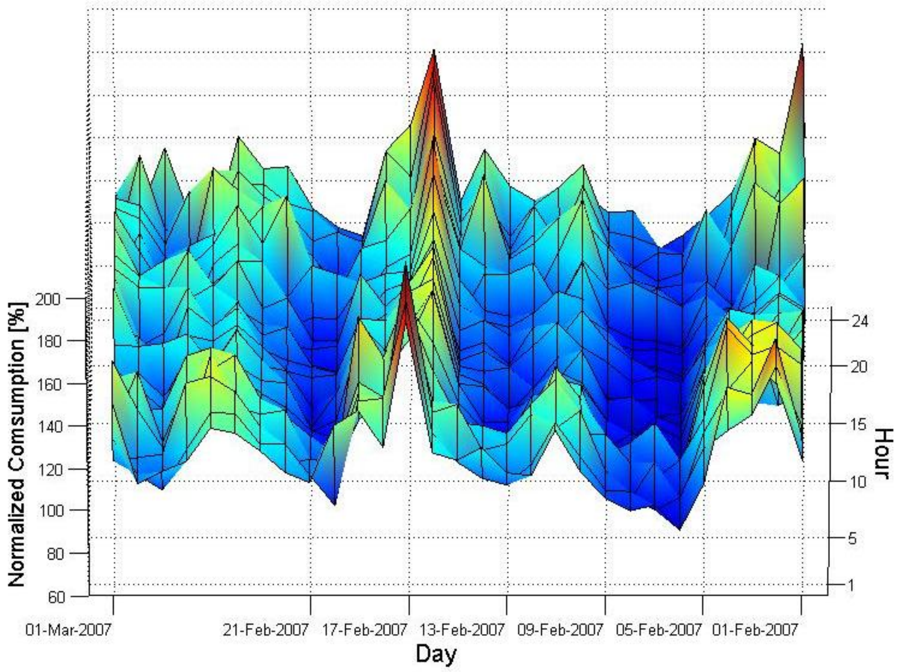


Figure 5.11 Hourly NHC for Gamle Kjemi building during February 2007

Since linear regressions involving two time-lagged variables (T, ΔT and 2ΔT as independent variables, fifth column in table 5.11) gave in all cases better results than calculations with one time-lagged variable (T and ΔT, fourth column in table 5.11), there is a reason to introduce time-lagged variables 2ΔT into the model. For fifteen buildings (all buildings except the five Dragvoll buildings, i.e., the last five buildings in table 5.11), heat consumption corresponds to mixed space heating and ventilation use. Calculations with three temperature independent variables produced higher coefficients of determination than linear regressions with temperature, solar radiation and wind speed for nine of the fifteen buildings. It can be concluded from stepwise regression that captured contributions of heat accumulation in walls contributed more to variations in heat consumption than did captured solar and wind influence. Since it is obvious that all variations due to heat accumulation in walls are not explained by the model due to the impossibility of developing an appropriate model, it can be concluded that heat accumulation is the main driving force of heat consumption of space heating, after the outdoor air temperature.

Appendix H presents CVs for six buildings with space heating (Table 0.169) and five buildings with ventilation heating (Table 0.171). CVs for four ways of data grouping, which are already presented in Appendix E, are presented in Appendix H, as well as the CVs obtained for calculations with time-lagged variables. The results are sorted in the same manner as for those in Appendix E (Tables 0.170 and 0.172). Introducing time-lagged variables has significantly improved the CVs in regard to calculations with daily data for space heating system (Tables 0.169). CVs for all buildings except for Sentral Bygg 1 building are lower for calculations with time-lagged variables than the CVs for calculations made with daily data. Calculations with time-lagged variables have the best overall score for space heating systems (Table 0.170). Calculations with time-lagged variables will be used in following analysis of space heating systems, rather than calculations with daily data or with mean values grouped by regimes. Introducing time-lagged variables did not significantly improve the CVs for five buildings with ventilation systems, except for the Dragvoll 2 building (Table 0.171). However, some improvements were obtained for all buildings, so thermal storage effect has some influence on ventilation heat consumption.

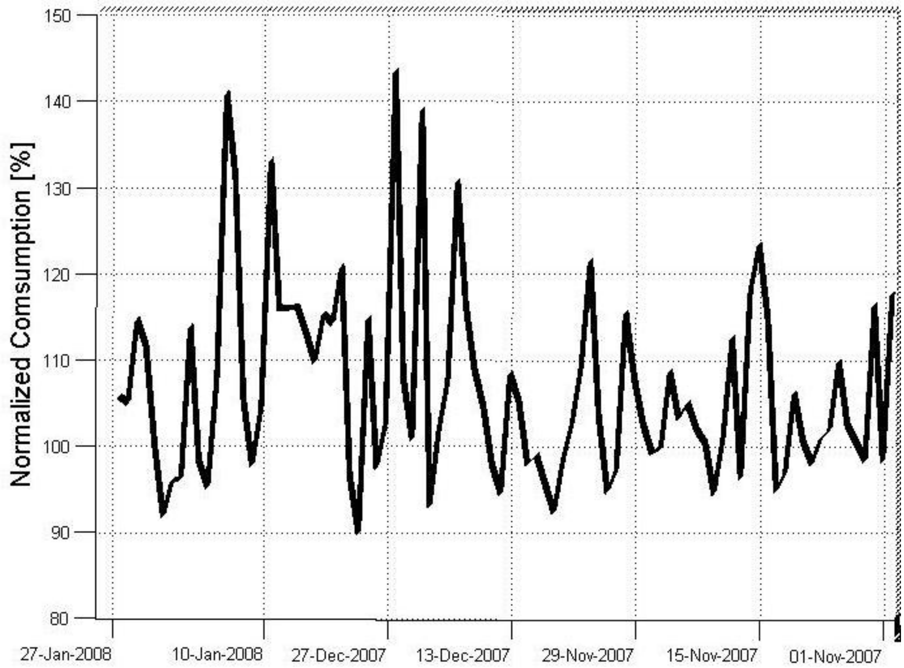


Figure 5.12 Daily NHC for the Gamle Kjemi, for calculations without change of daily temperature as the independent variable (November 1, 2007 - January 27, 2008)

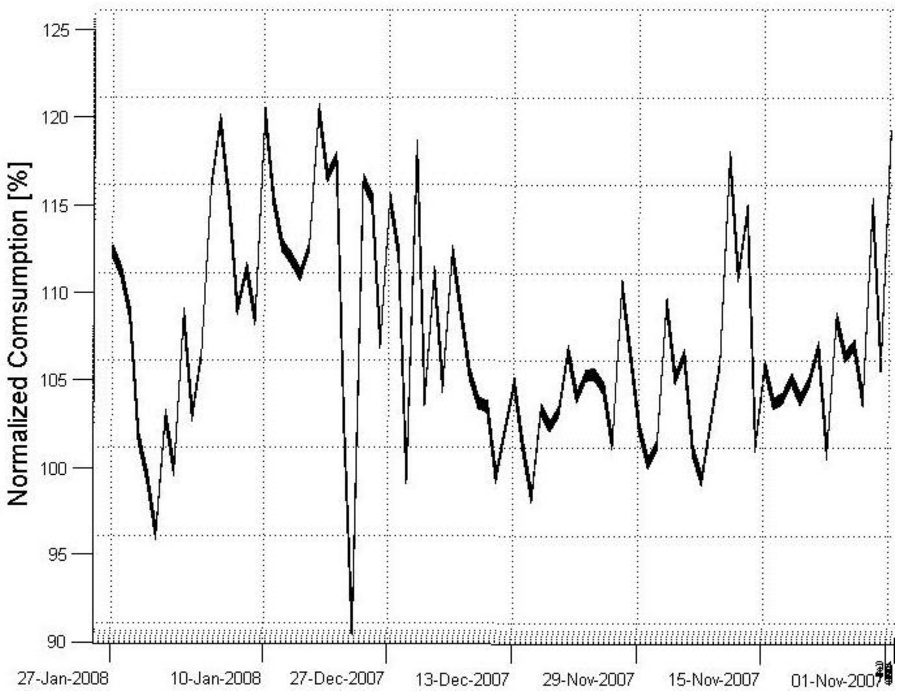


Figure 5.13 Daily NHC for the Gamle Kjemi building, for calculations with change of daily temperature as the independent variable (November 1, 2007 - January 27, 2008)

The significance of introducing temperature change is demonstrated through Figures 5.6 – 5.8. Points with the highest deviations from 100 % are much closer to 100 % after introducing the temperature change time-lagged variable. Figures 5.12 and 5.13 present normalized daily heat consumption for the Gamle Kjemi building, for the period between November 1, 2007 and January 27, 2008, for linear regression calculations without and with change of daily temperature as independent variable. There are ten points with NHC values over 120 % shown in Figure 5.12. All points on Figure 5.13 are within the 120% limit. Even if the CVs in Table 5.11 did not greatly increase with the introduction of time-lagged variables, the decrease in the normalized heat consumption deviations for ten points is very important. The CV increased by 2.11% by introducing time-lagged independent variables into the SLR model for the Gamle Kjemi building. Introducing time-lagged independent variables increased the CV by 1.44% for LR calculations including solar and wind influence. Even if this improvement does not sound like significant, introducing temperature change as an independent variable decreased peak deviations of NHC values. Figures 5.15 and 5.16 present normalized daily heat consumption for the same building for the period of January 1, 2007 to June 1, 2007, for calculations without and with change of daily temperature as independent variables. NHC values in Figure 5.15 are obviously higher than in Figure 5.16. The peak NHC values in Figure 5.15 correspond to days with a sudden change of outdoor temperature.

During the end of May 2007, there appeared a few points with lower normalized consumption (Figure 5.16). Outdoor temperatures were relatively high during this period (Figure 5.14). The model has a problem in predicting heat consumption for temperatures close to or over the change point temperature. Figure 5.17 shows hourly heat consumption for one of the NTNU's buildings for the weekday day regime. Lines represent the predicted heat consumption and are gained through simple linear regression. Even if absolute deviations from the predicted heat consumption are not high for the temperatures close to the change point temperature, relative deviations (normalized heat consumption) are high. Thus, normalized heat consumption cannot be a measure of quality for HVAC system operation under higher temperatures. Someone who checks the functioning of HVAC system through checking normalized heat consumption should reconsider the outdoor temperatures, and determined if these temperatures are close to the change point temperature. Too low or too high normalized heat consumption should not be considered to be a fault of the HVAC system operation in this case. During the analysis of HVAC operation for the twenty buildings, the summer months (June, July and August) were not analyzed, since the model does not give reliable normalized heat consumption for those months. Temperatures in Trondheim can be low enough, even during those months, that space heating is required. However, high changes in outdoor temperatures are characteristic for those days, so thermal storage will highly influence heat consumption.

For the analyzed heat consumption of all twenty buildings, most of the deviations of NHC are within the 20% limits after introducing the time-lagged temperature change as an independent variable, which can be concerned as reliable proof that HVAC systems are operating correctly. Reconsideration of hourly normalized heat consumption can prove that higher deviations of normalized heat consumption are result of significant changes in outdoor temperatures. It can be concluded that the HVAC system operation may become faulty if daily normalized heat consumptions are, for long time periods, at levels that significantly deviate from 100%. Fluctuations between 80% and 120% can be considered to be normal and a consequence of the inability of the model to fully explain building heat consumption, mostly due to the effects of thermal storage.

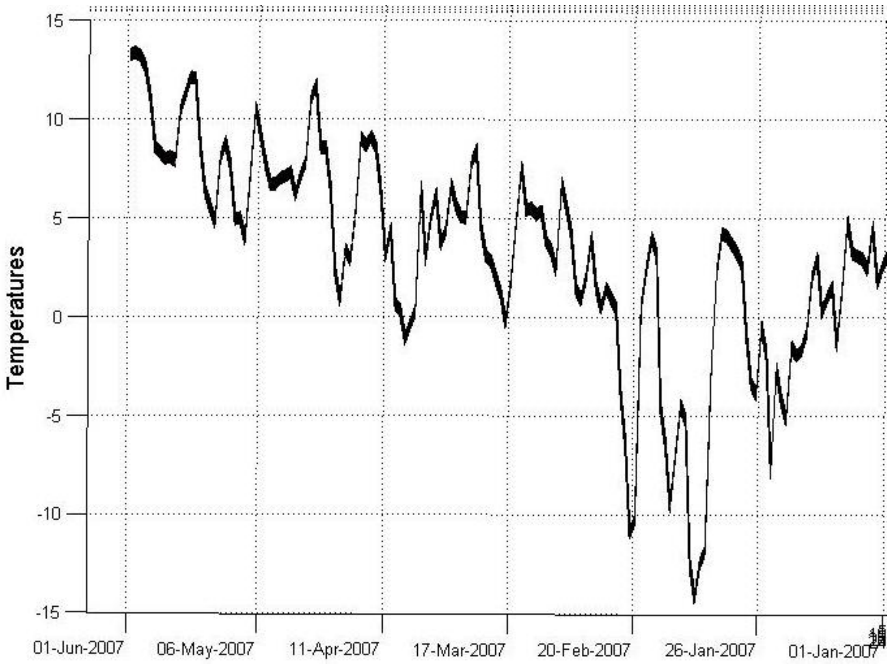


Figure 5.14 Mean daily temperatures between January 1, 2007 and Jun 1, 2007 in Trondheim

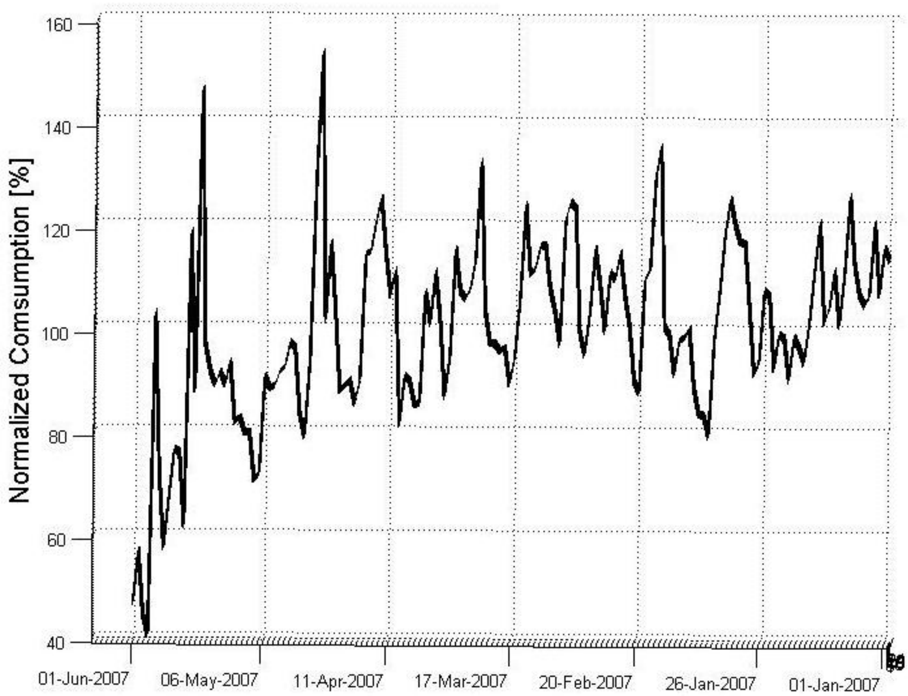


Figure 5.15 Daily NHC for the Gamle Kjemi building for calculations without change of daily temperature as the independent variable (January 1, 2007 - Jun 1, 2007)

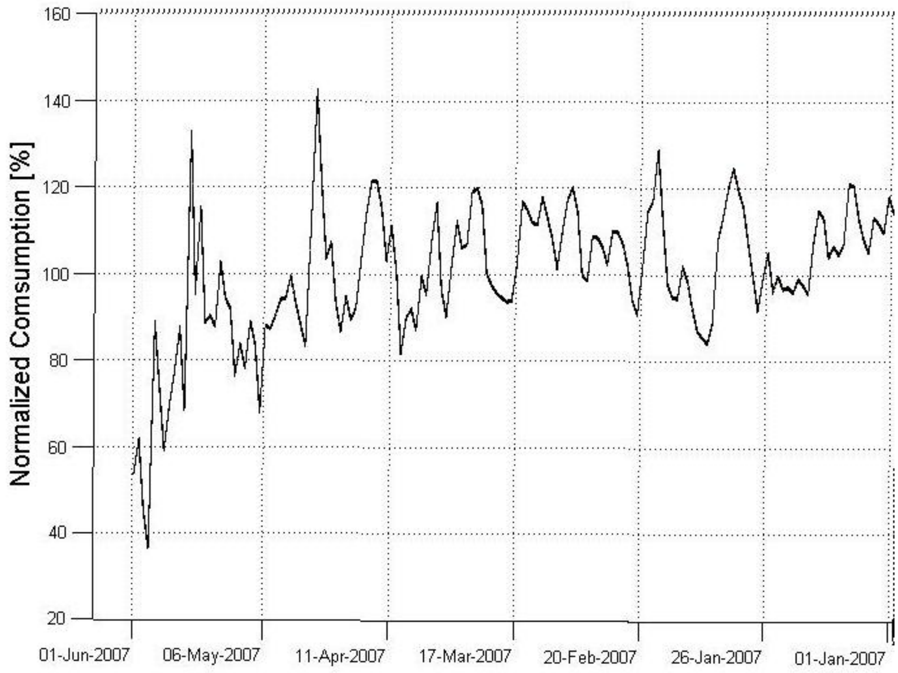


Figure 5.16 Daily NHC for the Gamle Kjemi building for calculations with change of daily temperature as the independent variable (January 1, 2007 - Jun 1, 2007)

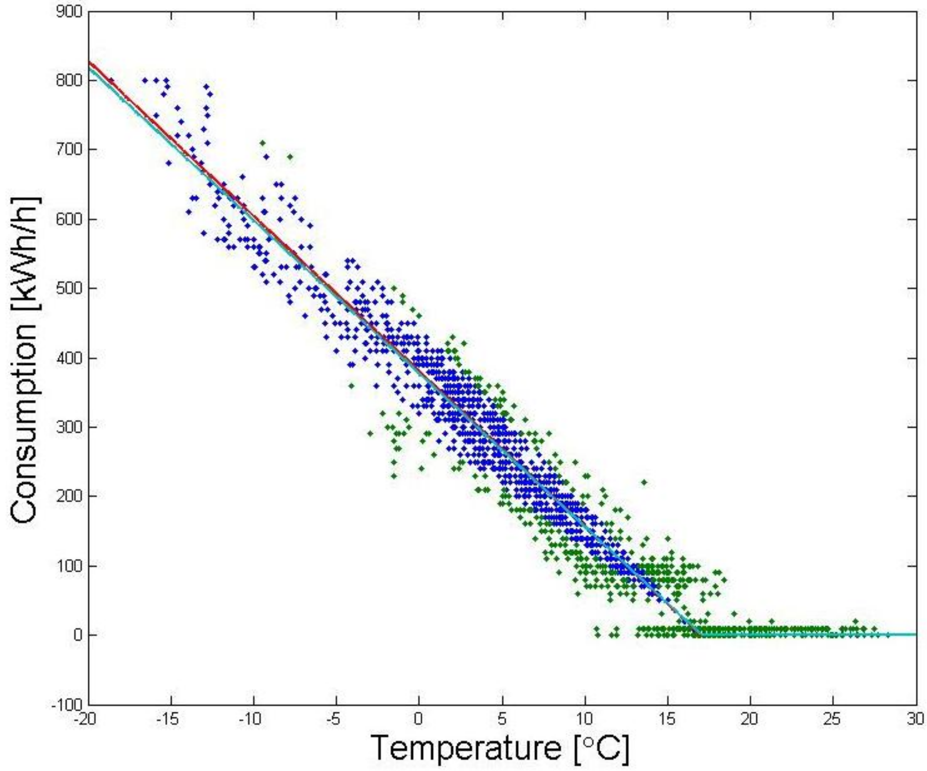


Figure 5.17 Hourly heat consumption for the Sydområdet NHL Forskning building for weekday daily control regime during the period January 1, 2007. - September 9, 2007

6. Trial use of Matlab application to follow building energy consumption in campus buildings in Trondheim

The method that is proposed in chapter 4 is quantitatively assessed in chapter 5. Qualitative assessment will now be presented in this chapter, through analysis of the heat consumption of nineteen NTNU's buildings.

It is assumed that operation of space heating and ventilation systems of the nineteen NTNU's buildings function without fault. If there is a deviation between the real heat consumption and that predicted by the model, this would be attributed to the inability of the model to describe the actual behavior of system. For all of the nineteen buildings, there were no significant events that could not be explained by the linear regression model or by using the developed Matlab application and employing simple logic. There were just a few events lasting for a few hours that did not show a systematic nature. Those events can be interpreted as measurement faults. Their influence on the overall heat consumption and indoor climate is insignificant.

It was not possible to develop a LR model that would fully cover thermal storage effects corresponding to changes in outdoor air temperature. Interpretation of deviations of normalized heat consumption for days with significant change of outdoor temperature is done through reviewing normalized hourly heat consumption and corresponding hourly outdoor temperatures. This requires logic which can be easily explained and understood.

It is obvious that the developed tool cannot be used for fully automated fault detection, which was not intention of this PhD thesis. Primarily, the aim of the proposed method is verification of HVAC system operation. However, fault detection comes as a consequence of reviewing historical monitoring data. The advantage of using the developed tool over a fully automated fault detection system is that the developed tool keeps operators engaged in following building heat consumption. Users of the developed tool can learn about the operation of the system they monitor through use of the tool.

The first step in the performed analysis was recognizing a relevant monitoring period, which must have an unchanged HVAC system operation. Recognizing a relevant monitoring period is done through reviewing 3-D heat consumption plots and 3-D plots of normalized heat consumption. This is explained in subchapter 4.3.2.

The next step in the analysis is to exclude periods with fault operation or periods with changed operation during holidays. This way, we obtain a more precise model of heat consumption. Periods with fault operation or periods with changed operation during holidays are recognized in 3-D plots of normalized heat consumption. By entering dates in the exception periods palette, those period are excluded from calculation.

The daily LR model involving time-lagged independent variables gives the most precise predictions of heat consumption for space heating systems (demonstrated in subchapter 5.5). Daily data are more suitable for reviewing normalized heat consumption 3-D diagrams than mean values grouped by regimes. However, calculations with mean values give more precise results than calculations with daily data for ventilation systems. 3-D diagrams presenting NHC for calculations with mean values can be reviewed if there is a special interest for certain period of monitoring history. Normalized daily heat consumption is mostly within the 20% limits for all of the analyzed buildings; indeed, most are actually within even more narrow limits. Normalized daily heat consumption should be reviewed first and after analyzed hourly values. Special attention should be paid to days with high deviations of normalized daily heat consumption. It is proven above, that calculations with HOD data give better results than calculations with hourly data grouped by regimes, so calculations with HOD data are used for this purpose. Periods with high changes in outdoor temperatures are treated with special attention. The model using HOD data does not use temperature change as an independent variable, but the user can easily check if there was significant change in outdoor temperature by reviewing the 3-D plot of outdoor temperatures. Temperature change is not as significant for ventilation systems as for space heating systems, so special attention should be placed on analyses for space heating systems. The model has a problem in providing reliable predictions of heat consumption for temperatures close to the change point temperature, as is explained in chapter 5.5. The user should, in this case, compare the outdoor temperature and the change point temperature. Chapter 5.5 explains also why summer heat consumption cannot be analyzed by the proposed method.

6.1 Performance verification of HVAC system operation for Sentral Bygg 1 building

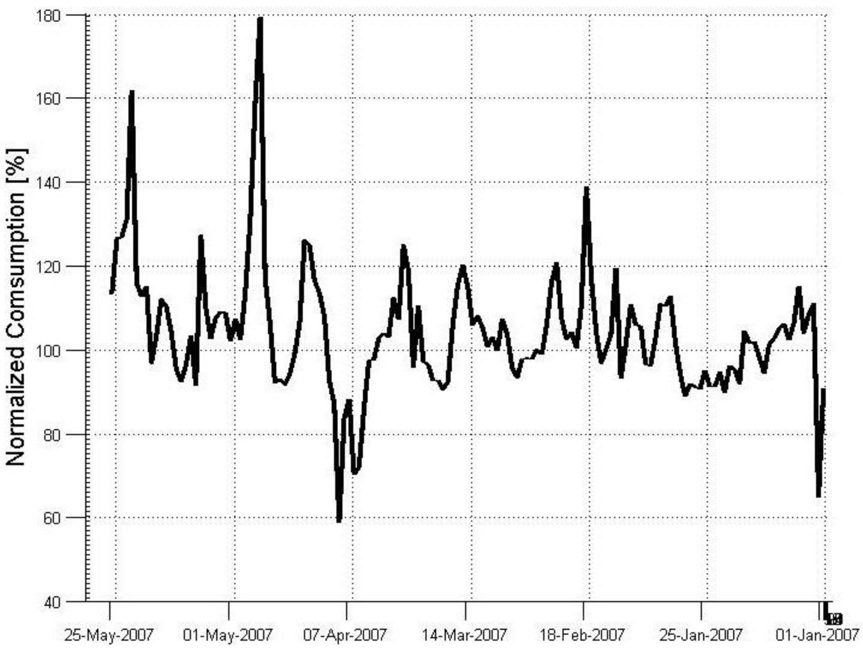


Figure 6.1 Daily NHC of the Sentral Bygg 1 building of NTNU campus from January 1, 2007 to May 25, 2007

The proposed method will be demonstrated through verification of HVAC system operation for the Sentral Bygg 1 building. The system operated from January 1, 2007 to December 1 2007, with unchanged control regimes. Figures 6.1 and 6.2 present normalized daily heat consumption. The LR model comprehends daily values of outdoor air temperature, solar radiation and wind influence, and two time-lagged variables for change of outdoor temperature. Normalized daily heat consumption is, for most days, within the 20 % limits. Higher deviations appeared for some days during May, which is a consequence of outdoor temperatures close to or over change point temperature; this cannot be accurately accounted for by the model. Calculated change point temperature is 15 °C. Lower consumption during beginning of April corresponds to Easter holydays. Deviations in Figure 6.2 are within the 20% limit for all except two days.

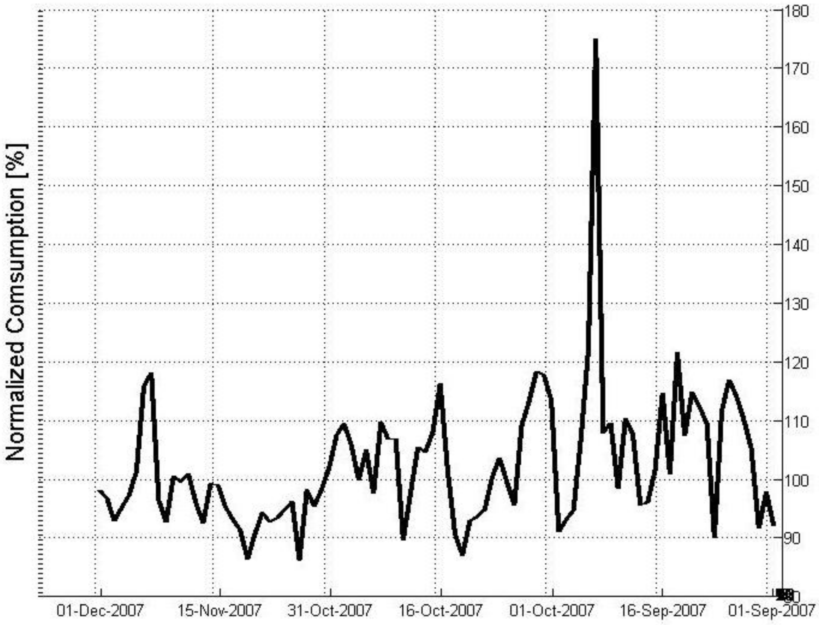


Figure 6.2 Daily NHC of the Sentral Bygg 1 building of NTNU campus from September 1, 2007 to December 1, 2007

Inspection of normalized hourly heat consumption reveals why daily heat consumption deviates significantly from predictions. Figures 6.3 and 6.4 present normalized hourly and daily heat consumption for January 2007. Lower heat consumption appeared for January 2, 2007. Inspection of the hourly values revealed that the system on that day was not turned to the daily regime operation. Normalized hourly and daily heat consumption for this building for the other months of the monitoring period are presented in Appendix I (Figures 0.12 – 0.20).

Higher normalized daily heat consumption appeared during February 2007 for two days 18th (Sunday) and 24th (Saturday) of February (Figure 0.12). Hourly heat consumption reveals that during the afternoons of these days, heat consumption was higher than predicted by the model (Figure 0.13). The HOD model did not cover changes in outdoor air temperatures. It is obvious that changes in outdoor temperatures are followed by corresponding changes in the normalized hourly heat consumption.

Higher normalized daily heat consumption was found for March 26 and 27 (Figure 0.15). It was found, through inspections of normalized hourly heat consumption, that during the night between March 26 and 27 operation of HVAC system was not reduced. Heat consumption was reduced during March 2 for 4h and 5h. The last event could be a measurement fault.

A few days with temperatures over the change point temperature appeared during April 2007 (Figure 0.16). High deviations of normalized hourly heat consumption correspond to high outdoor temperatures. The daily regime operation was not turned on during the Easter holidays (4th to 9th of April), which can be recognized as a hole in the normalized hourly heat consumption plot.

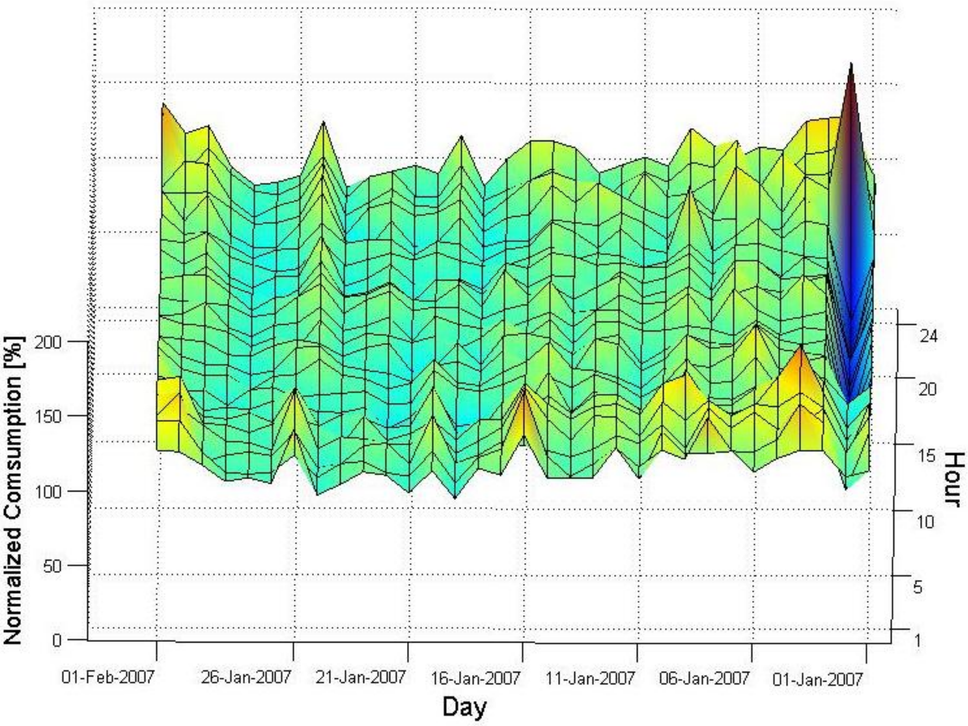


Figure 6.3 Hourly NHC of the Sentral Bygg 1 building for January 2007

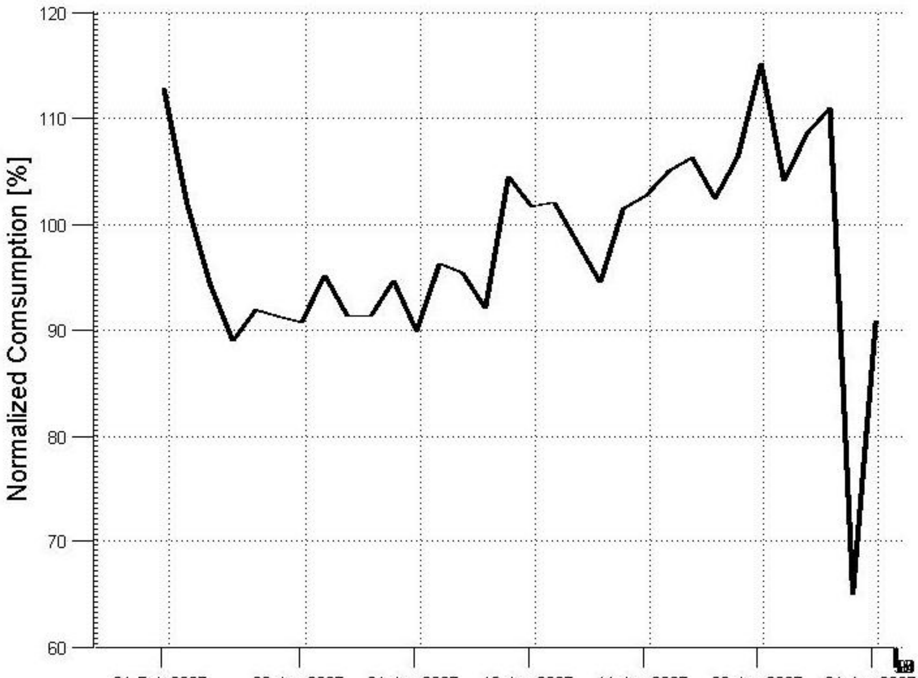


Figure 6.4 Daily NHC of the Sentral Bygg 1 building for January 2007

Low heat consumption appeared on May 8 from 18h to 22h (Figure 0.17). High temperatures during the periods 6th – 7th of May and 17th – 22nd of May resulted in the model not predicting correctly the heat consumption, so that high deviations appeared in that period. Deviations between the predicted and real heat consumption are high for summer months, Jun, July and August. Heat consumption corresponding to those months was not analyzed.

A high value of normalized heat consumption appeared on the September 25 due to a high outdoor temperature (Figure 0.18). The daily model covered variations properly for all other days. It can be seen from the Figure 0.18 that changes in outdoor temperatures have introduced deviations in the modeled hourly heat consumption. Those changes are properly accounted by the daily model. Lower heat consumption appeared for September 3 for 16$^{\underline{h}}$ and 17$^{\underline{h}}$. This could be a measurement fault.

There were no recognizable deviations between real heat consumption and modeled heat consumption during October and November 2007 (Figures 0.19 and 0.20). The daily model covered all variations properly. For example, the outdoor temperature changed significantly during October 26 and 28. The hourly model did not cover those changes, but the daily model did. Higher heat consumption appeared during the afternoons of November 24 and 25.

The analysis proved that it is possible to verify HVAC system operation through reviewing comparisons of modeled and real heat consumption. It is assumed that the system operated without any significant faults. Faults that were discovered were not significant for the overall operation of the HVAC system. Appendix I presents normalized daily heat consumption for seventeen more buildings on the NTNU campus (Figures 0.21 – 0.44). There were no significant faults in the operation of the HVAC systems in all seventeen buildings (see table 6.1).

6.2 Performance verification of HVAC system operation for seventeen NTNU campus buildings

There were just five days with deviations higher than 20 % for the Sydområdet NHL Forskning building for the ten month monitoring period (Figures 0.21 and 0.22). After the May 1, 2007, heat consumption was approximately 10% lower, which leads to the conclusion that some change in operation occurred after that day. Operation was reduced after May 1, 2007 for the most of the analyzed buildings. District heating in Trondheim changes its operation during sommer, so that recognized changes of HVAC system operation can be explained that way. Heat consumption was also reduced by 10% from October 5 to November 14, 2007. This reduction can be explained by a change of HVAC system operation. Otherwise, it can be concluded that a fault appeared in that period if there is no such an explanation. Notices gained through reviewing hourly data are presented in table 6.1.

	Number of days with deviation of heat consumption over 20 %	Notices about fault operation recognized on hourly level
Sydområdet NHL Forskning bygg 10 months monitoring period	5	- 25.03.2007 - 3^{h} - low heat consumption - 05.09.2009 - 11^{h} and 12^{h} - low heat consumption - 03.10.2009 - 11^{h} and 12^{h} - low heat consumption - Night between October 11 and 12, 2007 - low heat consumption
Gamle Fysikk 10 months monitoring period	9	- 25.03.2007 - 4^{h} and 5^{h} - low heat consumption - 03.04.2007 - 5^{h} - 6^{h} - low heat consumption - 19.04.2007 - 18^{h} - 22^{h} - low heat consumption - 17.09.2007 - 17^{h} - 18^{h} - low heat consumption
Berg 10 months monitoring period	10	- January 3 and 31, 2007 - low daily heat consumption - Night between December 27 and 28, 2007 - low heat consumption
Gamle Kjemi 10 months monitoring period	11	- 04.01.2007 - 17^{h} - low heat consumption - 25.03.2007 - 4^{h} - 5^{h} - low heat consumption (Fault happened also for Gamle Fysikk building. It seems that a fault occurred at the district heating level.) - 20.09.2007 - 9^{h} - 11^{h} - low heat consumption
Sentral Bygg 2 3 months monitoring period	4	No faults
Elektro B 5 months monitoring period	5	- 25.03.2007 - 4^{h} and 5^{h} - low heat consumption (Faults also occurred in other buildings, likely on the district heating level.)
Materialtekniske Laboratorier 4 months monitoring period	11	- 08.03.2007 - 13^{h} - low heat consumption - 25.03.2007 - 4^{h} and 5^{h} - low heat consumption (Faults also occurred in other buildings, likely on the district heating level.) - 30.03.2007 - 11^{h} and 5^{h} - low heat consumption - May 9 and 10, 2007 - 12^{h} and 15^{h} - unstable operation
Produktdesign 4 months monitoring period	2	- 25.03.2007 - 4^{h} and 5^{h} - low heat consumption (Faults also occurred in other buildings, likely on the district heating level.)
Elektro E and F 4 months monitoring period	2	- 13.03.2007 - 10^{h} - low heat consumption - 25.03.2007 - 4^{h} and 5^{h} - low heat consumption (Faults also occurred in other buildings, likely on the district heating level.)

Metallurgi 4 months monitoring period	1	- 08.03.2007 - 13^{h} - low heat consumption - 25.03.2007 - 4^{h} and 5^{h} - low heat consumption (Faults also occurred in other buildings, likely on the district heating level.) - 17.04.2007 - 18^{h} - 22^{h} - low heat consumption
Oppredning - gruvedrift 4 months monitoring period	3	- 25.03.2007 - 4^{h} and 5^{h} - low heat consumption (Faults also occurred in other buildings, likely on the district heating level.) - 17.04.2007 - 18^{h} - 22^{h} - low heat consumption (Faults also occurred in other buildings, likely on the district heating level.)
PFI 5 months monitoring period	13	- 25.03.2007 - 4^{h} and 5^{h} - low heat consumption (Faults also occurred in other buildings, likely on the district heating level.)
Verkstedtekniske Laboratorier 4 months monitoring period	3	- 25.03.2007 - 4^{h} and 5^{h} - low heat consumption (Faults also occurred in other buildings, likely on the district heating level.) - 28.04.2007 - 18^{h} and 19^{h} - low heat consumption
Tyholt Marintekniskenter 4 months monitoring period	0	- 06.02.2007 - 24^{h} - high heat consumption - 19.02.2007 - 16^{h} and 17^{h} - low heat consumption - 20.02.2007 - 6^{h} and 7^{h} - low heat consumption - 25.03.2007 - 4^{h} and 5^{h} - low heat consumption (Faults also occurred in other buildings, likely on the district heating level.) - March 30 and 31, 2007 - 14^{h} and 18^{h} - low heat consumption
Dragvoll 3 4 months monitoring period	15	- 19.03. 2008 - 14^{h} - 25.03.2008 - day regime operation was not turned on - 06.04. 2008 and 20.04.2008 (Sunday nights) - night operation was increased
Dragvoll 8 4.5 months monitoring period	6	- 26.09. 2007 - 19^{h} - 20^{h} - low heat consumption - 02.10. 2007 - 7^{h} - 8^{h} - low heat consumption - 18.10. 2007 - 7^{h} - 8^{h} - low heat consumption - 19.10. 2007 - 22^{h} - 23^{h} - low heat consumption - 21.10. 2007 - 15^{h} - 16^{h} - low heat consumption - 02.11. 2007 - 20^{h} - 24^{h} - low heat consumption - 03.11. 2007 - 20^{h} - 24^{h} - day regime operation was not turned on
Dragvoll Idrettssenteret 18 months monitoring period	5	- 08.01. 2007 13^{h} - low heat consumption - 25.03.2007 - 3^{h} - low heat consumption - 03.10. 2007 22^{h} - 04.10. 2007 7^{h} - low heat consumption

Dragvoll 2 4 months monitoring period	21	- 18.01. 2007 - $19^{\underline{h}}$ - $20^{\underline{h}}$ - low heat consumption - 06.02. 2007 - $22^{\underline{h}}$ - $23^{\underline{h}}$ - low heat consumption - 07.02. 2007 - $15^{\underline{h}}$ - $13^{\underline{h}}$ - low heat consumption - 13.02. 2007 - $16^{\underline{h}}$ - high heat consumption - 21.02. 2007 - $10^{\underline{h}}$ - $10^{\underline{h}}$ - low heat consumption - 08.03. 2007 - $13^{\underline{h}}$ - $14^{\underline{h}}$ - low heat consumption - 15.03. 2007 - $3^{\underline{h}}$ - $9^{\underline{h}}$ - low heat consumption - 16.03. 2007 - $9^{\underline{h}}$ - $10^{\underline{h}}$ - low heat consumption - 25.03. 2007 - $2^{\underline{h}}$ - $4^{\underline{h}}$ - low heat consumption - 13.04. 2007 - day control regime was not turned on - 16.04. 2007 - $12^{\underline{h}}$ - $13^{\underline{h}}$ - low heat consumption - 19.04. 2007 - $14^{\underline{h}}$ - $15^{\underline{h}}$ - low heat consumption

Table 6.1 Faults in HVAC system operation of seventeen NTNU campus buildings

There were nine days with deviations higher than 20 % for the Gamle fysikk building for the ten month monitoring period (Figures 0.23 and 0.24). Days during the Christmas and Easter holidays are not included among them. Holidays are also not included as days with faulty operation for the other buildings. High deviations are consequences of high outdoor temperatures or their significant changes for all of the remaining nine days. This was concluded by reviewing the hourly changes of outdoor air temperature and normalized hourly heat consumption.

There were ten days with deviations higher than 20 % for the Berg building for the ten month monitoring period (Figures 0.25 and 0.26). All deviations were a consequence of high outdoor temperatures or their significant changes except for deviations on January 30 and 31, 2007.

It is found for the PFI building that heat consumption increased between February 9 and 21, 2007 (Figure 0.36). Higher heat consumption appeared between $7^{\underline{h}}$ and $18^{\underline{h}}$ on May 8, 2007. Higher heat consumption appeared at same day period from May 23 to 25, 2007. Operation in this period had faults if maintaining personal do not have explanation for those events. High deviations of normalized daily heat consumption are consequences of high outdoor temperatures or their significant changes for all of the remaining ten buildings with space heating system (Figures 0.27 and 0.38).

Heat consumption for the five Dragvoll buildings represents ventilation heat consumption (Figures 0.39 – 0.44). The goodness of fit for Dragvoll 9 building was too poor to be able to verify performance of the ventilation system operation. Heat accumulation is not significant for the buildings, except for Dragvoll 2 building, as discussed in chapter 5, so modeling was done without outdoor temperature change as the independent variable. The Dragvoll 3 building has significant solar gains. Normalized daily heat consumption was within the 20 % limits for January and February. Predictions show a worse goodness of fit for the next two months (Figure 0.39). There were six days with high deviations from the normalized heat consumption during March. Three of those days were between March 19 and 25, when the day regime operation was not turned on, so those deviations do not represent a fault of the model. Goodness of fit was much worse for April, so it was not possible to verify HVAC system performance for the spring months for this building through reviewing the normalized daily heat consumption. The problem is that close to change point temperatures predictions of heat consumption are not precise enough. However, the HVAC system operation can be verified for this month through reviewing the normalized hourly heat consumption. For May, the deviations were too high so it was impossible to verify HVAC system performance.

Most of the higher deviations appeared for the Dragvoll 8 building for days with higher temperatures during September 2007 (Figure 0.40).

The monitoring period for the Dragvoll Idrettssenteret lasted eighteen months. For the period between February 1, 2008 and March 15, 2008, heat consumption was increased by 10% (Figure 0.43). Higher deviations appeared for May 2007, September 2007 and May 2008 for days with high temperatures (Figures 0.42 and 0.43). If we analyze the remaining months, there are five days with normalized daily heat consumption exceeding the 20 % limit, and all of these days had high outdoor temperatures. It is possible to verify operation of the HVAC system even for May and September through reviewing the hourly outdoor temperatures and normalized hourly heat consumption. Normalized daily heat consumption for the other months was within the 20% limit.

Normalized heat consumption exceeded the 20 % limit for the Dragvoll 2 building in the period between February 25, 2007 and April 25, 2007 (Figure 0.44). This can be considered to be an operation fault, which significantly influenced overall heat consumption.

From the presented analysis of the nineteen buildings, it can be concluded that significant deviations of heat consumption from the modeled values appeared for four buildings (Sydområdet NHL Forskning bygg, PFI, Dragvoll Idrettssenteret and Dragvoll 2). Other deviations, which are presented in table 6.1, did not significantly influence the performance of the analyzed HVAC systems.

7. Conclusions and recommendations for further work

7.1 Conclusions

This thesis has two main objectives: (1) developing LR models for radiator space heating and ventilation heat consumption and (2) evaluation of the ability of those models to detect O&M problems.

7.1.1 LR models of space heating and ventilation heat consumption

The variables that define heat consumption of space heating and ventilation systems are theoretically evaluated. The same LR model involving independent variables for outdoor temperature, wind speed and solar radiation is used for both space heating and ventilation. The ability of different data resolutions to consider these influences is evaluated, since these variables affect heat consumption at different time intervals. Stepwise regression is used to evaluate the contributions of different weather influences by comparing R^2. The thermal storage effect and building occupancy are not presented in the LR model as independent variables. These influences are covered by averaging data with lower resolution or by daily pattern for the HOD data grouping. Improvements in R^2 by engaging data with lower resolution are a consequence of averaging these influences. R^2 values are compared in two directions. The first direction is improvement of R^2 by engaging more independent variables (stepwise regression). This improvement shows the contribution of independent variables to heat consumption. The second direction is improvement of R^2 by averaging data with lower resolution. This improvement shows the contribution of the thermal storage effect and building occupancy to heat consumption.

Comparison of R^2 values through stepwise regression and comparison of sequential sums of squares showed that the outdoor temperature is the most significant variable. Wind was not significant for the analyzed buildings. However, solar radiation was significant for one building with modeled space heating. Although it is expected that solar radiation will influence only the heating demand for space heating, solar radiation was significant for two buildings with modeled ventilation heating; this is because part of the solar radiation energy was utilized in the economizer due to higher temperatures inside the buildings during sunny periods. Improvement of R^2 for simple LR calculations by engaging data with lower resolutions shows the extent of the thermal storage effect due to changes in the outdoor temperature for space heating systems, and the extent of the influence of occupancy. Occupancy influence can be recognized by comparing the R^2 values for unoccupied and occupied day periods. Since control regimes generally follow unoccupied and occupied day periods, it was difficult to evaluate the influence of heat gains related to occupancy. R^2 values for simple LR calculations with daily data are lower for weekends than for weekdays for all six buildings with space heating, which was not expected, since weekends are unoccupied periods. Weekday and weekend day regimes are the same for eight buildings with monitored heat consumption of space heating system. There are no significant differences between R^2 values, so occupancy did not influence significantly heat consumption. Weekday and weekend day regimes are the same for two buildings with monitored heat consumption of ventilation system. There are significant differences between R^2 values, so occupancy influenced significantly heat consumption. Improvement of R^2 for simple LR calculation by engaging data with lower resolutions is attributed to thermal storage effect due to changes in the outdoor temperature for the space heating system. This improvement also exists for five buildings with ventilation systems, but the reason for this improvement is building occupancy. Inspection of ventilation systems normalized heat consumption did not show time delay due to changes in the outdoor temperature, except for one building, so the thermal storage effect should not be significant for ventilation systems. Improvement of R^2 for simple LR calculation by engaging data with lower resolutions is higher than the improvement gained by introducing multiple LR models, which demonstrates that unexplained variations in the hourly model are generally due to the thermal storage effect, rather than wind or solar radiation. R^2 values of simple LR calculations with HOD data are higher than R^2 values for the same calculations conducted with hourly data grouped by regimes. However, calculations with daily data and mean values grouped by regimes produced much higher R^2s for simple LR calculation, and so considered thermal storage effects due to changes in the outdoor temperature and occupancy influences to a greater extent than the HOD grouping.

The thermal storage effect also exists for solar radiation. A comparison of the sequential sum of squares corresponding to solar radiation shows to what extent LR calculations with different data groupings cope with the thermal storage effect. Calculations with HOD data produced higher SSS values corresponding to solar radiation than calculations with hourly data grouped by regimes. Calculations with daily data and mean values produced the highest SSS values for this influence, so HOD grouping did not fully cover the solar radiation thermal storage effect.

Although literature sources claim that the thermal storage effect of the building envelope is not significant on a daily basis, this thesis has proven that, even with this time resolution, the thermal storage effect is significant. The model is improved by introducing the change in mean daily temperature as an independent variable in the daily LR model. Deviations of the actual daily heat consumption from the modeled daily heat consumption were found for days with significant changes in the mean daily temperature of up to 40% for calculations that did not involve changes of the mean daily temperature as an independent variable of LR model. Deviations were narrowed to 20% in most cases by introducing time-lagged variables that describe changes in the mean daily temperature in the model. The model is then applicable for diagnostics since 5% deviations that last for more than couple days can be detected.

Thermal storage effects did not significantly influence heat consumption of ventilation systems except for one building. Measurements were available for the heat consumption of ventilation system and for mixed heat consumption of radiator space heating and ventilation. Because of the different natures of ventilation and radiator space heating (thermal storage effects is significant for radiator space heating), it is recommended that energy use measurements of those two systems be distinguished. However, the proposed method can be used for diagnostics, even if measurements are not separated.

Deviations of the actual from the modeled heat consumption are higher for hourly data than deviations for daily data. Time-lagged variables were not introduced in the hourly LR model. Normalized heat consumption represents ratio of actual and modeled heat consumption. The thermal storage effect can be interpreted by the user of the developed tool by following normalized hourly heat consumption and hourly changes in the outdoor temperature. The user can verify the dynamic performance of the system by predicting that accumulated heat will be released by walls and that it will decrease heat demand if the outdoor temperature decreases. Normalized heat consumption should track along with changes in outdoor temperature. Accumulated heat will increase heat demand if the outdoor temperature increases.

It is important for O&M detection purposes that heat consumption predictions have the lowest possible deviations from actual heat consumption. The coefficient of variation is used to evaluate the prediction ability of calculations with different data resolutions. Other literature sources claimed that daily data produce the lowest CV values. Those sources analyzed space heating systems that operated without change of operation, i.e., without different control regimes for day and night. This thesis poses the hypothesis that calculations with daily data will give less accurate predictions for space heating and ventilation systems that operate with control regimes due to the inability of this model to cover control regime variation. This hypothesis is proved, since daily data calculations produced worse predictions (higher CV values) than calculations with other data groupings.

Calculations with higher resolutions introduce more information into the model. Calculations with lower resolutions better cover thermal storage effect and building occupancy heat gains. In this trade-off situation, calculations with HOD data and calculations with mean values grouped by regimes gave the lowest CV values for space heating. However, when the daily model, which includes the time-lagged variable of outdoor temperature change, was compared with other models, it gave the lowest CV values for space heating. The lowest CV values are obtained for calculations with HOD data to model ventilation heat consumption followed by calculations with mean values grouped by regimes. Introducing the time-lagged variable of outdoor temperature change into the daily model did not significantly decrease CV values for modeled ventilation heat consumption, proving that the thermal storage effect is not significant for heat consumption with a ventilation system.

Excluding outliers through the recommended statistical method did not improve model accuracy. In some cases, the solar radiation linear regression coefficients were underestimated, so that data points with high solar radiation were recognized as outliers and eliminated from the linear regression. As a result, model performance degraded, so this feature of the developed tool was turned-off in analysis.

Three months of monitoring history has proven to be sufficient for modeling both daily and hourly heat consumption of space heating and ventilation systems and recognize O&M problems through inspection of normalized heat consumption. Calculations with the three winter months produced the lowest CV values, so it is recommended to separate the winter monitoring period from spring and autumn in order to obtain a more accurate model. Predictions gained for spring and autumn were less accurate due to the greater influence of thermal storage effects for days with high outdoor temperatures.

7.1.2 Detection of O&M problems through developed tool

This thesis proposes a method for analyzing building energy performance, which is based on the following ideas: (1) using linear regression for modeling heat consumption of space heating and ventilation systems, (2) recognizing control regimes and relevant monitoring period with unchanged performance of the HVAC system by reviewing 3-D plots and (3) analysis of building energy performance through overview of 3-D diagrams. A tool with a graphical user interface is developed according to the proposed method. The tool enables:

- handling monitoring data through selecting monitoring period used for calculation
- defining control schedules
- excluding poor quality data points
- calculations with different data resolutions and different independent variables
- visual interpretation of results

3-D diagrams are selected for visual interpretation of results. Those diagrams offer a descriptive overview of the performance of a HVAC system both from hour to hour and from day to day. The operators monitoring the HVAC systems of NTNU's buildings found 3-D diagrams preferable to the diagrams that they currently use. Operators can recognize the control regime schedule of a monitored HVAC system by looking at the 3-D diagrams of heat consumption. Normalized heat consumption is used to detect O&M problems. Normalized hourly heat consumption is useful for interpreting interaction between the HVAC system and building.

The proposed method was used to analyze the heat consumption of nineteen NTNU's campus buildings in Trondheim. Normalized hourly and daily heat consumptions were inspected. O&M problems that could significantly influence building heat consumption appeared for four analyzed buildings. Those problems were spotted by inspecting normalized daily heat consumption. Other deviations of actual from modeled heat consumption were explained as a consequence of the inability of the LR model to consider the thermal storage effect, and as a consequence, the change point model could not give accurate predictions for data points with outdoor temperatures close to the change point. Those deviations could be explained by following hourly outdoor temperatures and normalized hourly heat consumption in parallel. This is proof that LR can be used for efficient modeling of radiator and ventilation heating, and the developed tool can be used to detect O&M problems. It should be emphasized that the complete analysis for the nineteen buildings took approximately two working days, so the developed program is an efficient diagnostic tool.

Regarding improvement of communication between operators and other players involved in building energy monitoring, this issue was not especially investigated in the thesis because of time limitations for writing this thesis. The tool was demonstrated to NTNU's HVAC system operators. The operators accepted the tool with optimism and have expressed their wish to start using it. Both the operators and the author of this thesis understood the performance of the analyzed HVAC systems in the same fashion, so it can be concluded that the developed tool helped to improve our communication. Using the developed tool requires engagement of the user to interpret the 3-D plots. Although that requires time, using program would force the user to continuously follow the operation of the monitored HVAC system.

7.2 Recommendations for further work

Further work can be classified into the following goals: (1) evaluation of the ability of the LR model to cover variations due to different influences, (2) further improvement of the LR model, and (3) introduction of the developed tool into practical use.

The influences that define building heat consumption and the ability of LR models to consider variations of heat consumption that are consequences of those influences are evaluated theoretically in this thesis. Developing a simulation model would enable verifying the theoretical considerations. Similar considerations as those suggested by Liu et al. (1995) (thermal storage effects due to changes in outdoor temperature and solar radiation for space heating systems) can be made for other influences, such as the thermal storage effect due to accumulated radiant lighting heat and thermal storage effect due to building warm up after the night temperature set-back.

Thermal storage effects due to changes in outdoor temperatures were not significant for ventilation systems in the analysis presented in this thesis. However, some variations were attributed to heat accumulation due to changes in the outdoor temperature. Solar heat gains and internal heat gains should only decrease heat consumption for the space heating system. However, solar radiation has proved to be significant for two of the analyzed ventilation systems, because part of the accumulated solar radiation was utilized through the economizer. Building occupancy was significant for analyzed ventilation systems, since the R^2 values were higher for weekends than for weekdays. Solar and internal heat gains influence both space heating and ventilation heat consumption. The proportion of heat gains that decrease space heating and ventilation consumption should be evaluated. It could be possible that this heat is utilized in the economizer only if heat gains are higher than heat losses, i.e., if there is no need for space heating. This mechanism can be elaborated through a simulation model.

A simulation model can be developed to produce a set of data that would be used for LR modeling, in order to evaluate how different groupings cover different influences. Such a model would enable different parameters to vary in order to find out if different models can spot those variations. Such a simulation model would represent a controlled experiment. Sequential sums of squares describe the contributions of independent variables to heat consumption. Comparing sequential sums of squares with contributions from simulation model would evaluate the capability of the LR model to represent variation due to different influences.

Hourly variations of heat consumption due to the thermal storage effect were interpreted in this thesis by following normalized hourly heat consumption and hourly outdoor temperatures in parallel. The daily model was improved by introducing time-lagged variables of outdoor temperature change. Time-lagged variables covered the thermal storage effect of daily outdoor temperature changes. This improvement was significant for space heating, since introducing time-lagged variables improved from the model that produced the worst predictions (the highest CV values) to the model that produced the best predictions. Thermal storage affects heat consumption on an hourly basis, so the hourly model can be improved the same way. Variations in hourly temperatures during the day are higher than variations in the mean daily temperatures, so the improvement should be significant.

Liu et al. (1995) showed that the thermal storage effect is significant for higher outdoor temperatures. This introduces nonlinearity into the model of heat consumption. Heat consumption for temperatures close to the change point temperature has a quadratic shape (Figure 3.3). Heat consumption predictions are more inaccurate for higher temperatures. Prediction accuracy for higher outdoor temperatures could be improved by introducing the square of the outdoor temperature as an independent variable of LR model.

The developed tool was adjusted to the analysis in this thesis. It is developed in modular form, so further improvements can be easily added to the current functions. The tool requires Matlab, but it is possible to convert the tool into an independent application that does not require installing Matlab. The tool uses data in the form of tables, which were available for the analyzed NTNU buildings. It should not be challenging to adapt the program to handle other table formats. Furthermore, it operates autonomously, i.e., it does not have to be connected to the building monitoring system. This is advantageous since it could be used for analysis by anyone who possesses data.

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Appendix A - Results of calculations with hourly data grouped by regimes

Appendix A.1 - Space heating systems

Sentral Bygg 1

Table 0.1 LR coefficients for simple LR

Control regimes	β_0	β_1 (Temperature)
Night	14.64	19.24
Weekdays day	84.18	27.16
Morning peak	381.56	22.25
Night peak	-0.42	4.77
Weekends day	60.87	20.71

Table 0.2 LR coefficients for multiple LR

Control regimes	β_0	β_1 (Temperature)	β_2 (Wind)	β_3 (Sun)
Night	-0.77	18.34	0.5060	-0.0466
Weekdays day	67.55	26.26	0.5058	0.0108
Morning peak	381.39	22.03	0.1261	-0.0342
Night peak	-2.72	4.72	0.0506	0.0011
Weekends day	58.30	19.51	0.5599	-0.0190

Table 0.3 Coefficients of determination for simple and multiple LR

Control regimes		Night	Weekdays day	Morning peak	Night peak	Weekends day
Simple	R^2	78.50 %	79.57 %	68.32 %	53.37 %	85.10 %
	$R^2_{overall}$	79.14 %				
Multiple	R^2	81.13 %	80.56 %	67.56 %	51.83 %	88.51 %
	$R^2_{overall}$	80.61 %				

Table 0.4 Sequential sums of squares for different regimes

Control regimes	Night	Weekdays day	Morning peak	Night peak	Weekends day
SSS Temperature	4 080 600	12 602 000	983 410	17 477	1 377 500
SSS Wind	151 820	211 160	1 503	165	49 187
SSS Sun	7 844	23 590	3 196	8	15 502

Sydområdet NHL Forskning

Table 0.5 LR coefficients for simple LR		
Control regimes	β_0	β_1 (Temperature)
Night	2.05	15.68
Day	2.87	23.82

Table 0.6 LR coefficients for multiple LR				
Control regimes	β_0	β_1 (Temperature)	β_2 (Wind)	β_3 (Sun)
Night	6.71	15.24	0.0791	-0.0215
Day	20.39	23.50	-0.1027	-0.0315

Table 0.7 Coefficients of determination for simple and multiple LR			
Control regimes		Night	Day
Simple	R^2	84.82 %	88.68 %
	$R^2_{overall}$	86.60 %	
Multiple	R^2	85.11 %	89.18 %
	$R^2_{overall}$	86.99 %	

Table 0.8 Sequential sums of squares for different regimes		
Control regimes	Night	Day
SSS Temperature	45 883 000	45 360 000
SSS Wind	43 311	34 116
SSS Sun	173 750	295 080

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Table 0.9 LR coefficients for simple LR		
Control regimes	β_0	β_1 (Temperature)
Day	9,0294	8,7705
Night	5,5648	5,9039
Morning peak	20,999	9,1341
Night peak	-0,090557	4,8125

Table 0.10 LR coefficients for multiple LR

Control regimes	β_0	β_1 (Temperature)	β_2 (Wind)	β_3 (Sun)
Day	-0.43	8.64	0.1591	0.0093
Night	3.45	5.59	0.1317	-0.0015
Morning peak	13.56	8.58	0.3571	0.0107
Night peak	-0.68	4.75	0.0211	-0.0003

Table 0.11 Coefficients of determination for simple and multiple LR

Control regimes		Day	Night	Morning peak	Night peak
Simple	R^2	82.49 %	87.42 %	79.61 %	88.75 %
	$R^2_{overall}$	83.24 %			
Multiple	R^2	83.86 %	88.57 %	82.89 %	88.58 %
	$R^2_{overall}$	84.73 %			

Table 0.12 Sequential sums of squares for different regimes

Control regimes	Day	Night	Morning peak	Night peak
SSS Temperature	2 231 500	614 360	231 910	18 830
SSS Wind	26 589	11 239	13 247	30
SSS Sun	25 570	19	451	1

Berg

Table 0.13 LR coefficients for simple LR

Control regimes	β_0	β_1 (Temperature)
Day weekdays	7.94	14.89
Night	10.69	13.64
Day weekends	4.69	12.34

Table 0.14 LR coefficients for multiple LR

Control regimes	β_0	β_1 (Temperature)	β_2 (Wind)	β_3 (Sun)
Day Weekdays	10.73	14.51	0.1001	-0.0140
Night	8.47	13.31	0.1277	-0.0187
Day weekends	5.57	11.80	0.1610	-0.0072

Table 0.15 Coefficients of determination for simple and multiple LR				
Control regimes		Day Weekdays	Night	Day weekends
Simple	R^2	89.12 %	83.23 %	84.50 %
	$R^2_{overall}$	86.08 %		
Multiple	R^2	89.52 %	83.76 %	85.01 %
	$R^2_{overall}$	86.56 %		

Table 0.16 Sequential sums of squares for different regimes			
Control regimes	Day Weekdays	Night	Day weekends
SSS Temperature	19 232 000	16 906 000	4 456 100
SSS Wind	40 810	79 613	34 214
SSS Sun	63 851	47 328	5 640

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Table 0.17 LR coefficients for simple LR		
Control regimes	β_0	β_1 (Temperature)
Day	18.38	15.17
Night	3.52	7.83
Midnight	7.38	11.45
Weekends night	9.57	7.89
7 a.m. -10 a.m.	8.51	10.57
6 a.m.	8.19	8.34
7 a.m.	17.06	9.41

Table 0.18 LR coefficients for multiple LR				
Control regimes	β_0	β_1 (Temperature)	β_2 (Wind)	β_3 (Sun)
Day	5.86	14.99	0.1463	0.0252
Night	2.37	7.54	0.0880	-0.0952
Midnight	7.27	11.42	0.0072	0.0000
Weekends night	4.96	7.34	0.2160	-0.1963
7 a.m. -10 a.m.	13.64	9.96	0.1218	-0.0223
6 a.m.	7.1952	7.7736	0.15749	-0.03924
7 a.m.	19.077	8.7577	0.109	-0.10644

Table 0.19 Coefficients of determination for simple and multiple LR								
Control regimes		Day	Night	Midnight	Weekends night	7 a.m. - 10 a.m.	6 a.m.	7 a.m.
Simple	R^2	72.38 %	75.75 %	80.28 %	66.68 %	84.29 %	70.68 %	66.65 %
	$R^2_{overall}$	72.75 %						
Multiple	R^2	74.04 %	76.45 %	80.45 %	68.49 %	85.48 %	72.30 %	68.16 %
	$R^2_{overall}$	74.32 %						

Table 0.20 Sequential sums of squares for different regimes							
Control regimes	Day	Night	Midnight	Weekend night	7 a.m. - 10 a.m.	6 a.m.	7 a.m.
SSS Temperature	9 876700	363 700	196 150	244 760	468 450	166 720	206 060
SSS Wind	31 427	2 228	3	7 358	2 565	2 884	1 243
SSS Sun	281 760	1 572	0	861	4 083	1 354	4 198

Varmetekniske laboratoriet

Table 0.21 LR coefficients for simple LR		
Control regimes	β_0	β_1 (Temperature)
Night	26.92	18.17
Day	22.38	17.19

Table 0.22 LR coefficients for multiple LR				
Control regimes	β_0	β_1 (Temperature)	β_2 (Wind)	β_3 (Sun)
Night	21.22	18.12	0.0947	0.0055
Day	21.48	16.98	0.0887	-0.0110

Table 0.23 Coefficients of determination for simple and multiple LR			
Control regimes		Night	Day
Simple	R^2	86.80 %	86.31 %
	$R^2_{overall}$	86.58 %	
Multiple	R^2	86.92 %	86.46 %
	$R^2_{overall}$	86.72 %	

Table 0.24 Sequential sums of squares for different regimes		
Control regimes	Night	Day
SSS Temperature	19 739 000	16 613 000
SSS Wind	28 679	23 144
SSS Sun	8 090	12 440

Appendix A.2 - Ventilation systems

Dragvoll Idrettsbygg

Table 0.25 LR coefficients for simple LR

Control regimes	β_0	β_1 (Temperature)
Night	9.92	3.83
6 a.m. and 7 a.m.	10.03	12.01
Weekdays day	51.26	19.14
9 p.m. – 12 p.m.	26.53	8.51
8 a.m. - 9 a.m. weekend	15.12	10.43
Weekend day	15.96	18.59
7 p.m. –12 p.m. Saturday	11.33	5.60
7 p.m. –12 p.m. Sunday	47.29	11.46

Table 0.26 LR coefficients for multiple LR

Control regimes	β_0	β_1 (Temperature)	β_2 (Wind)	β_3 (Sun)
Night	8.25	3.62	0.0884	-0.0449
6 a.m. and 7 a.m.	10.69	11.79	0.0440	-0.0482
Weekdays day	49.87	19.06	0.0466	0.0003
9 p.m. – 12 p.m.	25.52	8.39	0.0540	-0.0053
8 a.m. - 9 a.m. weekend	1.04	10.67	0.1477	0.0549
Weekend day	20.031	18.331	0.0235	-0.0074
7 p.m. –12 p.m. Saturday	5.9567	5.1285	0.2070	0.0082
7 p.m. –12 p.m. Sunday	39.966	11.306	0.1736	0.0233

Table 0.27 Coefficients of determination for simple and multiple LR

Control regimes		Night	6 a.m. - 7 a.m.	Weekdays day	9 p.m. - 12 p.m.	8 a.m. - 9 a.m. weekend	Weekend day	7 p.m. - 12 p.m. Saturday	7 p.m.- 12 p.m. Sunday
Simple	R^2	74.15 %	66.65 %	85.34 %	17.53 %	32.27 %	90.81 %	34.48 %	28.76 %
	$R^2_{overall}$	70.72 %							
Multiple	R^2	76.23 %	66.72 %	85.35 %	17.35 %	32.25 %	90.87 %	35.46 %	28.55 %
	$R^2_{overall}$	70.85 %							

Table 0.28 Sequential sums of squares for different regimes								
Control regimes	Night	6 a.m. and 7 a.m.	Weekdays day	9 p.m. – 12 p.m.	8 a.m. - 9 a.m. weekend	Weekend day	7 p.m. –12 p.m. Saturday	7 p.m. –12 p.m. Sunday
SSS Temp.	379 700	753 660	14597000	915 510	344 220	4 678 400	124 110	398 190
SSS Wind	10 770	598	4 632	1 865	4 521	388	8 004	4 345
SSS Sun	1 895	2 046	23	35	7 941	5 502	474	2 638

Dragvoll 8

Table 0.29 LR coefficients for simple LR		
Control regimes	β_0	β_1 (Temperature)
Night	6.21	2.82
Weekdays day	13.43	8.80
$7^{\underline{h}}$ - $8^{\underline{h}}$ Weekend	8.80	4.76
$17^{\underline{h}}$ - $18^{\underline{h}}$ Weekend	11.35	7.36
Weekend day	11.89	8.36

Table 0.30 LR coefficients for multiple LR				
Control regimes	β_0	β_1 (Temperature)	β_2 (Wind)	β_3 (Sun)
Night	3.78	2.77	0.0579	0.0030
Weekday Day	9.29	8.66	0.1180	-0.0035
$7^{\underline{h}}$ - $8^{\underline{h}}$ Weekend	0.18	5.03	0.0874	0.0222
$17^{\underline{h}}$ - $18^{\underline{h}}$ Weekend	6.42	7.53	0.0385	0.0041
Weekend day	-0.81	8.21	0.2629	0.0074

Table 0.31 Coefficients of determination for simple and multiple LR						
Control regimes		Night	Day weekday	$7^{\underline{h}}$ - $8^{\underline{h}}$ weekend	$17^{\underline{h}}$ - $18^{\underline{h}}$ weekend	Day weekend
Simple	R^2	78.77 %	83.33 %	71.54 %	88.57 %	80.88 %
	$R^2_{overall}$	82.91 %				
Multiple	R^2	80.90 %	84.29 %	73.99 %	88.77 %	84.52 %
	$R^2_{overall}$	84.22 %				

Table 0.32 Sequential sums of squares for different regimes					
Control regimes	Night	Day weekday	7^{h} - 8^{h} weekend	17^{h} - 18^{h} Weekend	Day weekend
SSS Temperature	225 590	4 082 800	20 272	82 672	411 610
SSS Wind	6 541	48 484	939	120	22 105
SSS Sun	100	3 250	467	423	1 973

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Table 0.33 LR coefficients for multiple LR				
Control regimes	β_0	β_1 (Temperature)	β_2 (Wind)	β_3 (Sun)
Night	1.34	-0.04	0.0108	-0.0003
Day	17.78	9.12	0.0087	-0.0191
6^{h} weekdays	4.42	-0.17	0.0374	-0.1451
23^{h} weekdays	24.04	8.83	0.0453	0.0000
9^{h} weekend	-2.82	0.36	0.1158	-0.0052
18^{h} weekend	37.8	9.11	0.0424	-0.0421

Table 0.34 Coefficients of determination for simple and multiple LR							
Control regimes		Night	Day	6^{h} weekdays	23^{h} weekdays	9^{h} weekend	18^{h} weekend
Simple	R^2	0.11 %	49.19 %	0.07 %	51.74 %	0.60 %	45.40 %
	$R^2_{overall}$	49.21 %					
Multiple	R^2	1.67 %	50.22 %	6.47 %	50.65 %	14.09 %	56.12 %
	$R^2_{overall}$	50.45 %					

Table 0.35 Sequential sums of squares for different regimes						
Control regimes	Night	Day	6^{h} weekday	23^{h} weekday	9^{h} weekend	18^{h} weekend
SSS Temperature	35	4 268 400	72	224 760	53	53 816
SSS Wind	205	258	258	401	438	71
SSS Sun	1	104 350	79	0	17	25 805

Dragvoll 2

Table 0.36 LR coefficients for multiple LR				
Control regimes	β_0	β_1 (Temperature)	β_2 (Wind)	β_3 (Sun)
Weekdays 1^h-6^h	7.72	6.63	0.0549	0.0213
Weekdays 7^h-21^h	8.09	8.24	0.1230	-0.0039
Weekdays 22^h-24^h	2.65	6.31	0.0953	0.0000
Weekends 1^h-8^h	5.00	7.21	0.1586	-0.0107
Weekends 9^h-18^h	7.51	9.33	0.0764	0.0003
Weekends 19^h-24^h	5.43	7.02	0.02	-0.0025

Table 0.37 Coefficients of determination for simple and multiple LR							
Control regimes		Weekdays 1^h-6^h	Weekdays 7^h-21^h	Weekdays 22^h-24^h	Weekends 1^h-8^h	Weekends 9^h-18^h	Weekends 19^h-24^h
Simple	R^2	77.47 %	60.84 %	72.45 %	70.35 %	78.18 %	82.70 %
	$R^2_{overall}$	66.22 %					
Multiple	R^2	77.72 %	61.47 %	73.26 %	73.09 %	78.23 %	82.60 %
	$R^2_{overall}$	66.85 %					

Table 0.38 Sequential sums of squares for different regimes						
Control regimes	Weekdays 1^h-6^h	Weekdays 7^h-21^h	Weekdays 22^h-24^h	Weekends 1^h-8^h	Weekends 9^h-18^h	Weekends 19^h-24^h
SSS Temp.	829 885	4 048 315	384 248	221 137	888 320	212 861
SSS Wind	3 640	47 433	5 367	10 858	2 384	65
SSS Sun	110	3 913	0	210	7	94

Appendix B - Results of calculations with HOD data

Appendix B.1 - Space heating systems

Sentral Bygg 1

Table 0.39 LR coefficients for multiple LR

	Weekdays				Weekends			
	β_0	β_1 Temperature	β_3 Wind	β_4 Sun	β_0	β_1 Temperature	β_3 Wind	β_4 Sun
1	-49.322	17.491	0.4018	0.0000	-55.628	17.44	0.3607	0.0000
2	-47.571	17.507	0.4561	0.0000	-40.3	16.723	0.2122	0.0000
3	13.577	16.106	1.2881	0.0000	-49.485	18.128	0.1016	0.0000
4	308.94	23.368	-0.0776	0.0000	-55.871	16.217	0.3960	0.0000
5	119.54	18.993	0.5404	-0.2447	-44.77	16.685	0.3725	-0.1484
6	140.63	19.725	0.4427	-0.2208	-51.406	16.889	0.4749	-0.2357
7	130.01	27.67	0.3215	-0.0594	-35.814	16.358	0.4701	-0.0266
8	142.75	28.477	0.3709	-0.0831	-62.162	16.401	0.5609	0.0023
9	174.28	28.66	-0.0287	-0.1298	-73.692	17.313	0.6194	-0.0137
10	182.9	28.327	0.2228	-0.1026	351.23	19.644	0.2615	0.0320
11	189.33	28.867	-0.0685	-0.0684	102.14	17.954	0.7586	0.0084
12	185.05	28.317	0.1979	-0.0619	106.25	19.239	0.2935	-0.0108
13	178.38	29.282	0.1450	-0.0619	94.832	17.725	0.5700	0.0090
14	145.06	28.401	0.3046	-0.0303	70.571	20.087	0.4957	0.0100
15	165.74	28.877	0.3582	-0.0615	82.458	18.523	0.7820	-0.0102
16	152.02	33.326	0.0152	-0.0393	71.774	21.473	0.7052	-0.0180
17	182.03	28.883	0.3172	-0.0319	99.219	22.679	0.2161	-0.0286
18	153.04	21.946	0.3230	-0.0311	105.72	17.888	0.7152	-0.0352
19	89.141	23.903	0.0342	0.0067	12.338	2.3411	-0.1903	0.0000
20	-6.7848	3.3343	0.1442	0.0073	-83.65	15.63	0.6153	-0.0774
21	-79.858	17.308	0.5633	0.0000	-65.013	16.586	0.4728	0.0000
22	-51.565	16.571	0.4937	0.0000	-64.856	15.001	1.0208	0.0000
23	-51.623	16.155	0.6452	0.0000	-72.755	16.123	0.9930	0.0000
24	-47.895	17.144	0.4256	0.0000	-67.338	17.39	0.7141	0.0000

Table 0.40 Coefficients of determination for simple and multiple LR						
	Simple			Multiple		
	R^2 Weekdays	R^2 Weekends	$R^2_{overall}$	R^2 Weekdays	R^2 Weekends	$R^2_{overall}$
1	85.61 %	88.40 %	77.06 %	87.19 %	89.24 %	79.18 %
2	80.18 %	89.64 %		82.11 %	89.87 %	
3	16.62 %	86.86 %		20.12 %	86.94 %	
4	44.25 %	88.94 %		44.27 %	90.69 %	
5	81.78 %	87.85 %		84.18 %	89.02 %	
6	84.93 %	88.74 %		86.94 %	92.44 %	
7	87.66 %	85.83 %		88.26 %	87.92 %	
8	89.14 %	87.86 %		90.43 %	92.64 %	
9	89.12 %	84.91 %		90.64 %	90.37 %	
10	81.64 %	59.57 %		84.54 %	60.09 %	
11	88.43 %	80.30 %		89.55 %	88.50 %	
12	88.12 %	88.20 %		89.84 %	89.77 %	
13	88.33 %	91.04 %		90.30 %	94.65 %	
14	86.86 %	87.85 %		87.89 %	89.82 %	
15	86.33 %	80.09 %		89.74 %	84.68 %	
16	83.57 %	78.47 %		85.67 %	82.41 %	
17	86.38 %	85.45 %		90.09 %	91.23 %	
18	85.82 %	86.05 %		87.67 %	93.73 %	
19	86.88 %	19.55 %		86.98 %	30.69 %	
20	45.08 %	66.05 %		48.32 %	69.52 %	
21	66.49 %	83.66 %		68.80 %	85.07 %	
22	72.75 %	77.71 %		74.70 %	82.48 %	
23	75.97 %	87.76 %		79.90 %	93.85 %	
24	82.59 %	83.46 %		84.30 %	85.74 %	

Table 0.41 Sequential sums of squares						
	SSS Temper. Weekdays	SSS Temper. Weekends	SSS Wind Weekdays	SSS Wind Weekends	SSS Sun Weekdays	SSS Sun Weekends
1	353 000	168 390	8 097	1 827	0	0
2	361 750	155 670	10 870	499	0	0
3	326 560	199 980	85 942	202	0	0
4	687 140	184 420	323	4 153	0	0
5	476 260	174 090	14 192	2 905	77	18
6	410 460	199 270	9 118	6 638	1 508	1 388

7	817 470	181 290	4 237	4 826	1 006	98
8	1 006 900	202 360	8 143	10 034	4 828	2
9	1 150 100	207 000	45	9 827	23 591	125
10	745 810	240 350	3 113	2 104	19 769	613
11	746 730	156 080	272	14 984	12 124	54
12	711 810	172 200	2 284	2 434	14 942	120
13	752 100	133 770	1 079	5 844	19 771	138
14	652 700	178 650	4 361	4 145	4 523	248
15	604 340	117 520	6 340	9 164	27 288	272
16	648 940	112 720	10	7 647	21 408	1 580
17	616 290	149 980	4 040	649	30 187	8 565
18	236 640	84 644	2 678	5 477	15 208	9 632
19	302 670	1 644	30	712	651	0
20	9 855	91 572	894	3 208	149	5 117
21	292 690	95 983	14 132	2 389	0	0
22	295 280	72 078	10 717	10 119	0	0
23	269 750	107 880	19 693	11 428	0	0
24	317 670	148 020	9 222	5 001	0	0

Table 0.42 Sequential sums of squares for two regimes

Control regimes	Weekdays day	Weekend day
SSS Temperature	10 566 360	1 345 914
SSS Wind	60 266	52 449
SSS Sun	196 881	21 222

Sentral Bygg 1 calculation with excluding outliers

Table 0.43 Sequential sums of squares

	SSS Temper. Weekdays	SSS Temper. Weekends	SSS Wind Weekdays	SSS Wind Weekends	SSS Sun Weekdays	SSS Sun Weekends
1	295 550	170 370	9 928	22	0	0
2	334 250	153 810	2 246	145	0	0
3	409 170	197 570	120 020	351	0	0
4	647 310	194 680	1 710	65	0	0
5	325 200	179 770	19 033	818	11	110
6	265 760	151 440	9 484	2 125	3 749	2 009
7	732 560	182 580	11 943	3 981	50	4
8	835 010	197 210	18 932	14 992	3 155	847
9	999 580	159 520	196	17 448	4 656	561

10	764 210	125 360	5 885	4 278	69	720
11	715 350	94 984	185	14 991	68	105
12	599 790	131 590	3 489	2 315	659	26
13	696 870	123 280	1 459	6 106	4 091	0
14	659 110	164 110	491	3 832	3 147	60
15	580 010	124 200	2 612	70	13 065	3 976
16	451 460	102 100	4 772	1 383	4 682	732
17	425 880	97 892	13 301	1 099	8 741	3 886
18	189 090	82 085	6 152	4 588	11 770	10 799
19	239 440	690	30	379	7	56
20	7 363	108 550	66	2 377	13	1 873
21	255 350	86 758	15 985	2 158	0	0
22	276 010	72 763	1 266	2 511	0	0
23	266 860	89 065	11 620	10 675	0	0
24	295 830	126 570	3 888	6 929	0	0

Sydområdet NHL Forskning

Table 0.44 Overall coefficients of determination for simple and multiple LR		
Simple LR	$R^2_{overall}$	86.62 %
Multiple LR	$R^2_{overall}$	87.66 %

Table 0.45 Sequential sums of squares

	SSS Temper. Weekdays	SSS Temper. Weekends	SSS Wind Weekdays	SSS Wind Weekends	SSS Sun Weekdays	SSS Sun Weekends
1	2 201 900	582 550	9	5 257	0	0
2	2 190 000	532 760	172	5 473	0	0
3	2 154 100	410 430	190	12 290	2 119	960
4	1 892 800	491 930	2 806	3 311	1 154	1 850
5	1 726 900	435 430	73	6 508	31 314	10 556
6	1 511 300	466 450	2 293	1 271	89 869	33 552
7	1 583 500	404 970	256	688	208 590	103 480
8	3 398 700	529 940	13 104	724	142 910	39 455
9	3 668 400	553 660	13 607	2 494	70 860	14 133
10	3 944 500	549 330	17 762	408	67 875	25 455
11	4 105 700	578 040	7 709	548	54 232	8 283
12	4 304 800	587 010	5 032	1 431	16 530	1 491
13	4 856 200	649 510	10 734	2 757	26 701	790
14	4 287 100	736 410	2 279	859	40 884	1 838

15	4 278 700	653 230	1 838	649	87 420	2 453
16	3 101 400	537 730	137	922	53 709	4 610
17	3 105 300	572 830	511	16	24 109	149
18	1 646 500	578 270	13	1 920	9 128	4 113
19	1 630 100	529 160	15	2 092	27 465	3 254
20	1 501 000	525 570	2 749	1 184	31 335	3 242
21	2 000 100	670 680	208	3 402	5 712	2 135
22	2 045 200	853 260	4 843	914	0	0
23	2 077 700	756 820	454	334	0	0
24	2 177 700	674 330	1 259	67	0	0

Sydområdet NHL Forskning calculation with excluding outliers

Table 0.46 Overall coefficients of determination for simple and multiple LR		
Simple LR	$R^2_{overall}$	93.45 %
Multiple LR	$R^2_{overall}$	93.88 %

Table 0.47 Sequential sums of squares						
	SSS Temper. Weekdays	SSS Temper. Weekends	SSS Wind Weekdays	SSS Wind Weekends	SSS Sun Weekdays	SSS Sun Weekends
1	2 010 400	617 620	603	4 752	0	0
2	2 012 600	530 460	479	3 303	0	0
3	1 968 100	397 130	537	4 362	1 194	847
4	1 431 100	483 740	7 217	1 946	2 413	1 434
5	1 621 400	370 880	2 999	10 581	27 247	4 839
6	1 123 200	425 110	143	2 034	87 350	28 620
7	1 408 900	420 330	287	77	156 680	71 794
8	3 068 100	558 400	5 009	108	61 229	18 536
9	3 393 300	537 480	15 458	4 462	20 592	6 283
10	3 441 000	521 800	13 806	668	9 693	16 147
11	3 565 100	561 670	4 754	2 257	5 828	7 771
12	4 026 900	606 120	331	31	4 368	728
13	4 333 200	652 630	11 051	1 818	4 005	339
14	4 152 800	715 840	3 398	1 695	53 414	6 876
15	3 992 900	630 590	9 830	29	151 830	1 785
16	2 627 300	496 800	3 703	3 203	10 584	112
17	2 674 300	532 890	8 071	526	2 101	383
18	1 004 300	600 240	8 933	298	25 244	6 385
19	1 473 000	518 180	429	1 415	26 544	5 366

20	1 149 800	494 790	899	1 511	29 535	3 976
21	1 818 700	723 330	7	4 894	4 738	5
22	1 840 400	859 640	12 284	2	0	0
23	2 006 300	651 070	3 276	2 314	0	0
24	1 705 100	710 440	5 064	322	0	0

Gamle-fysikk

Table 0.48 Overall coefficients of determination for simple and multiple LR		
Simple LR	$R^2_{overall}$	86.85 %
Multiple LR	$R^2_{overall}$	88.58 %

Table 0.49 Sequential sums of squares

	SSS Temper. Weekdays	SSS Temper. Weekends	SSS Wind Weekdays	SSS Wind Weekends	SSS Sun Weekdays	SSS Sun Weekends
1	47 972	24 681	914	240	0	0
2	55 527	22 010	1 158	746	0	0
3	44 783	27 633	16 759	327	0	0
4	90 600	22 563	625	684	13 578	123
5	64 733	20 427	3 480	269	3 040	1
6	53 151	20 421	3 389	282	3 878	139
7	67 377	21 223	2 685	269	285	289
8	106 790	29 183	1 831	157	830	153
9	148 620	26 983	581	120	135	87
10	140 470	65 664	1 573	3 114	216	81
11	131 180	38 432	186	1 087	306	69
12	156 240	40 838	21	508	383	3
13	139 000	32 488	145	385	1 712	416
14	135 030	35 472	83	41	824	1 479
15	135 380	28 561	11	338	1 073	14
16	134 400	19 034	112	202	875	721
17	143 480	33 544	0	22	144	36
18	50 060	29 547	166	1	1	96
19	38 111	7 510	46	257	450	0
20	11 730	13 996	80	234	274	229
21	49 558	13 293	93	142	132	212
22	48 902	14 729	458	215	0	0
23	48 553	16 759	1 837	517	0	0
24	33 177	23 404	1 057	255	0	0

Gamle-fysikk calculation with excluding outliers

Table 0.50 Overall coefficients of determination for simple and multiple LR		
Simple LR	$R^2_{overall}$	92.05 %
Multiple LR	$R^2_{overall}$	93.70 %

Table 0.51 Sequential sums of squares

	SSS Temper. Weekdays	SSS Temper. Weekends	SSS Wind Weekdays	SSS Wind Weekends	SSS Sun Weekdays	SSS Sun Weekends
1	47 213	17 415	1 295	398	0	0
2	48 388	17 945	826	874	0	0
3	35 438	25 273	1 781	284	0	0
4	83 562	24 706	1 372	669	18 581	170
5	65 372	20 493	3 140	518	2 976	15
6	46 689	12 842	2 171	508	3 293	145
7	55 720	20 578	899	276	1 163	208
8	105 020	27 215	1 549	273	66	58
9	146 900	28 193	919	308	14	15
10	132 450	37 399	1 367	1 618	357	127
11	105 230	22 815	138	621	49	39
12	135 120	32 919	94	60	225	203
13	116 400	32 488	94	385	1 184	416
14	110 490	30 164	6	109	777	457
15	109 370	23 164	10	515	1 215	0
16	115 460	18 856	26	107	2 113	143
17	120 940	33 639	102	1	191	354
18	32 028	25 439	51	13	270	100
19	29 251	7 352	19	343	1 441	2
20	8 229	7 589	156	340	106	69
21	37 430	14 967	229	71	332	50
22	38 262	12 032	455	386	0	0
23	42 270	16 828	1 844	142	0	0
24	40 211	19 425	1 363	126	0	0

Berg

Table 0.52 Overall coefficients of determination for simple and multiple LR		
Simple LR	$R^2_{overall}$	87.46 %
Multiple LR	$R^2_{overall}$	88.26 %

Gløshaugen Idrettsbygg

Table 0.53 LR coefficients for multiple LR

	Weekdays				Weekends			
	β_0	β_1 Temperature	β_3 Wind	β_4 Sun	β_0	β_1 Temperature	β_3 Wind	β_4 Sun
1	-11.594	6.226	0.0958	0.0000	-15.939	6.7289	0.0886	0.0000
2	-13.974	6.4403	0.0472	0.0000	-17.593	6.4499	0.1291	0.0000
3	-12.137	6.0579	0.0969	-0.3529	-14.624	6.2342	0.0700	-0.0642
4	-11.127	6.3447	0.0400	-0.0772	-18.543	6.118	0.1665	-0.0034
5	4.5688	8.1703	0.0839	-0.1297	-20.617	6.4177	0.1620	0.0153
6	-11.886	7.1177	0.1695	-0.0154	-14.883	6.2996	0.0473	-0.0155
7	-21.294	13.642	0.1918	0.0249	-9.0765	9.9697	0.0916	0.0026
8	-3.4586	14.667	0.1531	0.0086	10.299	11	0.1115	-0.0222
9	14.211	13.644	0.0840	-0.0115	9.3301	8.8614	0.1970	-0.0236
10	41.518	15.022	0.1214	-0.0061	12.535	9.7981	0.0336	-0.0387
11	19.245	14.968	0.0815	0.0049	-1.9401	10.995	0.0786	0.0054
12	31.627	14.729	-0.1162	0.0180	3.1824	14.023	0.0302	0.0268
13	19.798	15.111	-0.0445	0.0133	13.52	14.248	-0.1730	0.0366
14	21.752	15.49	-0.0578	0.0172	5.81	13.986	-0.0005	0.0366
15	10.379	15.695	-0.0088	0.0203	14.329	14.486	-0.0270	0.0123
16	15.146	15.645	0.0063	0.0182	24.023	14.321	0.1252	0.0025
17	18.407	17.188	0.0364	0.0141	31.099	13.771	0.0746	0.0076
18	0.22288	19.88	0.0337	0.0370	16.649	14.567	0.1253	0.0209
19	6.4764	19.611	0.1452	0.0213	7.7292	14.572	0.2528	0.0114
20	17.384	18.093	0.0710	-0.0121	4.2445	14.125	0.3234	0.0169
21	20.036	16.801	0.2643	-0.0879	-8.2248	11.385	0.1049	-0.0059
22	-1.2961	16.972	0.3381	0.0000	-13.334	10.223	0.3770	0.0000
23	-18.204	13.513	0.2554	0.0000	-15.388	9.8138	0.2548	0.0000
24	-13.961	10.099	0.0394	0.0000	-9.7502	6.3307	0.0970	0.0000

Table 0.54 Overall coefficients of determination for simple and multiple LR		
Simple LR	$R^2_{overall}$	79.93 %
Multiple LR	$R^2_{overall}$	80.87 %

Table 0.55 Sequential sums of squares						
	SSS Temper. Weekdays	SSS Temper. Weekends	SSS Wind Weekdays	SSS Wind Weekends	SSS Sun Weekdays	SSS Sun Weekends
1	97 373	45 601	626	184	0	0
2	106 250	40 302	173	364	0	0
3	103 720	40 979	697	157	2 125	20
4	115 940	41 715	130	1 119	1 452	1
5	196 760	42 229	532	889	8 214	27
6	140 750	48 050	2 279	93	378	148
7	475 700	116 430	2 465	298	1 351	9
8	599 370	156 910	1 936	593	237	912
9	491 100	96 513	544	1 601	542	1 166
10	527 870	114 950	1 193	48	180	2 867
11	449 290	125 850	502	251	140	63
12	376 470	175 680	974	42	2 190	1 799
13	355 860	139 870	117	813	1 560	4 448
14	344 510	127 290	183	0	2 896	5 220
15	315 140	121 310	4	14	5 355	712
16	266 190	84 632	2	298	6 859	52
17	449 930	98 107	70	105	9 315	878
18	585 660	103 830	45	278	50 788	6 587
19	576 730	143 400	924	2 102	14 149	1 070
20	603 630	118 670	311	1 775	1 757	577
21	535 910	75 464	4 217	245	23 245	46
22	622 270	67 036	6 289	2 788	0	0
23	395 480	78 574	3 771	1 572	0	0
24	220 520	38 624	100	204	0	0

Varmetekniske laboratoriet

Table 0.56 Overall coefficients of determination for simple and multiple LR		
Simple LR	$R^2_{overall}$	89.25 %
Multiple LR	$R^2_{overall}$	90.58 %

Appendix B.2 - Ventilation systems

Dragvoll 3

Table 0.57 LR coefficients for simple multiple LR - Weekdays						
	Simple		Multiple			
	β_0	β_1 Temperature	β_0	β_1 Temperature	β_3 Wind	β_4 Sun
1	-67.368	24.696	-76.123	23.706	0.5306	0.0000
2	-72.674	24.798	-80.665	23.8	0.5113	0.0000
3	-69.599	23.833	-84.072	23.019	0.6094	0.0000
4	-72.205	24.063	-38.792	21.121	0.3656	-5.7429
5	-66.165	23.639	-8.8254	19.251	0.4916	-1.3771
6	-87.918	27.078	7.1782	21.34	0.2571	-0.9911
7	-82.711	30.766	-5.4301	25.856	0.3346	-0.3222
8	-34.93	51.828	231	40.669	-0.7226	-0.6958
9	-8.0513	57.7	297.81	45.804	-0.4145	-0.7528
10	21.255	58.461	332.57	46.497	-0.0595	-0.6116
11	-19.66	61.831	248.87	52.8	-0.1600	-0.4790
12	-23.651	62.965	207.62	58.425	-0.4888	-0.4123
13	-64.391	65.946	94.048	62.565	0.0741	-0.2656
14	-60.793	65.496	95.055	60.985	0.2820	-0.2159
15	-60.817	65.684	118.19	60.665	0.1664	-0.2127
16	-58.768	65.61	162.96	59.56	0.1159	-0.2573
17	-63.307	63.75	158.02	54.364	-0.0458	-0.1686
18	-68.966	64.768	66.956	52.98	1.0951	-0.0919
19	-91.388	62.858	7.1876	54.544	0.6245	-0.0689
20	-88.727	59.384	2.2229	50.413	1.0147	-0.1778
21	-48.963	33.103	-38.226	29.223	0.9650	-0.2522
22	-52.406	27.84	-69.552	24.985	1.2726	0.0000
23	-52.288	26.46	-59.91	24.549	0.7915	0.0000
24	-25.521	22.768	-30.382	21.279	0.5580	0.0000

Table 0.58 LR coefficients for simple multiple LR - Weekends						
	Simple		Multiple			
	β_0	β_1 Temperature	β_0	β_1 Temperature	β_3 Wind	β_4 Sun
1	-22.263	22.828	-30.915	19.616	1.0451	0.0000
2	-21.278	22.147	-30.994	19.134	1.0973	0.0000

3	-24.292	21.924	-25.75	17.8	1.2150	0.0000
4	-20.89	21.397	-5.7293	16.683	1.1649	-2.4114
5	-26.113	21.864	27.143	16.346	0.7634	-1.2046
6	-30.359	23.974	58.805	16.67	0.8041	-1.1551
7	-16.2	25.271	71.79	18.195	0.8620	-0.4876
8	22.358	22.694	71.73	18.194	0.7373	-0.2258
9	23.633	23.622	74.065	19.701	0.5999	-0.1857
10	19.504	24.191	111.85	20.1	0.5075	-0.2624
11	6.2889	25.668	97.462	22.155	0.3899	-0.2063
12	-9.3064	27.209	73.1	24.165	0.4411	-0.1656
13	-8.1285	27.541	49.33	25.322	0.5433	-0.1128
14	2.026	27.091	59.125	25.998	0.0860	-0.0821
15	1.6309	27.54	69.299	24.649	0.2903	-0.0858
16	17.12	26.643	81.047	25.677	-0.2404	-0.0672
17	6.8209	27.276	58.728	25.176	0.0228	-0.0518
18	10.863	26.813	9.7379	26.43	0.1160	-0.0011
19	-8.5752	27.638	-34.067	28.279	0.2292	0.0204
20	-18.039	27.947	-9.4724	26.364	0.2936	-0.0444
21	-18.064	26.67	5.2851	25.486	-0.0997	-0.1205
22	-29.524	26.682	-27.133	27.274	-0.1982	0.0000
23	-18.599	25.292	-22.944	24.536	0.2862	0.0000
24	-7.9495	23.182	-12.575	22.701	0.2369	0.0000

Table 0.59 Coefficients of determination for simple and multiple LR

	Simple			Multiple		
	R^2 Weekdays	R^2 Weekends	$R^2_{overall}$	R^2 Weekdays	R^2 Weekends	$R^2_{overall}$
1	65.08 %	78.38 %		66.14 %	83.20 %	
2	63.41 %	82.59 %		64.40 %	86.33 %	
3	71.04 %	78.82 %		72.74 %	85.31 %	
4	73.04 %	75.50 %		76.15 %	84.69 %	
5	72.05 %	74.22 %		79.04 %	82.23 %	
6	76.36 %	74.91 %		82.20 %	86.59 %	
7	79.35 %	70.74 %		82.61 %	81.68 %	
8	61.76 %	69.99 %		66.84 %	78.50 %	
9	56.28 %	70.99 %	68.60 %	65.45 %	78.95 %	74.43 %
10	64.20 %	74.43 %		75.71 %	86.83 %	
11	66.74 %	79.77 %		74.92 %	89.16 %	
12	67.76 %	82.82 %		75.23 %	90.26 %	
13	69.94 %	82.09 %		73.82 %	86.32 %	
14	69.55 %	82.66 %		72.75 %	85.83 %	
15	68.71 %	82.25 %		73.83 %	87.31 %	
16	70.31 %	76.46 %		82.98 %	82.86 %	
17	70.31 %	78.04 %		79.38 %	82.26 %	

18	69.99 %	79.91 %		71.91 %	79.94 %	
19	67.90 %	78.61 %		68.81 %	78.99 %	
20	65.53 %	78.42 %		68.52 %	78.97 %	
21	62.75 %	79.07 %		66.28 %	80.09 %	
22	57.48 %	79.71 %		62.31 %	79.83 %	
23	69.56 %	77.78 %		72.08 %	78.02 %	
24	70.39 %	77.71 %		72.14 %	77.86 %	

Table 0.60 Sequential sums of squares

	SSS Temper. Weekdays	SSS Temper. Weekends	SSS Wind Weekdays	SSS Wind Weekend s	SSS Sun Weekdays	SSS Sun Weekend s
1	1 258 400	393 250	24 150	42 321	0	0
2	1 234 100	451 870	22 716	37 862	0	0
3	1 254 800	361 550	33 266	63 260	0	0
4	842 180	317 500	12 042	55 478	42 819	16 567
5	721 420	262 680	20 351	24 059	107 430	40 974
6	769 360	279 400	6 438	31 266	122 860	73 138
7	1 075 300	346 000	8 579	22 858	65 127	98 763
8	2 915 500	421 550	49 699	29 066	602 480	41 849
9	4 289 400	534 330	16 867	22 609	1 419 600	46 501
10	4 741 600	576 980	415	11 632	1 659 600	112 540
11	5 688 700	621 690	2 890	6 294	1 232 200	92 931
12	7 236 500	683 540	22 887	10 214	1 131 900	71 436
13	8 161 300	685 580	468	8 504	614 080	42 661
14	7 595 400	748 650	6 931	215	497 900	33 909
15	7 305 800	546 480	2 339	2 548	821 480	51 421
16	7 321 600	521 540	1 225	1 936	2 060 300	53 982
17	5 449 100	576 420	160	17	1 254 900	43 975
18	3 232 100	497 600	79 245	330	187 300	14
19	3 195 800	551 150	29 772	1 724	93 769	3 116
20	4 389 400	527 270	94 567	2 208	300 320	3 530
21	1 601 600	504 270	76 088	234	74 124	11 086
22	1 213 200	659 470	140 420	1 242	0	0
23	1 154 900	566 260	54 940	2 366	0	0
24	928 530	576 510	30 705	1 416	0	0

Table 0.61 Sequential sums of squares for four regimes				
Control regimes	Weekday 8^h-20^h	Weekday night	Weekend 8^h-20^h	Weekend night
SSS Temperature	71 522 200	12 053 790	7 492 780	4 718 760
SSS Wind	307 463	429 695	97 296	282 362
SSS Sun	11 875 829	412 360	597 865	240 528

Dragvoll 3 calculation with excluding outliers

Table 0.62 Overall coefficients of determination for simple and multiple LR		
Simple LR	$R^2_{overall}$	88.46 %
Multiple LR	$R^2_{overall}$	90.66 %

Table 0.63 Sequential sums of squares for four regimes				
Control regimes	Weekday 8^h-20^h	Weekday night	Weekend 8^h-20^h	Weekend night
SSS Temperature	76 798 300	7 299 730	10 238 310	4 538 510
SSS Wind	822 846	74 192	337 618	206 817
SSS Sun	3 185 496	161 326	415 097	80 684

Dragvoll Idrettsbygg

Table 0.64 LR coefficients for simple multiple LR								
	Weekdays				Weekends			
	β_0	β_1 Temperature	β_3 Wind	β_4 Sun	β_0	β_1 Temperature	β_3 Wind	β_4 Sun
1	1.6717	3.5965	0.0895	0.0000	-0.1567	3.6098	0.0814	0.0000
2	2.6457	3.5159	0.0939	0.0000	-1.0748	3.5966	0.0852	0.0000
3	-0.74788	3.7286	0.0888	0.0000	4.2784	3.1526	0.0542	0.0000
4	1.3614	3.5859	0.0764	-0.2042	-2.9803	3.6659	0.0808	-0.1869
5	2.3611	3.3611	0.1231	-0.1388	-2.7139	3.6641	0.0941	-0.0787
6	-27.27	8.442	0.0518	-0.1601	-0.97313	3.7872	0.0255	-0.0569
7	-32.475	12.815	-0.0146	-0.0534	-0.67924	3.4329	0.1247	-0.0340
8	-12.639	19.022	0.0059	-0.0286	4.49	3.3237	0.0971	-0.0318
9	7.9986	18.767	-0.0262	0.0019	-40.878	16.686	-0.0714	-0.0082
10	40.681	18.683	-0.0156	0.0071	-21.19	17.634	-0.0305	-0.0012
11	29.292	18.689	-0.0211	-0.0006	-11.393	17.733	-0.0382	-0.0100
12	40.437	18.805	-0.0009	-0.0082	-4.857	17.845	0.0203	-0.0087

13	31.093	18.985	-0.0096	0.0008	11.196	18.477	0.0582	-0.0190
14	45.328	18.66	0.0435	0.0086	12.954	18.173	0.0589	-0.0128
15	25.326	19.734	0.0270	0.0049	18.353	18.204	-0.0451	-0.0166
16	47.911	18.948	0.0192	-0.0095	21.588	18.767	-0.0949	-0.0155
17	40.445	19.339	0.0274	-0.0110	16.592	18.733	0.0254	-0.0170
18	36.586	19.73	0.2235	-0.0047	17.789	19.436	-0.1351	-0.0125
19	39.686	20.078	-0.0396	-0.0041	5.5518	14.308	-0.1673	-0.0028
20	48.493	20.221	-0.0192	-0.0322	1.7011	14.681	-0.5283	-0.0394
21	35.118	17.635	-0.0683	-0.1123	-3.0351	7.8901	-0.1392	0.0069
22	-2.4698	10.856	0.0301	0.0000	-3.3698	7.0296	-0.1025	0.0000
23	13.677	4.1479	0.0446	0.0000	6.0562	3.8061	0.0549	0.0000
24	4.975	3.5894	0.0730	0.0000	2.8764	3.3897	0.0812	0.0000

Table 0.65 Coefficients of determination for simple and multiple LR

	Simple			Multiple		
	R^2 Weekdays	R^2 Weekends	$R^2_{overall}$	R^2 Weekdays	R^2 Weekends	$R^2_{overall}$
1	73.63 %	84.21 %	88.79 %	75.21 %	85.59 %	89.15 %
2	68.06 %	84.76 %		70.06 %	86.10 %	
3	72.92 %	70.93 %		74.43 %	71.72 %	
4	72.24 %	83.96 %		73.55 %	85.86 %	
5	68.27 %	82.16 %		73.52 %	84.66 %	
6	75.99 %	84.34 %		77.25 %	85.19 %	
7	87.70 %	80.55 %		88.06 %	85.26 %	
8	93.59 %	77.77 %		93.69 %	83.70 %	
9	92.18 %	94.11 %		92.19 %	94.20 %	
10	86.81 %	95.02 %		86.84 %	95.03 %	
11	90.69 %	96.48 %		90.70 %	96.54 %	
12	90.04 %	96.28 %		90.08 %	96.33 %	
13	90.78 %	94.92 %		90.78 %	95.21 %	
14	86.29 %	94.87 %		86.39 %	95.11 %	
15	91.33 %	93.36 %		91.37 %	93.74 %	
16	89.87 %	90.52 %		90.10 %	91.29 %	
17	90.59 %	92.65 %		91.03 %	93.54 %	
18	89.04 %	94.25 %		89.41 %	94.74 %	
19	91.22 %	67.58 %		91.26 %	67.91 %	
20	87.69 %	63.69 %		88.26 %	67.14 %	
21	86.36 %	52.45 %		87.52 %	53.01 %	
22	78.49 %	50.53 %		78.51 %	50.85 %	
23	65.08 %	75.24 %		65.40 %	75.63 %	
24	72.82 %	79.23 %		74.24 %	80.34 %	

Table 0.66 Sequential sums of squares						
	SSS Temper. Weekdays	SSS Temper. Weekends	SSS Wind Weekdays	SSS Wind Weekends	SSS Sun Weekdays	SSS Sun Weekends
1	44 826	22 149	1 160	492	0	0
2	44 215	26 321	1 480	552	0	0
3	54 567	17 867	1 203	279	0	0
4	45 493	23 397	907	600	57	112
5	38 396	20 913	2 339	803	1 246	225
6	247 160	23 156	426	55	4 421	258
7	523 290	20 724	33	1 007	2 827	651
8	1 194 800	20 242	6	820	1 557	1 118
9	1 149 300	547 270	120	622	12	126
10	1 182 900	610 690	49	73	325	4
11	1 155 300	575 000	84	101	3	357
12	1 157 600	559 720	0	34	730	343
13	1 261 300	580 120	14	232	8	2 074
14	1 145 400	568 540	306	319	1 410	1 381
15	1 192 500	479 210	114	162	705	2 894
16	1 210 600	452 870	61	782	4 124	4 116
17	1 139 500	506 590	104	46	7 470	6 698
18	938 650	520 890	6 028	1 032	852	3 105
19	1 010 200	282 990	191	1 807	532	84
20	1 244 600	308 290	56	16 045	11 575	3 354
21	964 180	94 931	644	1 184	15 115	41
22	400 180	79 032	131	553	0	0
23	58 428	22 582	331	155	0	0
24	42 915	20 927	1 002	375	0	0

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Table 0.67 Coefficients of determination for simple and multiple LR						
	Simple			Multiple		
	R^2 Weekdays	R^2 Weekends	$R^2_{overall}$	R^2 Weekdays	R^2 Weekends	$R^2_{overall}$
1	87.50 %	83.17 %	84.28 %	89.33 %	87.55 %	86.15 %
2	86.77 %	79.32 %		88.29 %	84.10 %	
3	85.37 %	76.60 %		86.58 %	83.34 %	

4	85.49 %	75.37 %		87.71 %	81.31 %	
5	85.19 %	76.90 %		88.10 %	82.76 %	
6	80.58 %	77.37 %		83.81 %	84.08 %	
7	84.21 %	81.44 %		86.76 %	83.62 %	
8	81.27 %	84.36 %		83.81 %	86.02 %	
9	78.18 %	77.91 %		78.97 %	84.39 %	
10	82.91 %	75.68 %		83.55 %	83.40 %	
11	86.76 %	78.63 %		87.42 %	82.06 %	
12	84.03 %	81.93 %		85.18 %	85.28 %	
13	87.88 %	83.02 %		88.96 %	87.84 %	
14	87.20 %	84.24 %		88.76 %	86.34 %	
15	86.78 %	85.15 %		88.99 %	86.45 %	
16	87.85 %	81.88 %		87.92 %	83.83 %	
17	89.39 %	91.22 %		89.97 %	91.72 %	
18	89.15 %	90.29 %		92.01 %	91.11 %	
19	81.14 %	69.04 %		84.35 %	70.66 %	
20	78.69 %	72.09 %		81.86 %	73.42 %	
21	84.06 %	73.35 %		85.42 %	73.42 %	
22	82.17 %	65.23 %		83.69 %	65.29 %	
23	83.98 %	70.08 %		85.56 %	70.09 %	
24	84.45 %	86.18 %		85.97 %	89.34 %	

Table 0.68 Sequential sums of squares

	SSS Temper. Weekdays	SSS Temper. Weekends	SSS Wind Weekdays	SSS Wind Weekends	SSS Sun Weekdays	SSS Sun Weekends
1	27 604	5 609	577	350	0	0
2	29 103	4 181	508	388	0	0
3	29 284	4 188	429	599	3	43
4	25 963	4 658	744	513	181	45
5	22 928	3 637	570	371	181	208
6	21 787	3 682	746	200	6 089	11
7	204 320	8 521	1 440	302	6 100	72
8	214 880	13 676	1 993	352	1 873	256
9	199 270	38 374	399	5 095	923	176
10	204 820	40 053	897	6 251	239	354
11	234 660	41 007	1 825	2 232	19	216
12	242 990	46 665	3 501	2 307	538	375
13	234 080	56 005	2 055	3 607	1 276	170
14	191 130	57 760	1 821	1 543	1 870	222
15	204 210	54 051	2 772	923	92	10
16	222 160	41 067	174	1 150	71	158
17	202 040	45 113	1 753	149	6 485	337
18	227 620	36 001	4 566	21	6 876	33

19	191 440	1 961	1 788	36	4 691	1
20	196 230	3 003	3 774	81	0	0
21	245 550	3 834	4 041	4	0	0
22	166 570	3 207	3 176	3	0	0
23	159 110	3 914	3 043	1	0	0
24	22 023	5 729	407	255	0	0

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Table 0.69 Overall coefficients of determination for simple and multiple LR

Simple LR	$R^2_{overall}$	50.28 %
Multiple LR	$R^2_{overall}$	54.35 %

Table 0.70 Sequential sums of squares

	SSS Temper. Weekdays	SSS Temper. Weekends	SSS Wind Weekdays	SSS Wind Weekends	SSS Sun Weekdays	SSS Sun Weekends
1	21	8	8	8	0	0
2	16	0	12	14	0	0
3	9	1	5	10	0	0
4	9	3	1	24	0	0
5	11	7	4	7	7	0
6	63	6	264	32	94	0
7	98 421	8	7	42	38 279	10
8	202 840	31	311	45	38 901	85
9	181 360	53	1 083	438	31 304	17
10	192 530	26 862	1 085	9 241	10 659	9 118
11	197 400	33 231	511	3 935	3 481	12 915
12	214 870	55 255	1 137	1 646	1 668	5 958
13	238 940	76 842	884	6 662	3 646	2 066
14	217 830	112 920	2 983	1 673	6 303	6 785
15	264 300	102 820	2 337	1 081	22 889	6 872
16	187 620	61 335	1 314	3 427	4 188	4 952
17	186 820	41 136	831	1 716	9 326	17 472
18	173 660	51 802	7 117	3	66 530	23 540
19	180 200	29	579	81	40 212	16
20	229 720	1	280	20	0	0

21	234 940	1	25	0	0	0
22	235 200	1	226	11	0	0
23	224 760	0	401	7	0	0
24	33	0	0	18	0	0

Table 0.71 Sequential sums of squares for four regimes

Control regimes	Weekdays day	Weekdays night	Weekend day	Weekend night
SSS Temperature	3 461 411	562 203	161	151
SSS Wind	21 111	29 384	295	759
SSS Sun	277 385	89 678	101	129

Dragvoll 9 calculation with excluding outliers

Table 0.72 Overall coefficients of determination for simple and multiple LR

Simple LR	$R^2_{overall}$	56.85 %
Multiple LR	$R^2_{overall}$	65.25 %

Table 0.73 Sequential sums of squares

	SSS Temper. Weekdays	SSS Temper. Weekends	SSS Wind Weekdays	SSS Wind Weekends	SSS Sun Weekdays	SSS Sun Weekends
1	0	6	0	2	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	51	0	1	0	41	0
7	24 292	0	6 529	0	33 375	0
8	153 240	0	197	0	46 340	0
9	158 750	134	1 807	263	34 382	13
10	127 570	15 663	1 387	10 708	8 846	17 981
11	61 518	13 686	7 033	10 615	10 650	24 834
12	108 700	24 487	6 589	4 249	1 924	22 522
13	140 640	50 257	5 077	14 090	3 510	5 010
14	149 630	91 604	9 718	3 228	2 290	8 810
15	225 870	81 872	3 010	256	15 432	11 417
16	206 900	45 414	4 846	48	469	14 534
17	102 870	26 808	555	53	23 493	29 182

18	120 020	32 305	1 450	1 928	62 645	18 609
19	118 560	15	4 926	46	54 495	6
20	251 260	0	75	0	0	0
21	153 780	0	3 376	0	0	0
22	203 250	0	928	0	0	0
23	217 900	0	1 828	0	0	0
24	15	0	12	0	0	0

Table 0.74 Sequential sums of squares for four regimes

Control regimes	Weekdays day	Weekdays night	Weekend day	Weekend night
SSS Temperature	2 524 750	382 096	66	155
SSS Wind	59 329	45 174	12	310
SSS Sun	152 899	152 899	41	20

Dragvoll 2

Table 0.75 Coefficients of determination for simple and multiple LR

	Simple			Multiple		
	R^2 Weekdays	R^2 Weekends	$R^2_{overall}$	R^2 Weekdays	R^2 Weekends	$R^2_{overall}$
1	86.10 %	75.48 %	66.00 %	85.75 %	77.55 %	69.21 %
2	82.25 %	73.95 %		82.59 %	78.02 %	
3	82.47 %	72.84 %		82.70 %	79.14 %	
4	83.27 %	72.29 %		84.03 %	76.64 %	
5	72.10 %	71.74 %		73.12 %	73.94 %	
6	73.67 %	85.51 %		75.86 %	85.95 %	
7	62.45 %	84.45 %		66.87 %	84.87 %	
8	52.70 %	77.27 %		60.82 %	84.30 %	
9	51.70 %	75.91 %		56.93 %	83.41 %	
10	43.99 %	72.27 %		48.23 %	77.03 %	
11	41.62 %	72.29 %		47.33 %	74.29 %	
12	39.89 %	75.62 %		48.23 %	76.02 %	
13	42.80 %	73.84 %		44.93 %	74.76 %	
14	55.41 %	80.58 %		56.80 %	80.88 %	
15	59.18 %	81.03 %		59.56 %	81.60 %	
16	76.20 %	78.93 %		78.55 %	80.24 %	
17	76.56 %	80.06 %		77.86 %	80.08 %	
18	75.28 %	75.50 %		81.89 %	78.65 %	
19	67.02 %	86.56 %		76.24 %	89.15 %	
20	65.23 %	84.27 %		71.09 %	84.55 %	

21	72.38 %	85.14 %		74.60 %	85.19 %	
22	71.69 %	83.91 %		72.86 %	83.91 %	
23	67.59 %	81.68 %		69.13 %	82.10 %	
24	82.12 %	83.22 %		82.94 %	83.59 %	

Table 0.76 Sequential sums of squares

	SSS Temper. Weekdays	SSS Temper. Weekends	SSS Wind Weekdays	SSS Wind Weekends	SSS Sun Weekdays	SSS Sun Weekends
1	178 517	39 568	275	1 307	0	0
2	187 564	30 220	157	2 778	0	0
3	180 218	28 751	1	4 597	124	0
4	155 703	30 189	391	2 902	1 514	277
5	108 548	24 668	1 980	1 449	5	38
6	96 496	23 832	1 008	54	245	120
7	152 824	20 405	5 440	42	13 288	114
8	168 213	18 668	7 617	401	15 966	3 733
9	202 479	42 929	8 439	2 885	4 946	6 516
10	164 763	46 617	3 579	2 279	2 292	2 581
11	183 290	49 485	5 020	856	878	1 504
12	203 663	70 119	5 614	273	3 495	206
13	181 145	91 105	1 579	231	412	1 071
14	213 729	106 098	338	55	161	296
15	252 199	95 334	884	89	1 324	767
16	320 185	88 360	718	177	7 351	1 963
17	232 460	88 021	1 532	26	167	4
18	205 856	72 957	6 960	275	20 498	3 897
19	193 924	31 067	610	188	25 962	1 394
20	226 428	38 922	2 659	162	7 394	9
21	312 006	45 664	944	30	248	0
22	137 948	45 384	1 795	0	0	0
23	128 865	38 726	1 580	256	0	0
24	165 665	46 516	519	237	0	0

Table 0.77 Sequential sums of squares for two regimes

Control regimes	Weekdays day	Weekend day
SSS Temperature	3 213 163	905 751
SSS Wind	51 934	7 970
SSS Sun	104 384	24 056

Dragvoll 2 calculation with excluding outliers

Table 0.78 Sequential sums of squares for two regimes		
Control regimes	Weekdays day	Weekend day
SSS Temperature	3 010 016	799 401
SSS Wind	21 101	10 167
SSS Sun	105 466	33 805

Appendix B.3 - Power of wind in wind independent variable giving best goodness of fit

Table 0.79

	Gamle Kjemi		Gløshaugenn Berg	
	Weekdays	Weekends	Weekdays	Weekends
1	1	1	1	1
2	1	1	1	1
3	1	1	1	1
4	1	1	1	1
5	1	1	½	1
6	1	1	½	1
7	½	1	½	1
8	½	1	½	½
9	½	1	½	1
10	½	1	½	½
11	½	1	½	½
12	½	1	½	1
13	½	1	½	½
14	½	1	½	1
15	½	1	½	½
16	½	1	½	½
17	½	1	½	1
18	1	1	1	½
19	1	1	½	½
20	1	1	1	½
21	1	1	1	1
22	1	1	1	½
23	1	1	1	1
24	1	1	1	½

Appendix C - Results of calculations with mean values grouped by regimes

Appendix C.1 - Space heating systems

Sentral Bygg 1

Table 0.80 Coefficients of determination for simple and multiple LR

Control regimes		Weekdays day	Weekdays night	Weekend day	Weekend night
Simple	R^2	93.00 %	67.55 %	90.98 %	90.57 %
	$R^2_{overall}$	90.27 %			
Multiple	R^2	95.50 %	71.61 %	96.09 %	95.32 %
	$R^2_{overall}$	93.28 %			

Table 0.81 Sequential sums of squares

Control regimes	Weekdays day	Weekdays night	Weekend day	Weekend night
SSS Temperature	11 482 400	1 084 960	1 445 850	1 677 900
SSS Wind	31 798	74 702	79 403	88 605
SSS Sun	334 304	20 146	6 085	9 367

Sentral Bygg 1 calculation with excluding outliers

Table 0.82 Sequential sums of squares

Control regimes	Weekdays day	Weekdays night	Weekend day	Weekend night
SSS Temperature	10 987 200	1 145 520	1 209 690	1 668 150
SSS Wind	30 338	110 512	76 244	7 788
SSS Sun	61 805	859	7 400	871

Sydområdet NHL Forskning

Table 0.83 Coefficients of determination for simple and multiple LR					
Control regimes		Weekdays night	Weekdays day	Weekend night	Weekend day
Simple	R^2	91.16 %	92.36 %	87.38 %	93.56 %
	$R^2_{overall}$	91.58 %			
Multiple	R^2	92.22 %	93.74 %	88.26 %	94.04 %
	$R^2_{overall}$	92.73 %			

Gamle-fysikk

Table 0.84 Coefficients of determination for simple and multiple LR					
Control regimes		Weekdays day	Weekdays night	Weekend day	Weekend night
Simple	R^2	95.55 %	91.11 %	90.75 %	92.35 %
	$R^2_{overall}$	94.38 %			
Multiple	R^2	95.85 %	93.57 %	92.00 %	94.20 %
	$R^2_{overall}$	95.14 %			

Gløshaugen Idrettsbygg

Table 0.85 Coefficients of determination for simple and multiple LR							
Control regimes		Weekday day	Weekday night	Weekend day	Weekend night	Weekday $5^{\underline{h}}$ - $6^{\underline{h}}$	Weekend $7^{\underline{h}}$ - $11^{\underline{h}}$
Simple	R^2	86.64 %	79.21 %	87.22 %	78.49 %	74.23 %	90.28 %
	$R^2_{overall}$	86.34 %					
Multiple	R^2	86.89 %	79.95 %	88.72 %	80.18 %	75.71 %	91.33 %
	$R^2_{overall}$	86.86 %					

Varmetekniske laboratoriet

Table 0.86 Coefficients of determination for simple and multiple LR					
Control regimes		Weekdays day	Weekdays night	Weekend day	Weekend night
Simple	R^2	93.64 %	94.67 %	92.83 %	91.55 %
	$R^2_{overall}$	93.71 %			
Multiple	R^2	94.00 %	96.46 %	93.13 %	94.66 %
	$R^2_{overall}$	94.82 %			

Appendix C.2 - Ventilation systems

Dragvoll 3

Table 0.87 Coefficients of determination for simple and multiple LR					
Control regimes		Weekdays day	Weekdays night	Weekend day	Weekend night
Simple	R^2	70.69 %	78.33 %	83.19 %	82.74 %
	$R^2_{overall}$	73.16 %			
Multiple	R^2	82.06 %	84.17 %	89.31 %	88.93 %
	$R^2_{overall}$	83.26 %			

Table 0.88 LR coefficients for simple LR		
Control regimes	β_0	β_1 (Temperature)
Weekdays day	-8.94	63.65
Weekdays night	-15.37	28.82
Weekend day	-9.70	27.40
Weekend night	-17.77	25.34

Table 0.89 LR coefficients for multiple LR				
Control regimes	β_0	β_1 (Temperature)	β_2 (Wind)	β_3 (Sun)
Weekdays day	369.53	51.02	-0.7535	-0.5125
Weekdays night	45.56	22.19	0.6703	-1.5780
Weekend day	64.60	23.27	0.5962	-0.1484
Weekend night	26.90	18.04	1.2122	-1.0803

Table 0.90 Sequential sums of squares for different regimes				
Control regimes	Weekdays day	Weekdays night	Weekend day	Weekend night
SSS Temperature	56 438 200	6 946 170	6 701 370	2 316 600
SSS Wind	419 757	225 115	109 996	301 169
SSS Sun	21 620 300	964 799	772 785	283 690

Dragvoll 3 calculation with excluding outliers

Table 0.91 Sequential sums of squares for different regimes

Control regimes	Weekdays day	Weekdays night	Weekend day	Weekend night
SSS Temperature	60 114 600	5 137 000	6 488 560	2 330 020
SSS Wind	45 822	494 219	4 424	180 719
SSS Sun	7 031 310	708 147	87 289	75 249

Dragvoll Idrettsbygg

Table 0.92 Coefficients of determination for simple and multiple LR

Control regimes		Weekdays day	Weekdays night	Weekend day	Weekend night
Simple	R^2	95.67 %	80.76 %	97.02 %	87.66 %
	$R^2_{overall}$	95.69 %			
Multiple	R^2	95.84 %	83.44 %	97.33 %	88.84 %
	$R^2_{overall}$	95.94 %			

Dragvoll 8

Table 0.93 Coefficients of determination for simple and multiple LR

Control regimes		Weekdays night	Weekdays day	Weekend night	Weekend day
Simple	R^2	88.46 %	89.93 %	89.23 %	89.05 %
	$R^2_{overall}$	89.87 %			
Multiple	R^2	91.35 %	91.98 %	92.59 %	91.65 %
	$R^2_{overall}$	92.01 %			

Dragvoll 9

Table 0.94 Coefficients of determination for simple and multiple LR

Control regimes		Weekdays day	Weekdays night	Weekend day	Weekend night
Simple	R^2	58.36 %	0.99 %	51.75 %	1.69 %
	$R^2_{overall}$	57.61 %			
Multiple	R^2	64.45 %	5.75 %	61.70 %	9.06 %
	$R^2_{overall}$	64.37 %			

Table 0.95 Sequential sums of squares for different regimes				
Control regimes	Weekdays day	Weekdays night	Weekend day	Weekend night
SSS Temperature	3 768 730	196	444 474	32
SSS Wind	6 555	141	36 816	565
SSS Sun	426 989	129	125 667	91

Dragvoll 9 calculation with excluding outliers

Table 0.96 Sequential sums of squares for different regimes				
Control regimes	Weekdays day	Weekdays night	Weekend day	Weekend night
SSS Temperature	1 777 860	16	199 467	0
SSS Wind	42 078	23	64 075	13
SSS Sun	409 666	17	187 479	4

Dragvoll 2

<table>
<tr><th colspan="6">Table 0.97 Coefficients of determination for simple and multiple LR</th></tr>
<tr><td colspan="2">Control regimes</td><td>Weekdays night</td><td>Weekdays day</td><td>Weekdays night</td><td>Weekends day</td></tr>
<tr><td rowspan="2">Simple</td><td>R^2</td><td>84.11 %</td><td>75.40 %</td><td>80.09 %</td><td>85.89 %</td></tr>
<tr><td>$R^2_{overall}$</td><td colspan="4">78.84 %</td></tr>
<tr><td rowspan="2">Multiple</td><td>R^2</td><td>85.25 %</td><td>76.85 %</td><td>84.19 %</td><td>86.26 %</td></tr>
<tr><td>$R^2_{overall}$</td><td colspan="4">80.21 %</td></tr>
</table>

Table 0.98 Sequential sums of squares for two regimes		
Control regimes	Weekdays day	Weekend day
SSS Temperature	4 156 481	1 051 957
SSS Wind	41 447	3 372
SSS Sun	48 398	3 418

Table 0.99 Sequential sums of squares for weekdays and weekends		
Control regimes	Weekdays	Weekends
SSS Temperature	5 138 336	1 348 484
SSS Wind	49 347	4 801
SSS Sun	53 246	25 538

Dragvoll 2 calculation with excluding outliers

Table 0.100 Sequential sums of squares for two regimes		
Control regimes	Weekdays day	Weekend day
SSS Temperature	3 798 963	940 110
SSS Wind	18 937	21 238
SSS Sun	72 116	4 649

Appendix D - Results of calculations with daily data

Appendix D.1 - Space heating systems

Sentral Bygg 1

Table 0.101 Coefficients of determination for simple and multiple LR			
Control regimes		Weekdays	Weekends
Simple	R^2	91.81 %	91.77 %
	$R^2_{overall}$	91.96%	
Multiple	R^2	94.62 %	97.46 %
	$R^2_{overall}$	95.24%	

Table 0.102 Sequential sums of squares for weekdays and weekends		
Control regimes	Weekdays	Weekend
SSS Temperature	10 946 880	2 902 080
SSS Wind	104 064	205 284
SSS Sun	290 136	14 437

Sentral Bygg 1 calculation with excluding outliers

Table 0.103 Sequential sums of squares for weekdays and weekends		
Control regimes	Weekdays	Weekend
SSS Temperature	9 657 996	2 795 502
SSS Wind	65 998	10 698
SSS Sun	28 421	6 613

Sydområdet NHL Forskning

Table 0.104 Coefficients of determination for simple and multiple LR			
Control regimes		Weekdays	Weekends
Simple	R^2	93.64 %	92.13 %
	$R^2_{overall}$	93.37 %	
Multiple	R^2	95.09 %	92.71 %
	$R^2_{overall}$	94.64 %	

Gamle-fysikk

Table 0.105 Coefficients of determination for simple and multiple LR			
Control regimes		Weekdays	Weekends
Simple	R^2	95.28 %	94.95 %
	$R^2_{overall}$	95.18 %	
Multiple	R^2	95.76 %	96.48 %
	$R^2_{overall}$	95.98 %	

Gløshaugen Idrettsbygg

Table 0.106 Coefficients of determination for simple and multiple LR			
Control regimes		Weekdays	Weekends
Simple	R^2	87.69 %	86.12 %
	$R^2_{overall}$	87.47 %	
Multiple	R^2	87.88 %	88.11 %
	$R^2_{overall}$	88.02 %	

Varmetekniske laboratoriet

Table 0.107 Coefficients of determination for simple and multiple LR			
Control regimes		Weekdays	Weekends
Simple	R^2	94.30 %	92.76 %
	$R^2_{overall}$	93.98 %	
Multiple	R^2	94.90 %	93.39 %
	$R^2_{overall}$	94.58 %	

Appendix D.2 - Ventilation systems

Dragvoll 3

Table 0.108 Coefficients of determination for simple and multiple LR			
Control regimes		Weekdays	Weekends
Simple	R^2	74.71 %	83.79 %
	$R^2_{overall}$	76.08 %	
Multiple	R^2	85.77 %	91.03 %
	$R^2_{overall}$	86.56 %	

Table 0.109 Sequential sums of squares for weekdays and weekends		
Control regime	Weekdays	Weekend
SSS Temperature	78 528 000	10 177 920
SSS Wind	27 816	339 480
SSS Sun	20 965 680	1 358 520

Dragvoll 3 calculation with excluding outliers

Table 0.110 Sequential sums of squares for weekdays and weekends		
Control regime	Weekdays	Weekend
SSS Temperature	76 331 449	9 151 141
SSS Wind	62 546	11
SSS Sun	11 073 087	270 987

Dragvoll Idrettsbygg

Table 0.111 Coefficients of determination for simple and multiple LR			
Control regimes		Weekdays	Weekends
Simple	R^2	94.89 %	95.31 %
	$R^2_{overall}$	95.02 %	
Multiple	R^2	95.66 %	96.75 %
	$R^2_{overall}$	95.94 %	

Dragvoll 8

Table 0.112 Coefficients of determination for simple and multiple LR			
Control regimes		Weekdays	Weekends
Simple	R^2	90.35 %	91.37 %
	$R^2_{overall}$	90.59 %	
Multiple	R^2	93.12 %	94.20 %
	$R^2_{overall}$	93.34 %	

Dragvoll 9

Table 0.113 Coefficients of determination for simple and multiple LR			
Control regimes		Weekdays	Weekends
Simple	R^2	57.34 %	40.93 %
	$R^2_{overall}$	56.02 %	
Multiple	R^2	64.55 %	62.98 %
	$R^2_{overall}$	64.86 %	

Table 0.114 Sequential sums of squares for weekdays and weekends		
Control regime	Weekdays	Weekend
SSS Temperature	2 663 040	100 949
SSS Wind	2 455	38 040
SSS Sun	355 368	77 345

Dragvoll 9 calculation with excluding outliers

Table 0.115 Sequential sums of squares for weekdays and weekends		
Control regime	Weekdays	Weekend
SSS Temperature	1 525 744	32 976
SSS Wind	22 100	15 196
SSS Sun	310 711	101 891

Dragvoll 2

Table 0.116 Coefficients of determination for simple and multiple LR			
Control regimes		Weekdays	Weekends
Simple	R^2	81.68 %	87.88 %
	$R^2_{overall}$	83.30 %	
Multiple	R^2	83.15 %	89.07 %
	$R^2_{overall}$	84.69 %	

Table 0.117 Sequential sums of squares for weekdays and weekends		
Control regime	Weekdays	Weekends
SSS Temperature	5 947 218	1 502 863
SSS Wind	50 018	6 721
SSS Sun	61 650	19 584

Appendix E - Comparison of monitoring data resolutions

Appendix E.1 - Space heating systems

Table 0.118 Overall scores for space heating

	Hourly data	HOD	Mean values	Daily data
Overall score CV	14	12	12	22
Overall score MBE	7	12	18	23

Sentral Bygg 1

Table 0.119 Comparison of coefficients of determination for simple and multiple LR

		Hourly data	HOD	Mean values	Daily data
Simple	$R^2_{overall}$	79.14 %	77.06 %	90.27 %	91.96%
	Difference	0 %	-2.08 %	11.13 %	12.82 %
Multiple	$R^2_{overall}$	80.61 %	79.18 %	93.28 %	95.24%
Improvement MLR - SLR		1.47 %	2.12 %	3.01 %	3.28 %

Table 0.120 Comparison of overall sequential sums of squares

	Hourly data	HOD	Mean values	Daily data
SSS - temperature	19 060 987	16 328 476	15 691 110	13 848 960
SSS - sun	50 140	225 000	369 902	304 573

Table 0.121 Comparison of CVs and MBEs

	Hourly data	HOD	Mean values	Daily data
CV	9.40 %	10.94 %	11.74 %	13.44 %
Score CV	1	2	3	4
MBE	0.08 %	5.44 %	6.71 %	8.17 %
Score MBE	1	2	3	4

Sydområdet NHL Forskning

Table 0.122 Comparison of coefficients of determination for simple and multiple LR					
		Hourly data	HOD	Mean values	Daily data
Simple	$R^2_{overall}$	86.60 %	86.62 %	91.58 %	93.37 %
	Difference	0 %	0.02 %	4.98 %	6.77 %
Multiple	$R^2_{overall}$	86.99 %	87.66 %	92.73 %	94.64 %
Improvement MLR - SLR		0.39 %	1.04 %	1.15 %	1.27 %

Table 0.123 Comparison of CVs and MBEs				
	Hourly data	HOD	Mean values	Daily data
CV	12.76 %	12.36 %	12.03 %	12.53 %
Score CV	4	2	1	3
MBE	0.17 %	-0.03 %	-1.20 %	-1.74 %
Score MBE	2	1	3	4

Gamle-fysikk

Table 0.124 Comparison of coefficients of determination for simple and multiple LR					
		Hourly data	HOD	Mean values	Daily data
Simple	$R^2_{overall}$	83.24 %	86.85 %	94.38 %	95.28 %
	Difference	0 %	3.61 %	11.14 %	12.04 %
Multiple	$R^2_{overall}$	84.73 %	88.58 %	95.14 %	95.98 %
Improvement MLR - SLR		1.49 %	1.73 %	0.76 %	0.70 %

Table 0.125 Comparison of CVs and MBEs				
	Hourly data	HOD	Mean values	Daily data
CV	9.86 %	10.75 %	11.82 %	13.25 %
Score CV	1	2	3	4
MBE	-0.08 %	4.75 %	5.58 %	7.12 %
Score MBE	1	2	3	4

Berg

Table 0.126 Comparison of coefficients of determination for simple and multiple LR					
		Hourly data	HOD	Mean values	Daily data
Simple	$R^2_{overall}$	86.08 %	87.46 %	94.13 %	95.05 %
	Difference	0 %	1.38 %	8.05 %	8.97 %
Multiple	$R^2_{overall}$	86.56 %	88.26 %	94.89 %	95.88 %
Improvement MLR - SLR		0.48 %	0.80 %	0.76 %	0.83 %

Table 0.127 Comparison of CVs and MBEs				
	Hourly data	HOD	Mean values	Daily data
CV	12.56 %	13.06 %	12.64 %	13.10 %
Score CV	1	3	2	4
MBE	0.17 %	2.79 %	2.94 %	2.95 %
Score MBE	1	2	3	4

Gløshaugen Idrettsbygg

Table 0.128 Comparison of coefficients of determination for simple and multiple LR					
		Hourly data	HOD	Mean values	Daily data
Simple	$R^2_{overall}$	72.75 %	79.93 %	86.34 %	87.47 %
	Difference	0 %	7.18 %	13.59 %	14.72 %
Multiple	$R^2_{overall}$	74.32 %	80.87 %	86.86 %	88.02 %
Improvement MLR - SLR		1.57 %	0.94 %	0.52 %	0.55 %

Table 0.129 Comparison of CVs and MBEs				
	Hourly data	HOD	Mean values	Daily data
CV	29.96 %	29.35 %	29.80 %	33.73 %
Score CV	3	1	2	4
MBE	-0.20 %	4.10 %	3.66 %	9.89 %
Score MBE	1	3	2	4

Varmetekniske laboratoriet

Table 0.130 Comparison of coefficients of determination for simple and multiple LR

		Hourly data	HOD	Mean values	Daily data
Simple	$R^2_{overall}$	86.58 %	89.25 %	93.71 %	93.98 %
	Difference	0 %	2.67 %	7.13 %	7.40 %
Multiple	$R^2_{overall}$	86.72 %	90.58 %	94.82 %	94.58 %
Improvement MLR - SLR		0.14 %	1.33 %	1.11 %	0.60 %

Table 0.131 Comparison of CVs and MBEs

	Hourly data	HOD	Mean values	Daily data
CV	11.08 %	9.89 %	9.83 %	11.00 %
Score CV	4	2	1	3
MBE	-0.09 %	0.58 %	0.85 %	0.63 %
Score MBE	1	2	4	3

Appendix E.2 - Ventilation systems

Table 0.132 Overall scores for ventilation				
	Hourly data	HOD	Mean values	Daily data
Overall score CV	13	8	12	17
Overall score MBE	5	13	16	16

Table 0.133 CV scores for Dragvoll 2, 8 and Dragvoll Idrettsbygg (insignificant solar influence)				
	Hourly data	HOD	Mean values	Daily data
Overall score CV	5	4	9	12

Table 0.134 CV scores for Dragvoll 3 and Dragvoll 9 (significant solar influence)				
	Hourly data	HOD	Mean values	Daily data
Overall score CV	8	4	3	5

Dragvoll 3

Table 0.135 Comparison of coefficients of determination for simple and multiple LR					
		Hourly data	HOD	Mean values	Daily data
Simple	$R^2_{overall}$	65.26 %	68.60 %	73.16 %	76.08 %
	Difference	0 %	3.34 %	7.90 %	10.82 %
Multiple	$R^2_{overall}$	67.92 %	74.43 %	83.26 %	86.56 %
Improvement MLR - SLR		2.66 %	5.83 %	10.10 %	10.48 %

Table 0.136 Comparison of overall sequential sums of squares				
	Hourly data	HOD	Mean values	Daily data
SSS - temperature	100 209 500	95 787 530	72 402 340	88 705 920
SSS - sun	5 066 399	13 126 582	23 641 574	22 324 200

Table 0.137 Comparison of CVs and MBEs				
	Hourly data	HOD	Mean values	Daily data
CV	23.70 %	22.17 %	20.47 %	21.29 %
Score CV	4	3	1	2
MBE	0.09 %	3.49 %	1.35 %	1.34 %

Score MBE	1	4	3	2

Dragvoll Idrettsbygg

Table 0.138 Comparison of coefficients of determination for simple and multiple LR

		Hourly data	HOD	Mean values	Daily data
Simple	$R^2_{overall}$	70.72 %	88.79 %	95.69 %	95.02 %
	Difference	0 %	18.07 %	24.97 %	24.30 %
Multiple	$R^2_{overall}$	70.85 %	89.15 %	95.94 %	95.94 %
Improvement MLR - SLR		0.13 %	0.36 %	0.25 %	0.92 %

Table 0.139 Comparison of CVs and MBEs

	Hourly data	HOD	Mean values	Daily data
CV	8.35 %	8.28 %	8.37 %	9.00 %
Score CV	2	1	3	4
MBE	-0.01 %	0.48 %	1.14 %	1.84 %
Score MBE	1	2	3	4

Dragvoll 8

Table 0.140 Comparison of coefficients of determination for simple and multiple LR

		Hourly data	HOD	Mean values	Daily data
Simple	$R^2_{overall}$	82.91 %	84.28 %	89.87 %	90.59 %
	Difference	0 %	1.37 %	6.96 %	7.68 %
Multiple	$R^2_{overall}$	84.22 %	86.15 %	92.01 %	93.34 %
Improvement MLR - SLR		1.31 %	1.87 %	2.14 %	2.75 %

Table 0.141 Comparison of CVs and MBEs

	Hourly data	HOD	Mean values	Daily data
CV	15.87 %	17.48 %	18.12 %	19.05 %
Score CV	1	2	3	4
MBE	-0.01 %	6.07 %	7.64 %	8.71 %
Score MBE	1	2	3	4

Dragvoll 9

Table 0.142 Comparison of coefficients of determination for simple and multiple LR

		Hourly data	HOD	Mean values	Daily data
Simple	$R^2_{overall}$	49.21 %	50.28 %	57.61 %	56.02 %
	Difference	0 %	1.07 %	8.40 %	6.81 %
Multiple	$R^2_{overall}$	50.45 %	54.35 %	64.37 %	64.86 %
Improvement MLR - SLR		1.24 %	4.07 %	6.76 %	8.84 %

Table 0.143 Comparison of overall sequential sums of squares

	Hourly data	HOD	Mean values	Daily data
SSS - temperature	4 547 136	4 023 926	4 213 433	2 763 989
SSS - sun	130 252	367 293	552 876	432 713

Table 0.144 Comparison of CVs and MBEs

	Hourly data	HOD	Mean values	Daily data
CV	29.36 %	28.21 %	28.27 %	28.70 %
Score CV	4	1	2	3
MBE	-0.0025 %	0.72 %	0.73 %	2.38 %
Score MBE	1	2	3	4

Dragvoll 2

Table 0.145 Comparison of coefficients of determination for simple and multiple LR

		Hourly data	HOD	Mean values	Daily data
Simple	$R^2_{overall}$	66.22 %	66.00 %	78.84 %	83.30 %
	Difference	0 %	-0.22 %	12.62 %	17.08 %
Multiple	$R^2_{overall}$	66.85 %	69.21 %	80.21 %	84.69 %
Improvement MLR - SLR		0.63 %	3.21 %	1.37 %	1.39 %

Table 0.146 Comparison of CVs and MBEs				
	Hourly data	HOD	Mean values	Daily data
CV	20.95 %	20.68 %	21.21 %	21.48 %
Score CV	2	1	3	4
MBE	0.08 %	3.43 %	4.12 %	4.90 %
Score MBE	1	2	3	4

Appendix F – Excluding outliers

Appendix F.1 - Space heating systems

Sentral Bygg 1

Table 0.147 Comparison of sequential sums of squares for solar radiation - Weekdays day regime				
	Hourly data	HOD	Mean values	Daily data
Calculation without excluding outliers	23 590	196 881	334 304	290 136
Calculation with excluding outliers	40 184	57 921	61 805	28 421

Table 0.148 Comparison of CVs for calculations without and with excluding outliers				
	Hourly data	HOD	Mean values	Daily data
CV without excluding outliers	9.40 %	10.94 %	11.74 %	13.44 %
CV with excluding outliers	9.50 %	12.48 %	12.78 %	13.01 %

Sydområdet NHL Forskning

Table 0.149 Comparison of CVs for calculations without and with excluding outliers				
	Hourly data	HOD	Mean values	Daily data
CV without excluding outliers	12.76 %	12.36 %	12.03 %	12.53 %
CV with excluding outliers	12.85 %	12.38 %	12.01 %	12.46 %

Gamle-fysikk

Table 0.150 Comparison of CVs for calculations without and with excluding outliers				
	Hourly data	HOD	Mean values	Daily data
CV without excluding outliers	9.86 %	10.75 %	11.82 %	13.25 %
CV with excluding outliers	9.91 %	10.77 %	12.29 %	13.59 %

Berg

Table 0.151 Comparison of CVs for calculations without and with excluding outliers				
	Hourly data	HOD	Mean values	Daily data
CV without excluding outliers	12.56 %	13.06 %	12.64 %	13.10 %
CV with excluding outliers	12.54 %	12.98 %	12.51 %	12.83 %

Gløshaugen Idrettsbygg

Table 0.152 Comparison of CVs for calculations without and with excluding outliers				
	Hourly data	HOD	Mean values	Daily data
CV without excluding outliers	29.96 %	29.35 %	29.80 %	33.73 %
CV with excluding outliers	30.39 %	29.22 %	30.31 %	34.98 %

Varmetekniske laboratoriet

Table 0.153 Comparison of CVs for calculations without and with excluding outliers				
	Hourly data	HOD	Mean values	Daily data
CV without excluding outliers	11.08 %	9.89 %	9.83 %	11.00 %
CV with excluding outliers	10.93 %	9.74 %	10.48 %	11.55 %

Appendix F.2 - Ventilation systems

Dragvoll 3

Table 0.154 Comparison of sequential sums of squares for solar radiation - Weekdays day regime				
	Hourly data	HOD	Mean values	Daily data
Calculation without excluding outliers	4 716 500	11 875 829	21 620 300	20 965 680
Calculation with excluding outliers	467 090	3 185 496	7 031 310	11 073 087

Table 0.155 Comparison of CVs for calculations without and with excluding outliers				
	Hourly data	HOD	Mean values	Daily data
CV without excluding outliers	23.70 %	22.17 %	20.47 %	21.29 %
CV with excluding outliers	25.15 %	23.15 %	21.20 %	21.60 %

Dragvoll Idrettsbygg

Table 0.156 Comparison of CVs for calculations without and with excluding outliers				
	Hourly data	HOD	Mean values	Daily data
CV without excluding outliers	8.35 %	8.28 %	8.37 %	9.00 %
CV with excluding outliers	9.92 %	8.55 %	8.53 %	9.10 %

Dragvoll 8

Table 0.157 Comparison of CVs for calculations without and with excluding outliers				
	Hourly data	HOD	Mean values	Daily data
CV without excluding outliers	15.87 %	17.48 %	18.12 %	19.05 %
CV with excluding outliers	15.95 %	16.68 %	18.08 %	20.25 %

Dragvoll 9

Table 0.158 Comparison of sequential sums of squares for solar radiation - Weekdays day regime				
	Hourly data	HOD	Mean values	Daily data
Calculation without excluding outliers	104 350	277 385	426 989	355 368
Calculation with excluding outliers	144 570	297 851	409 666	310 711

Table 0.159 Comparison of CVs for calculations without and with excluding outliers				
	Hourly data	HOD	Mean values	Daily data
CV without excluding outliers	29.36 %	28.21 %	28.27 %	28.70 %
CV with excluding outliers	30.16 %	29.02 %	30.43 %	31.36 %

Dragvoll 2

Table 0.160 Comparison of CVs for calculations without and with excluding outliers				
	Hourly data	HOD	Mean values	Daily data
CV without excluding outliers	20.95 %	20.68 %	21.21 %	21.48 %
CV with excluding outliers	21.64 %	20.59 %	20.59 %	21.24 %

Appendix G – Evaluation of monitoring sample duration

Appendix G.1 - Space heating systems

Table 0.161 Percentage of calculations which accomplished lower CV than CV_Appl

	Hourly data	HOD	Mean values	Daily data
6 months	100 %	67 %	67 %	67 %
3 months	100 %	100 %	89 %	100 %

Sentral Bygg 1

Table 0.162 Comparison between CVs computed for six and three months periods with CVs obtained from predictions for the same period calculated from LR coefficients gained from calculations with year period (CV_Appl)

		Hourly data	HOD	Mean values	Daily data
01.01.2007 - 02.12.2007	CV	15.59 %	15.38 %	15.85 %	15.98 %
01.01.2007 - 01.07.2007	CV	14.85 %	14.72 %	15.34 %	15.41 %
	CV_Appl	15.23 %	15.00 %	15.12 %	15.21 %
04.06.2007- 02.12.2007	CV	15.58 %	17.80 %	18.20 %	20.34 %
	CV_Appl	17.20 %	16.77 %	19.19 %	20.83 %
01.01.2007 - 01.04.2007	CV	10.50 %	10.42 %	10.48 %	10.63 %
	CV_Appl	11.45 %	11.39 %	11.01 %	11.04 %
03.09.2007- 02.12.2007	CV	6.70 %	8.16 %	8.21 %	7.99 %
	CV_Appl	8.14 %	8.48 %	9.02 %	9.02 %
02.04.2007 - 01.07.2007	CV	20.19 %	19.78 %	21.89 %	23.33 %
	CV_Appl	23.89 %	23.23 %	25.57 %	25.56 %

Sydområdet NHL Forskning

Table 0.163 Comparison between CVs computed for six and three months periods with CVs obtained from predictions for the same period calculated from LR coefficients gained from calculations with year period (CV_Appl)

		Hourly data	HOD	Mean values	Daily data
01.01.2007 - 30.12.2007	CV	11.89 %	11.53 %	11.45 %	12.31 %
01.01.2007 - 01.07.2007	CV	8.53 %	8.16 %	8.33 %	9.38 %
	CV_Appl	9.87 %	10.31 %	11.01 %	12.18 %
02.07.2007 - 30.12.2007	CV	11.64 %	11.50 %	11.69 %	11.91 %
	CV_Appl	14.01 %	12.89 %	12.37 %	12.90 %
01.01.2007 - 01.04.2007	CV	5.34 %	5.26 %	5.44 %	5.70 %
	CV_Appl	5.70 %	6.14 %	7.12 %	7.69 %
02.04.2007 - 01.07.2007	CV	8.84 %	8.76 %	11.00 %	12.40 %
	CV_Appl	18.90 %	19.40 %	18.69 %	20.14 %
01.10.2007-31.12.2007	CV	9.30 %	9.03 %	9.16 %	8.73 %
	CV_Appl	11.42 %	10.49 %	9.79 %	9.37 %

Berg

Table 0.164 Comparison between CVs computed for six and three months periods with CVs obtained from predictions for the same period calculated from LR coefficients gained from calculations with year period (CV_Appl)

		Hourly data	HOD	Mean values	Daily data
01.01.2007 - 30.12.2007	CV	12.49 %	12.53 %	12.08 %	12.67 %
01.01.2007 - 01.07.2007	CV	11.29 %	11.40 %	11.11 %	11.43 %
	CV_Appl	11.67 %	11.00 %	10.81 %	11.32 %
02.07.2007 - 30.12.2007	CV	12.27 %	12.86 %	13.16 %	13.19 %

	CV_Appl	13.49 %	14.45 %	14.25 %	14.37 %
01.01.2007 - 01.04.2007	CV	7.23 %	7.88 %	7.90 %	7.80 %
	CV_Appl	7.62 %	7.94 %	7.68 %	7.95 %
02.04.2007 - 01.07.2007	CV	13.47 %	14.22 %	16.43 %	15.26 %
	CV_Appl	22.83 %	19.38 %	17.80 %	17.58 %
01.10.2007 - 31.12.2007	CV	8.59 %	8.92 %	8.58 %	8.08 %
	CV_Appl	11.92 %	11.81 %	10.60 %	10.23 %

Appendix G.2 - Ventilation systems

Table 0.165 Percentage of calculations which accomplished lower CV than CV_Appl

	Hourly data	HOD	Mean values	Daily data
6 months	100 %	67 %	67 %	100 %
3 months	100 %	100 %	100 %	75 %

Dragvoll Idrettsbygg

Table 0.166 Comparison between CVs computed for six and three months periods with CVs obtained from predictions for the same period calculated from LR coefficients gained from calculations with year period (CV_Appl)

		Hourly data	HOD	Mean values	Daily data
01.01.2007 - 15.06.2008	CV	9.75 %	9.57 %	9.52 %	10.48 %
01.01.2007 – 01.07.2007	CV	9.18 %	8.90 %	8.74 %	9.80 %
	CV_Appl	9.78 %	9.50 %	9.27 %	10.06 %
02.07.2007 - 30.12.2007	CV	8.96 %	9.09 %	9.67 %	10.46 %
	CV_Appl	9.80 %	9.65 %	9.94 %	11.30 %
31.12.2007 - 15.06.2008	CV	9.34 %	9.48 %	10.20 %	10.75 %
	CV_Appl	9.49 %	9.41 %	10.13 %	11.54 %
01.01.2007 - 01.04.2007	CV	4.68 %	4.72 %	4.89 %	5.79 %
	CV_Appl	5.03 %	5.13 %	5.06 %	5.75 %
02.04.2007 - 01.07.2007	CV	16.71 %	16.79 %	15.87 %	19.11 %
	CV_Appl	21.28 %	20.27 %	18.37 %	19.51 %
03.09.2007 - 02.12.2007	CV	5.09 %	5.93 %	6.88 %	9.67 %
	CV_Appl	6.46 %	6.37 %	7.24 %	8.47 %

31.12.2007 – 30.03.2008	CV	5.11 %	5.33 %	5.49 %	6.12 %
	CV_Appl	6.83 %	6.68 %	7.14 %	8.06 %

Dragvoll 3

Table 0.167 Comparison between CVs computed for three months periods with CVs obtained from predictions for the same period calculated from LR coefficients gained from calculations with six months period (CV_Appl)

		Hourly data	HOD	Mean values	Daily data
07.01.2008.-15.06.2008	CV	23.70 %	22.17 %	20.47 %	21.29 %
07.01.2008.-07.04.2008	CV	18.35 %	15.74 %	14.13 %	14.35 %
	CV_Appl	20.77 %	19.25 %	16.53 %	16.43 %
03.03.2008.-01.06.2008	CV	23.85 %	23.53 %	23.91 %	24.66 %
	CV_Appl	29.38 %	26.09 %	26.85 %	28.92 %

Dragvoll 8

Table 0.168 Comparison between CVs computed for three months periods with CVs obtained from predictions for the same period calculated from LR coefficients gained from calculations with six months period (CV_Appl)

		Hourly data	HOD	Mean values	Daily data
01.01.2007.-01.07.2007	CV	16.51 %	18.29 %	19.10 %	20.08 %
01.01.2007.-01.04.2007	CV	8.83 %	10.27 %	10.17 %	10.32 %
	CV_Appl	11.27 %	14.26 %	14.75 %	15.52 %
12.02.2007.-13.05.2007	CV	16.63 %	16.99 %	18.58 %	18.80 %
	CV_Appl	17.28 %	17.68 %	19.61 %	20.91 %

Appendix H –Introducing daily change of outdoor air temperature into the heat consumption model

Dragvoll Idrettssenteret

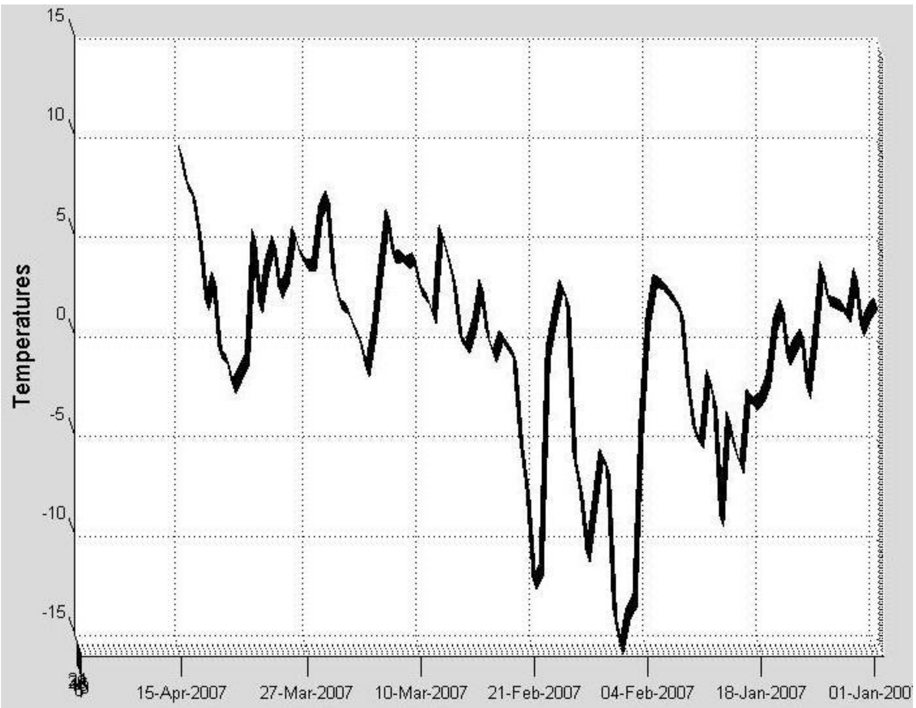

Figure 0.1 Mean daily temperatures between 01.01.2007 and 15.04.2007 in Trondheim

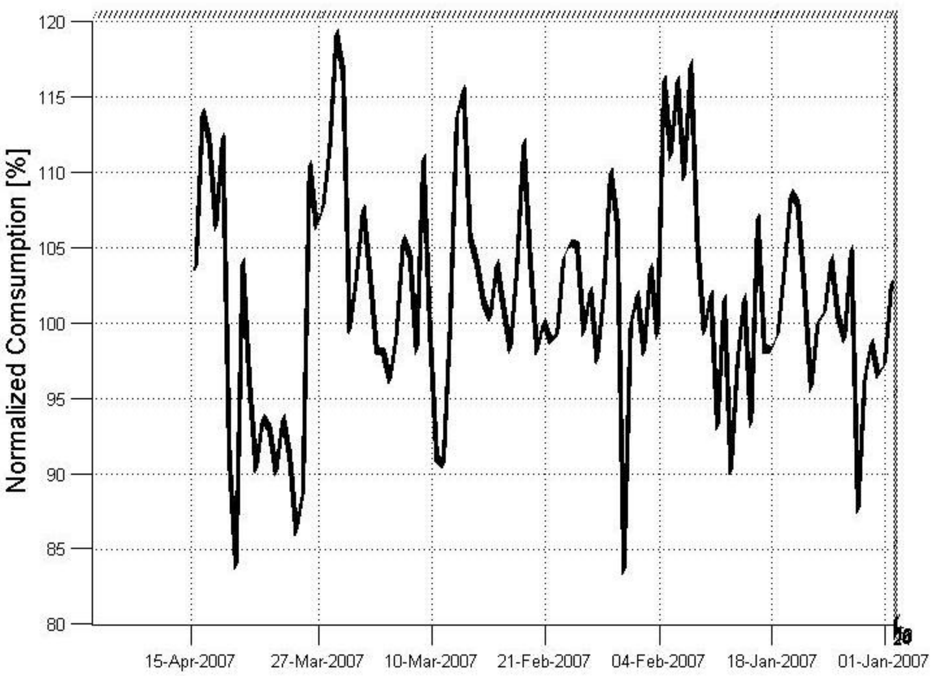

Figure 0.2 Normalized daily heat consumptions for calculations without change of daily temperature as independent variable (01.01.2007 - 15.04.2007)

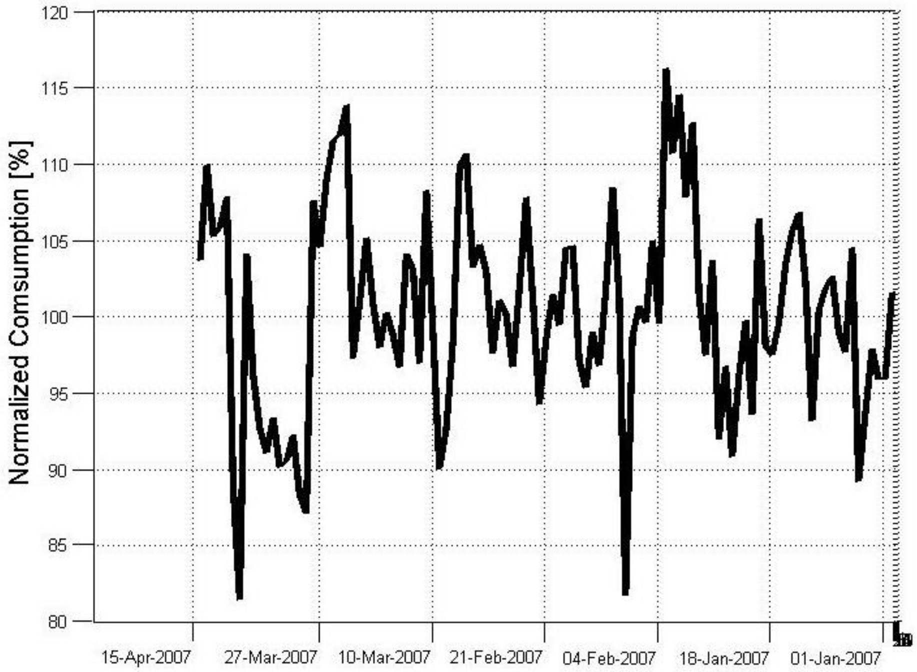

Figure 0.3 Normalized daily heat consumptions for calculations with change of daily temperature as independent variable (01.01.2007 - 15.04.2007)

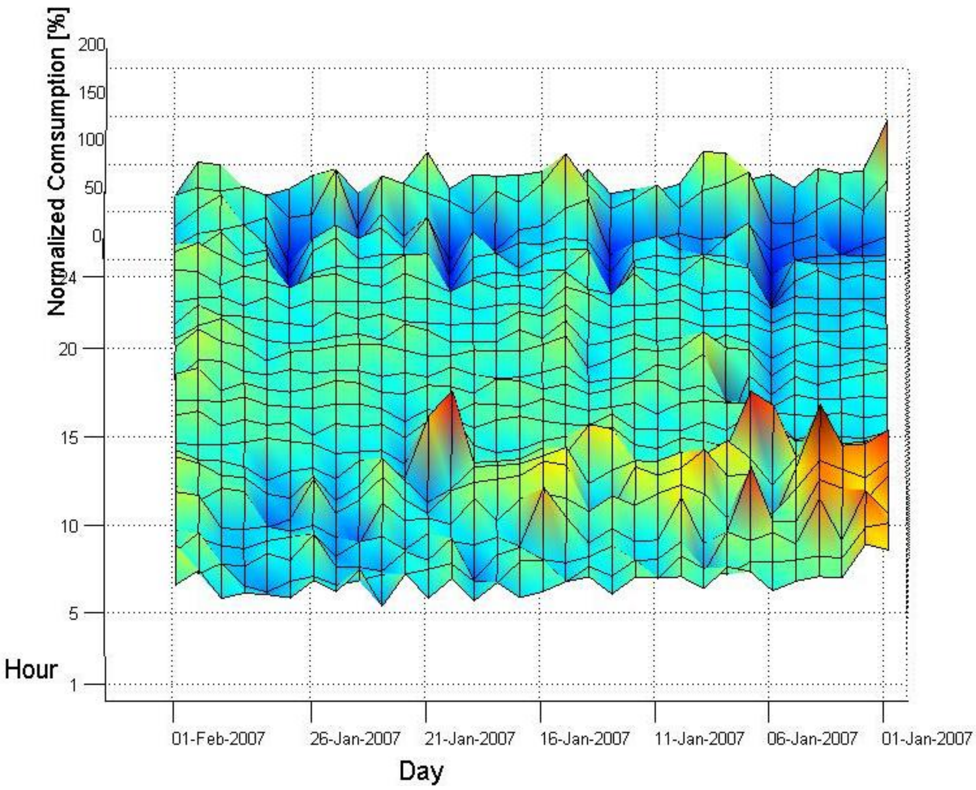

Figure 0.4 Normalized hourly heat consumptions during January 2007

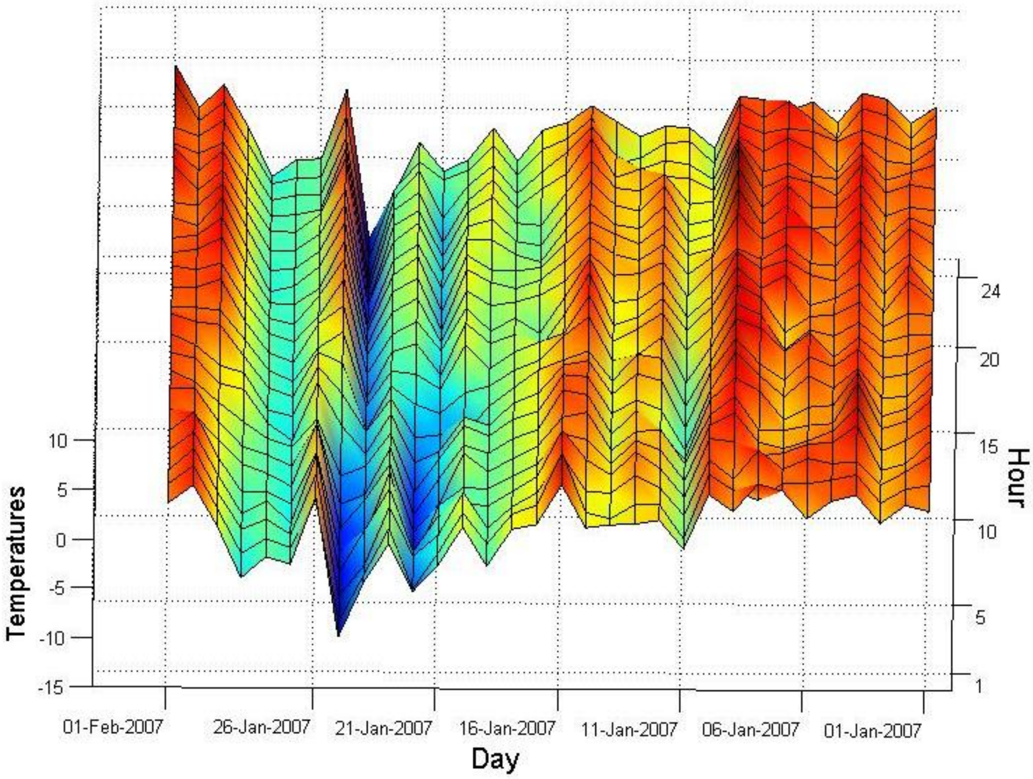

Figure 0.5 Hourly outdoor air temperatures during January 2007 in Trondheim

Dragvoll 2

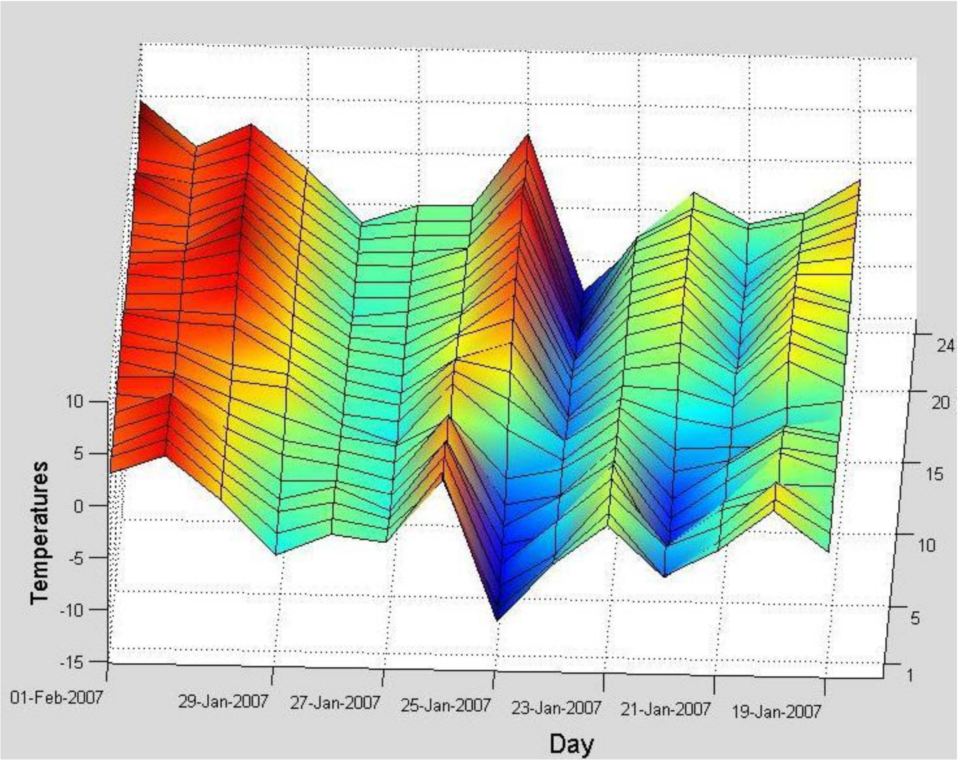

Figure 0.6 Hourly outdoor air temperatures between 19.01.2007 and 01.02.2007 in Trondheim

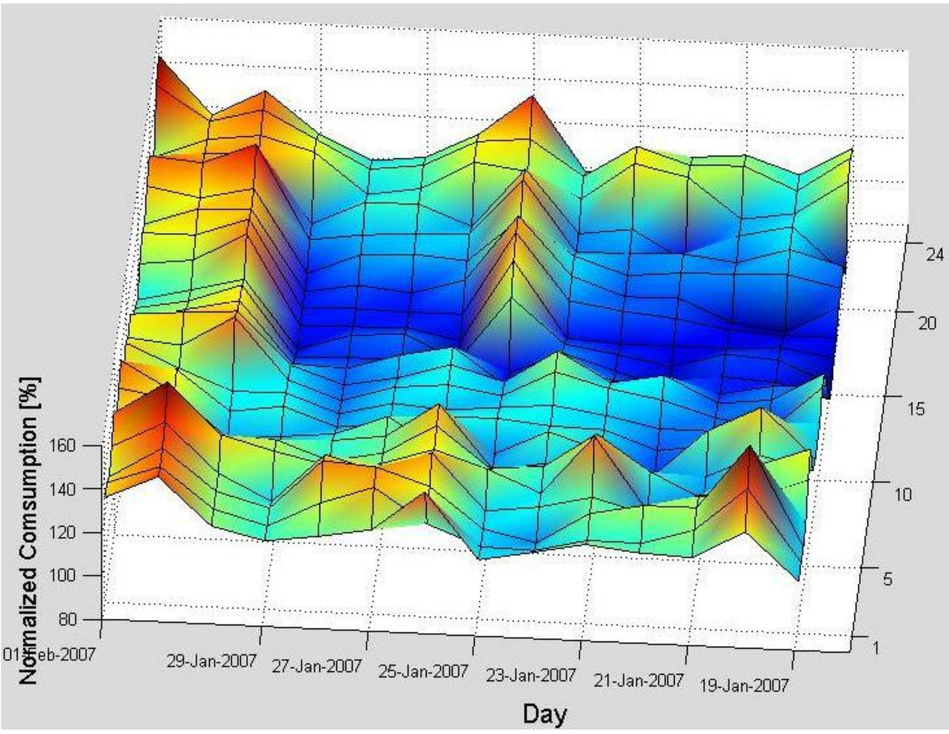

Figure 0.7 Normalized hourly heat consumptions between 19.01.2007 and 01.02.2007

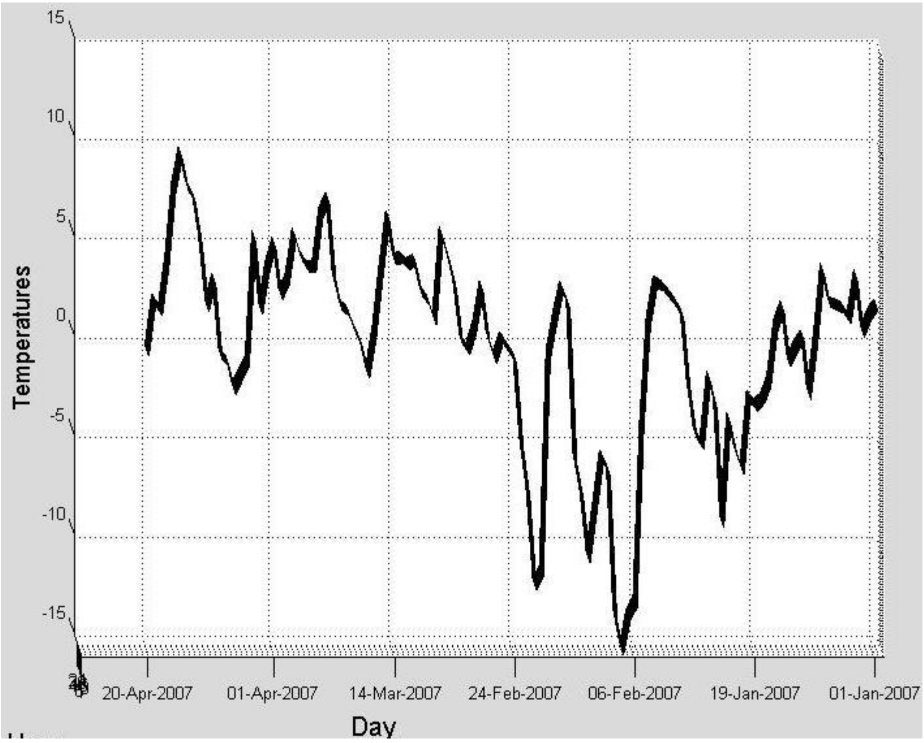

Figure 0.8 Mean daily temperatures between 01.01.2007 and 20.04.2007 in Trondheim

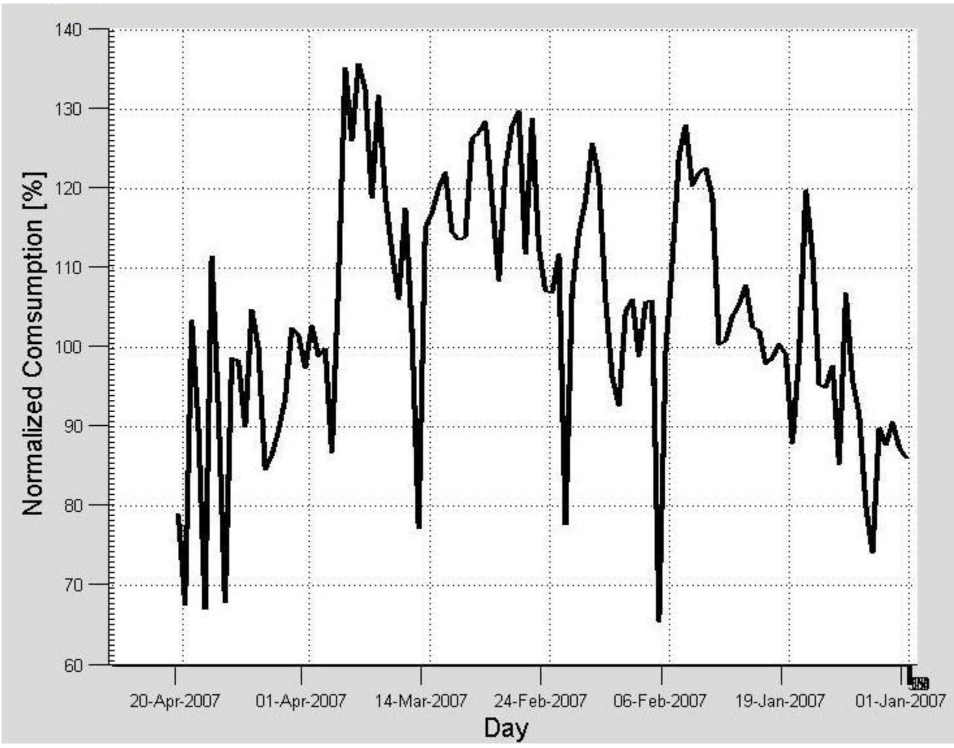

Figure 0.9 Normalized daily heat consumptions gained with model not involving time-lagged variables (01.01.2007 - 20.04.2007)

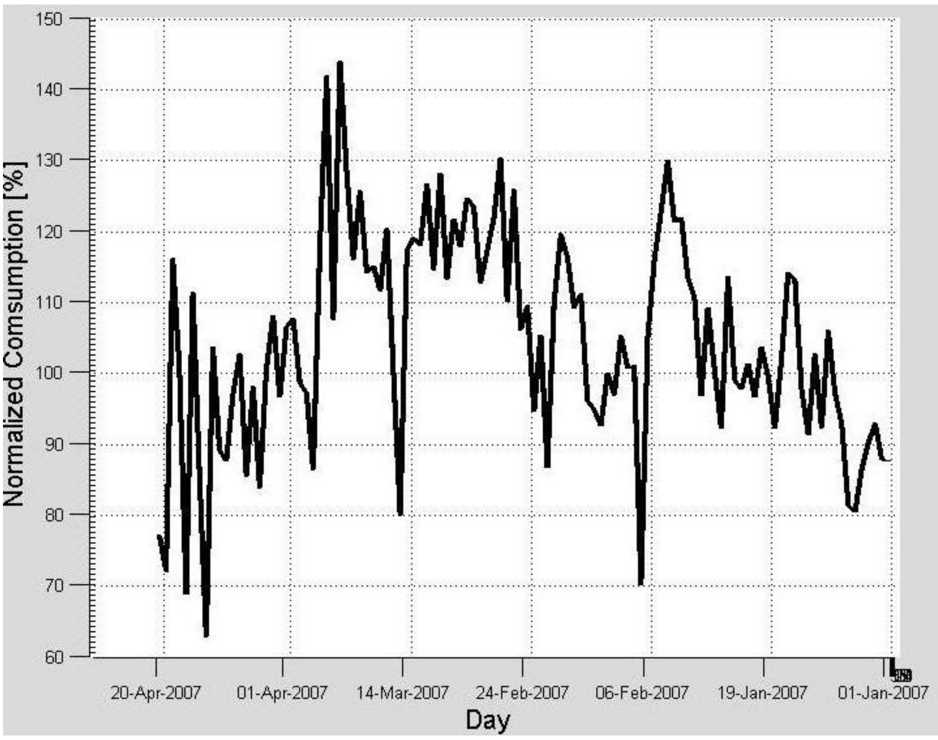

Figure 0.10 Normalized daily heat consumptions gained with model involving time-lagged variables (01.01.2007 - 20.04.2007)

Gamle Kjemi

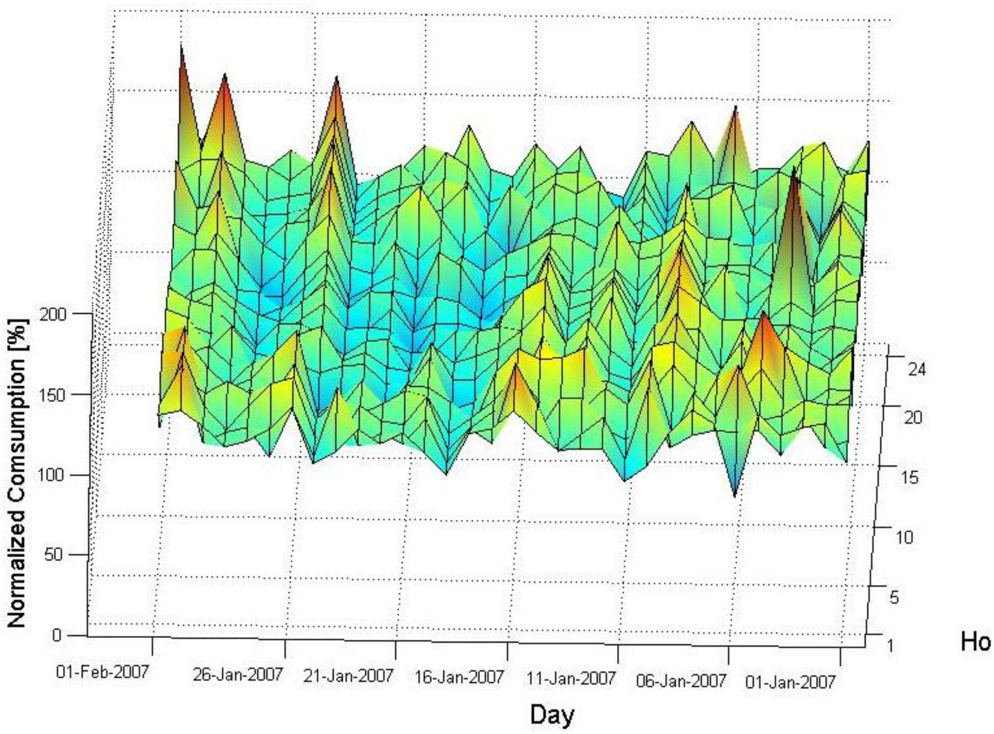

Figure 0.11 Normalized hourly heat consumptions during January 2007

Space heating

Table 0.169 Comparison of CVs for different data groupings					
	Hourly data	HOD	Mean values	Daily data	Daily data with time-lagged variable
Sentral Bygg 1	9.40 %	10.94 %	11.74 %	13.44 %	13.65 %
Score	1	2	3	4	5
Sydområdet NHL Forskning	12.76 %	12.36 %	12.03 %	12.53 %	12.22 %
Score	5	3	1	4	2
Gamle-fysikk	9.86 %	10.75 %	11.82 %	13.25 %	10.67 %
Score	1	3	4	5	2
Berg	12.56 %	13.06 %	12.64 %	13.10 %	12.17 %
Score	2	4	3	5	1
Gløshaugen Idrettsbygg	29.96 %	29.35 %	29.80 %	33.73 %	29.73 %
Score	4	1	3	5	2
Varmetekniske laboratoriet	11.08 %	9.89 %	9.83 %	11.00 %	9.32 %
Score	5	3	2	4	1

Table 0.170 Overall scores for buildings with space heating				
Hourly data	HOD	Mean values	Daily data	Daily data with time-lagged variable
18	16	16	27	13

Ventilation systems

Table 0.171 Comparison of CVs for different data groupings					
	Hourly data	HOD	Mean values	Daily data	Daily data with time-lagged variable
Dragvoll 3	23.70 %	22.17 %	20.47 %	21.29 %	20.97 %
Score	5	4	1	3	2
Dragvoll Idrettsbygg	8.35 %	8.28 %	8.37 %	9.00 %	8.64 %
Score	2	1	3	5	4
Dragvoll 8	15.87 %	17.48 %	18.12 %	19.05 %	19.08 %
Score	1	2	3	4	5
Dragvoll 9	29.36 %	28.21 %	28.27 %	28.70 %	28.41 %
Score	5	1	2	4	3
Dragvoll 2	20.95 %	20.68 %	21.21 %	21.48 %	19.84 %
Score	3	2	4	5	1

Table 0.172 Overall scores for buildings with ventilation systems				
Hourly data	HOD	Mean values	Daily data	Daily data with time-lagged variable
16	10	13	21	15

Appendix I - Verification of HVAC system operation

Appendix I.1 - Space heating systems

Sentral Bygg 1

February 2007

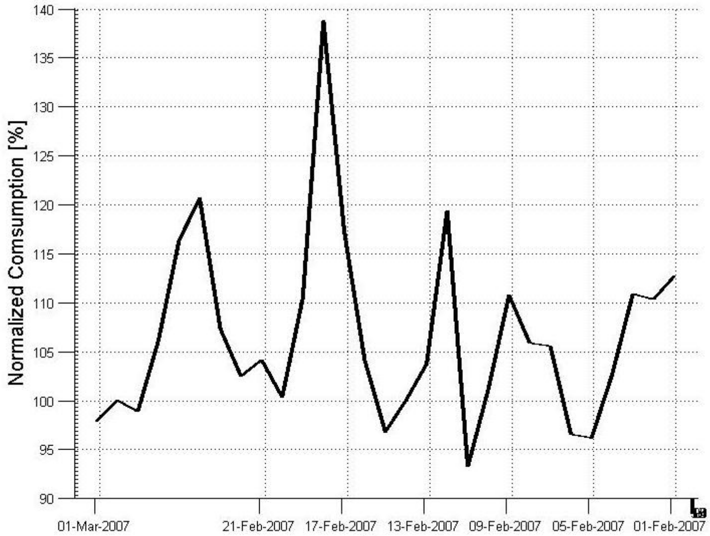

Figure 0.12 Normalized daily heat consumptions for February 2007

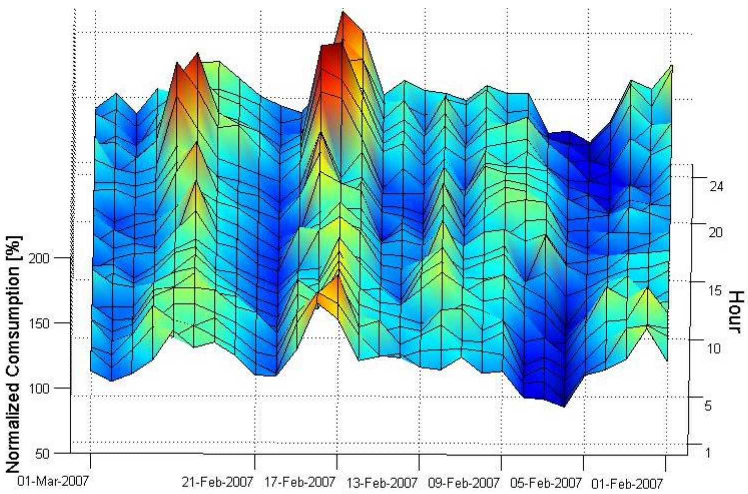

Figure 0.13 Normalized hourly heat consumptions between for February 2007

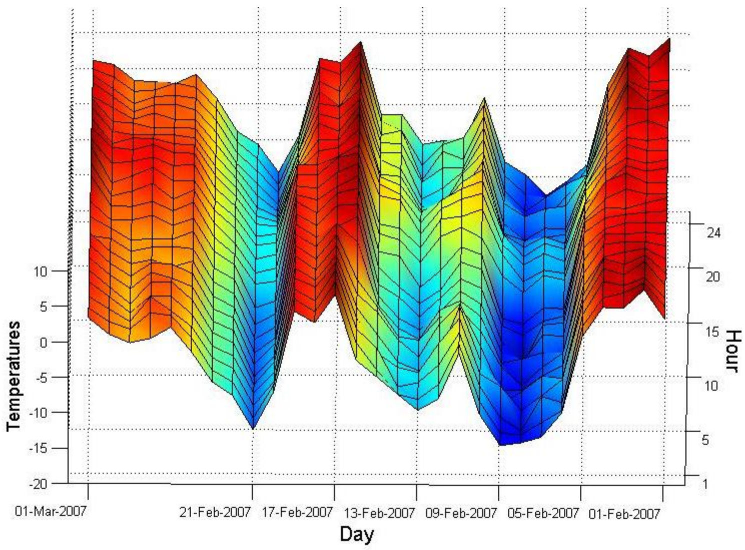

Figure 0.14 Hourly outdoor temperatures for February 2007

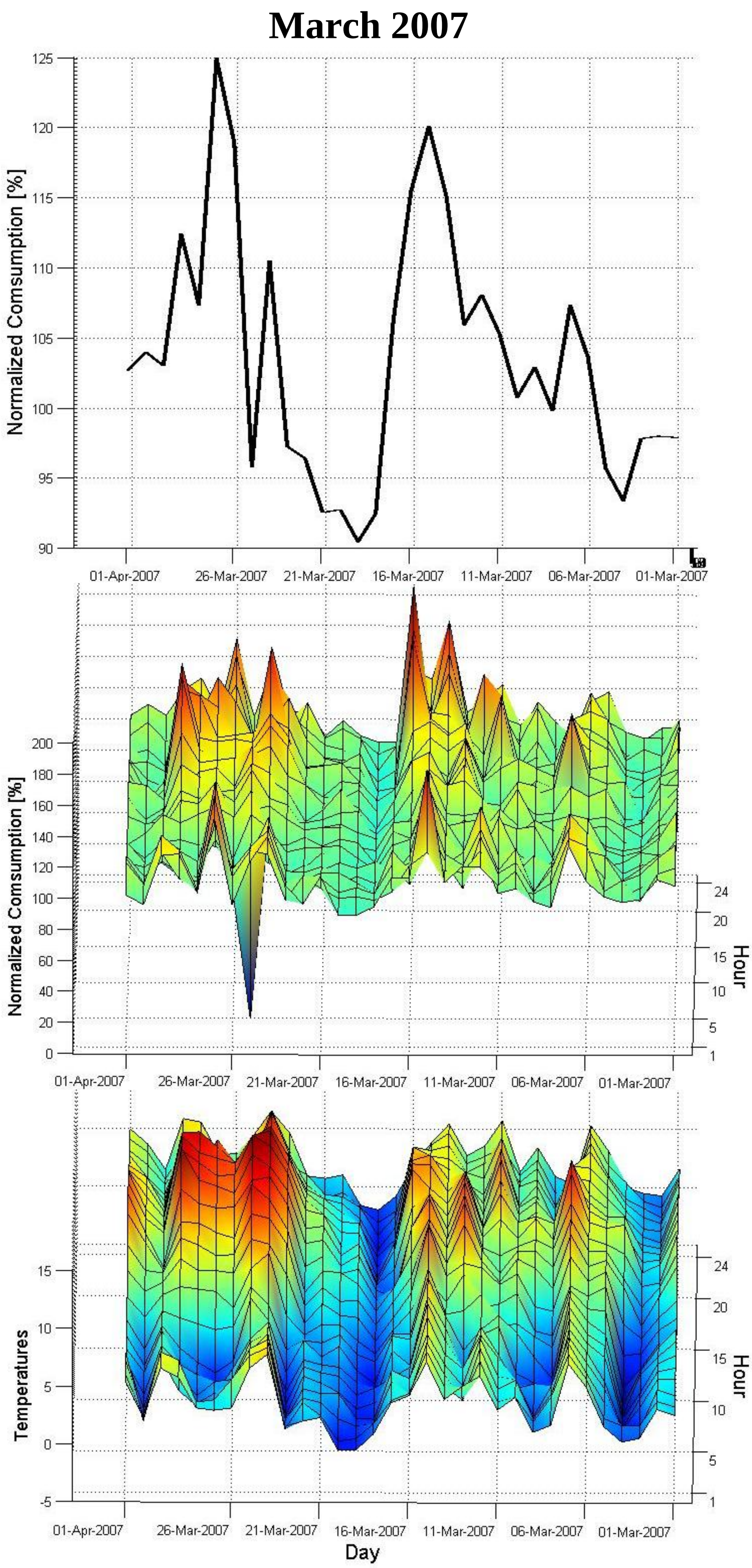

Figure 0.15 Normalized daily and hourly heat consumptions and hourly outdoor temperatures for March 2007

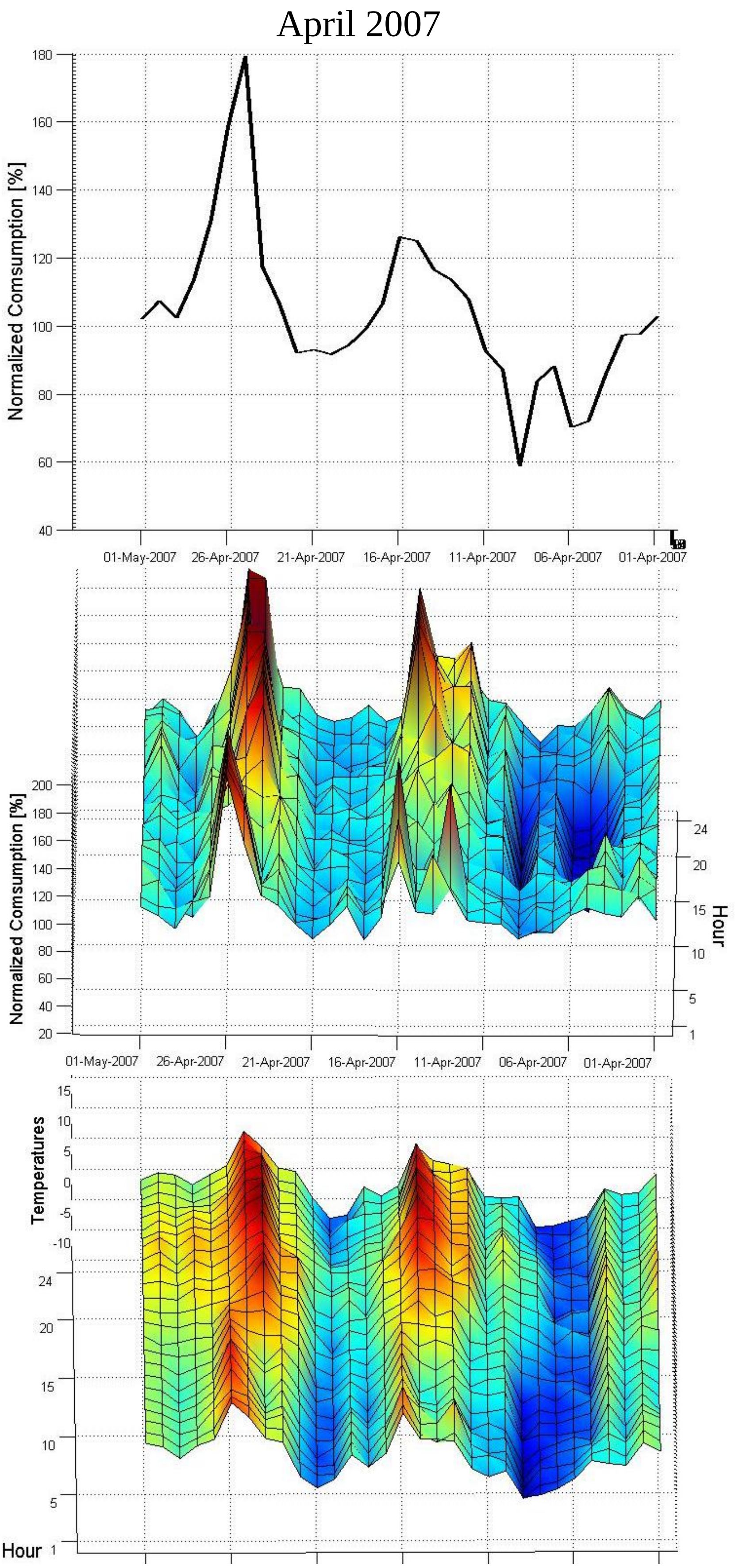

Figure 0.16 Normalized daily and hourly heat consumptions and hourly outdoor temperatures for April 2007

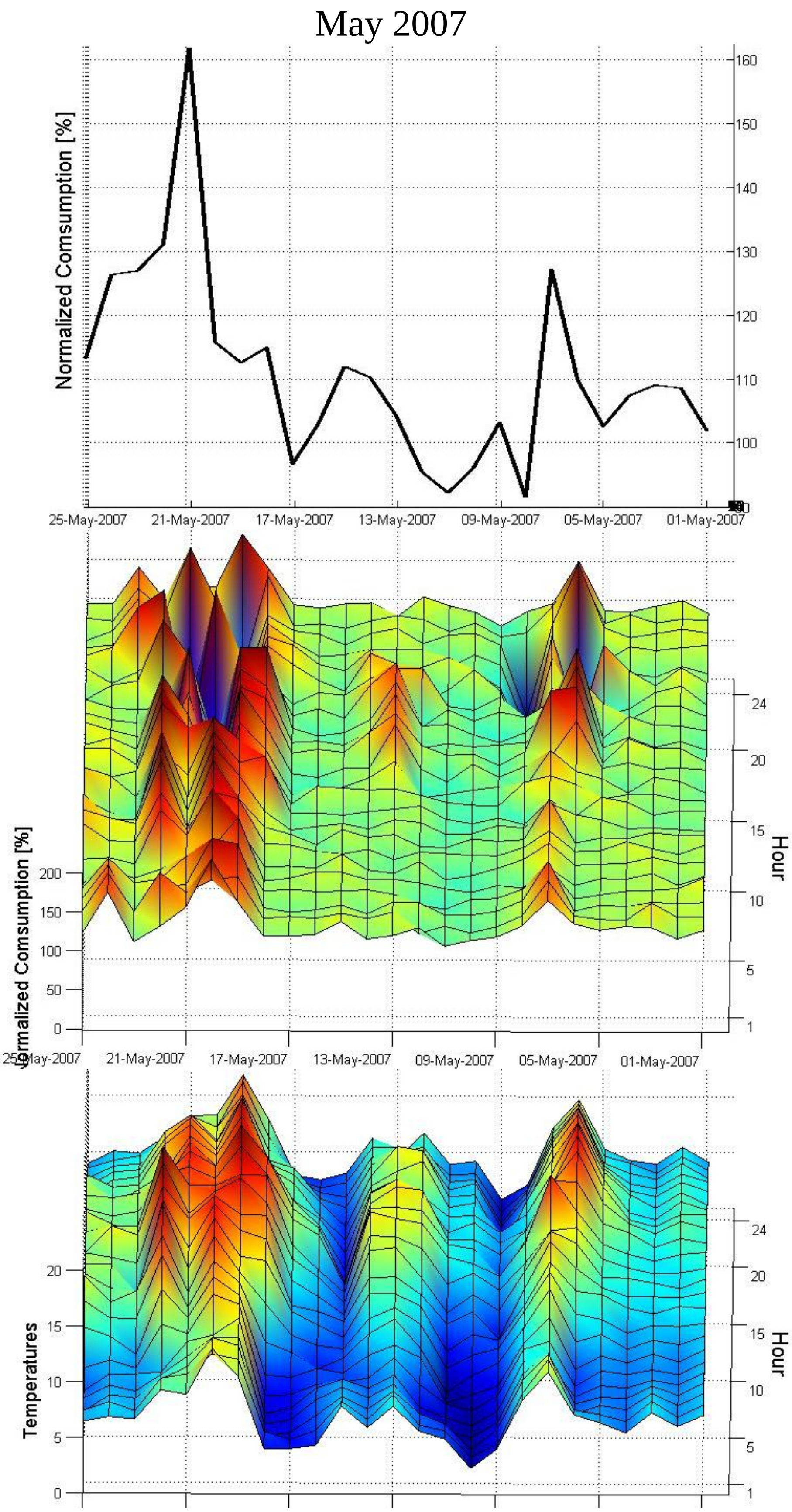

Figure 0.17 Normalized daily and hourly heat consumptions and hourly outdoor temperatures for May 2007

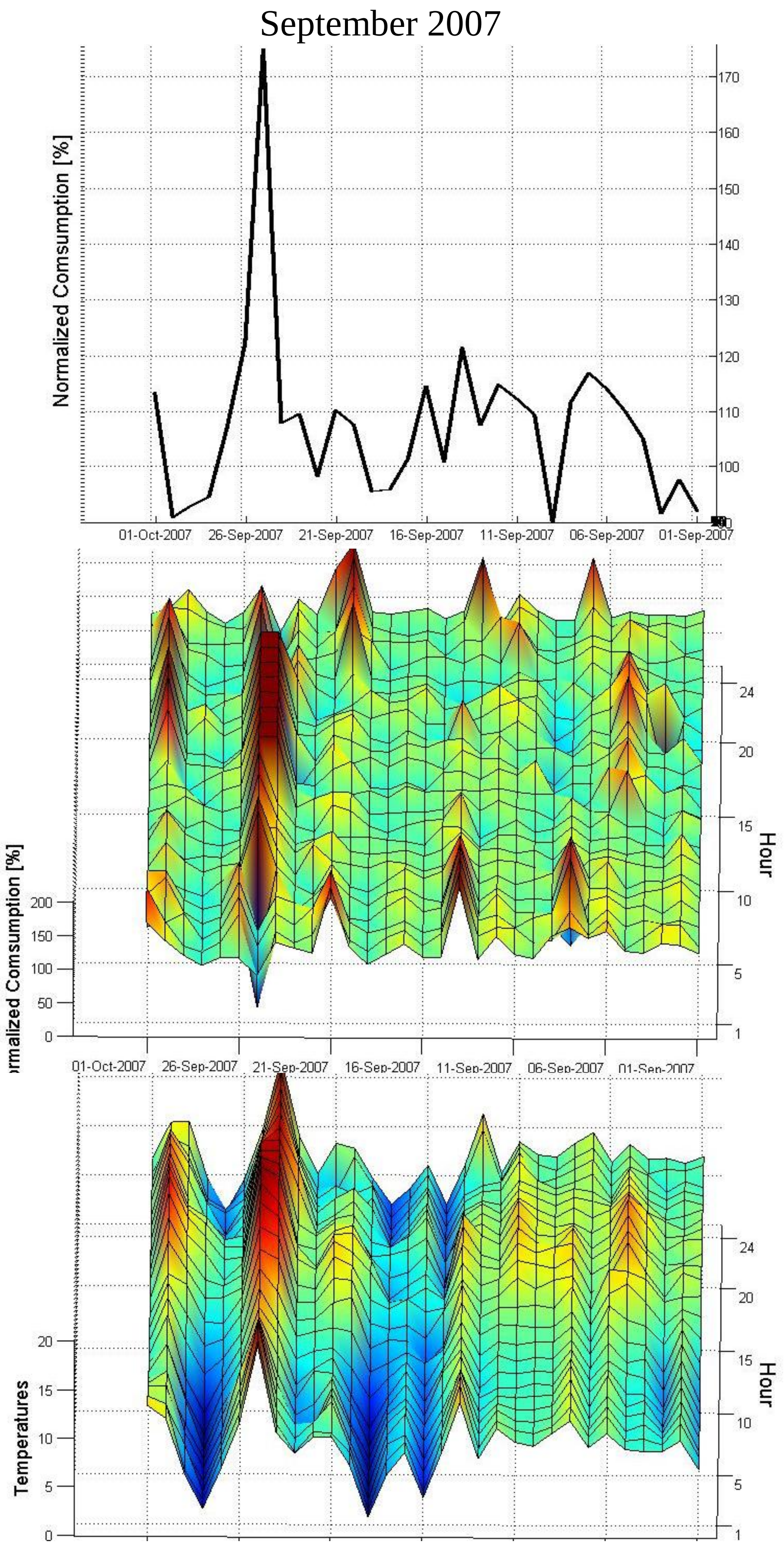

Figure 0.18 Normalized daily and hourly heat consumptions and hourly outdoor temperatures for September 2007

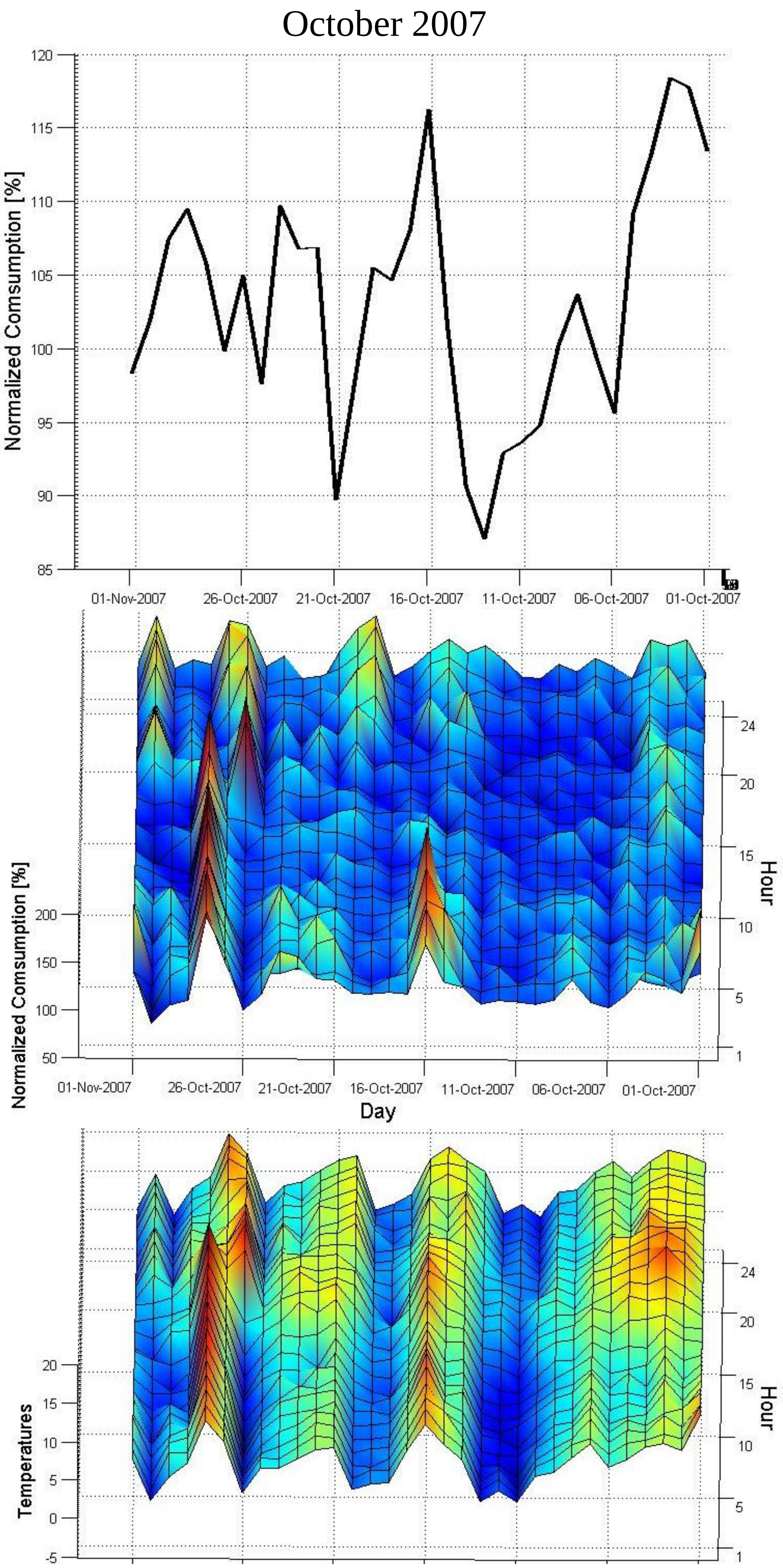

Figure 0.19 Normalized daily and hourly heat consumptions and hourly outdoor temperatures for October 2007

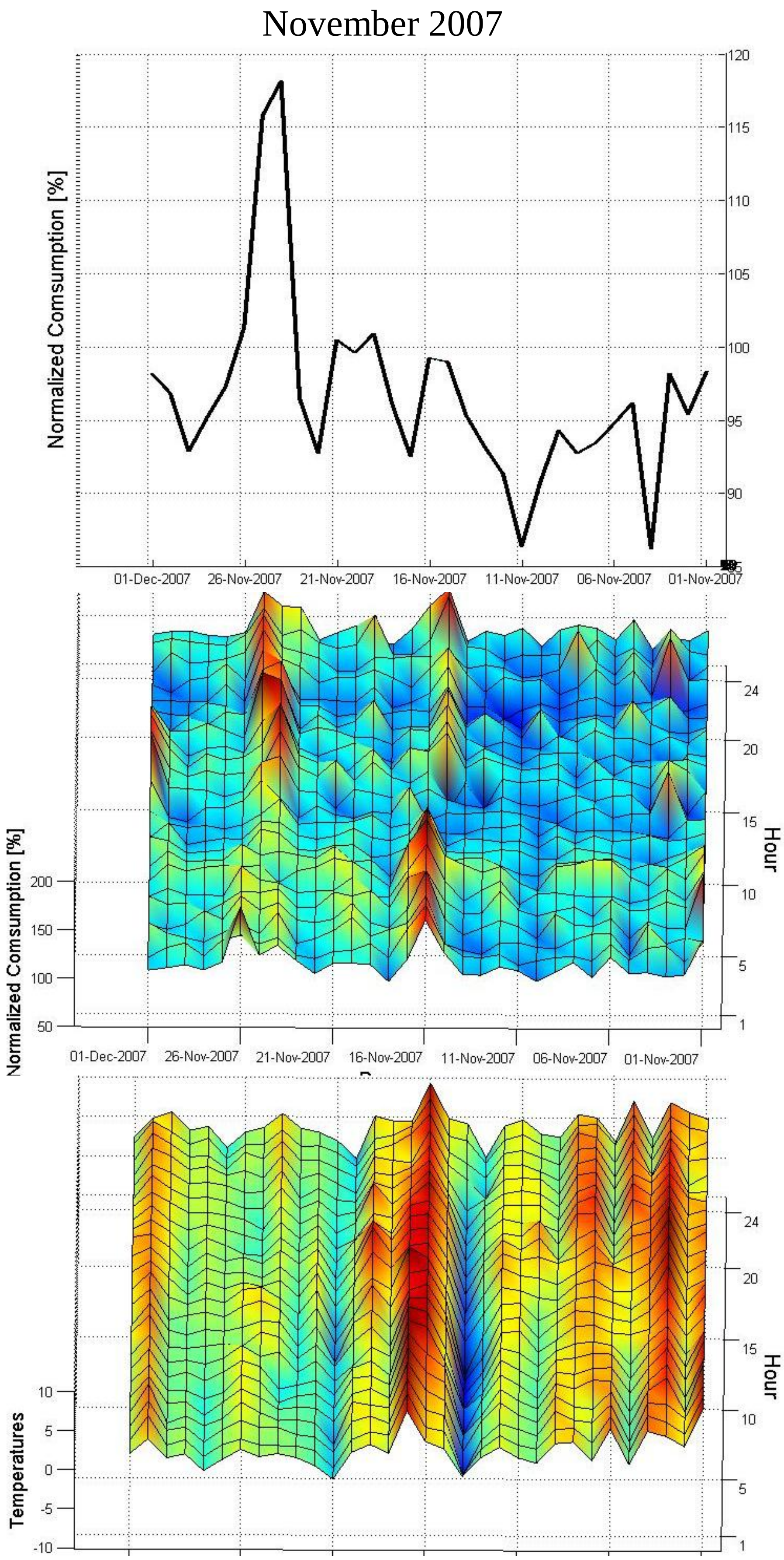

Figure 0.20 Normalized daily and hourly heat consumptions and hourly outdoor temperatures for November 2007

Sydområdet NHL Forskning

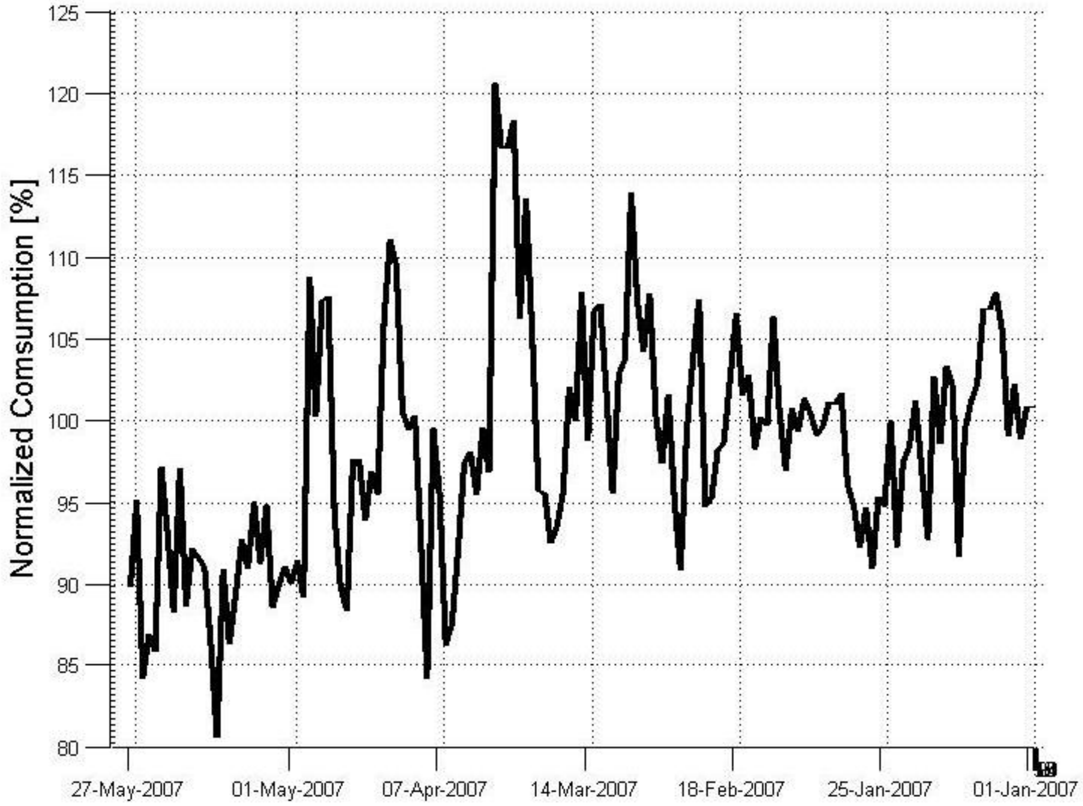

Figure 0.21 Normalized daily heat consumptions between 01.01.2007 and 27.05.2007

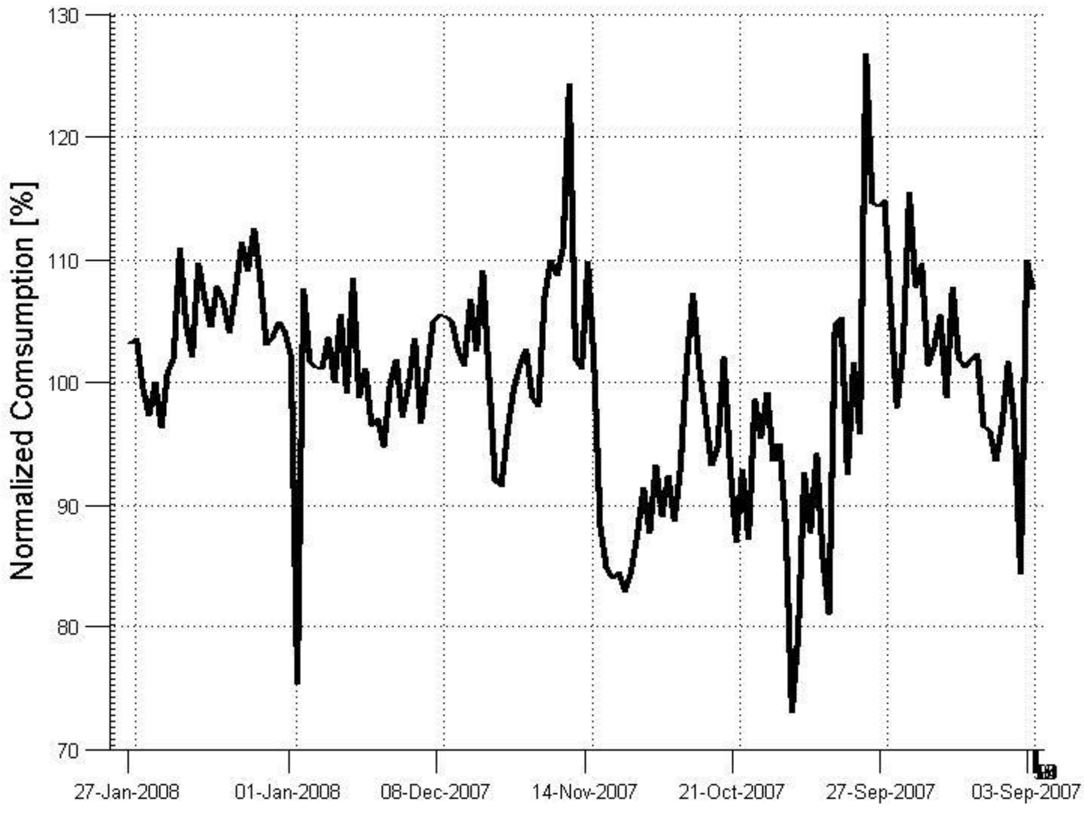

Figure 0.22 Normalized daily heat consumptions between 03.09.2007 and 27.01.2008

Gamle-fysikk

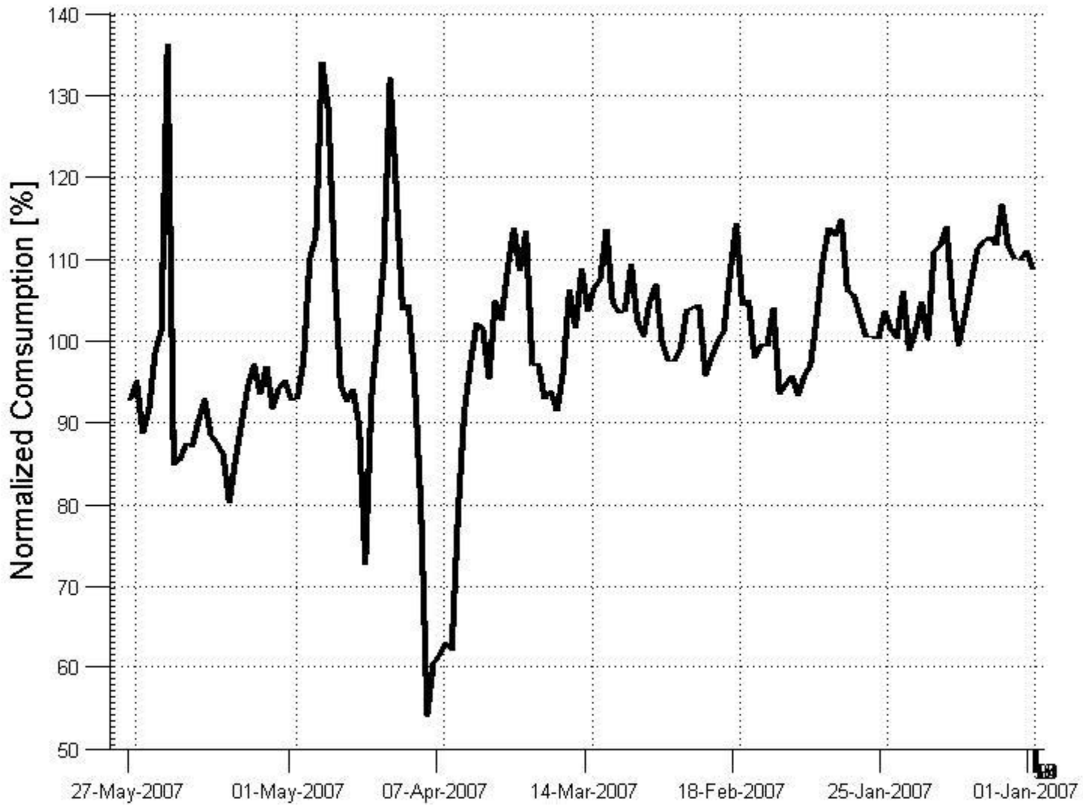

Figure 0.23 Normalized daily heat consumptions between 01.01.2007 and 27.05.2007

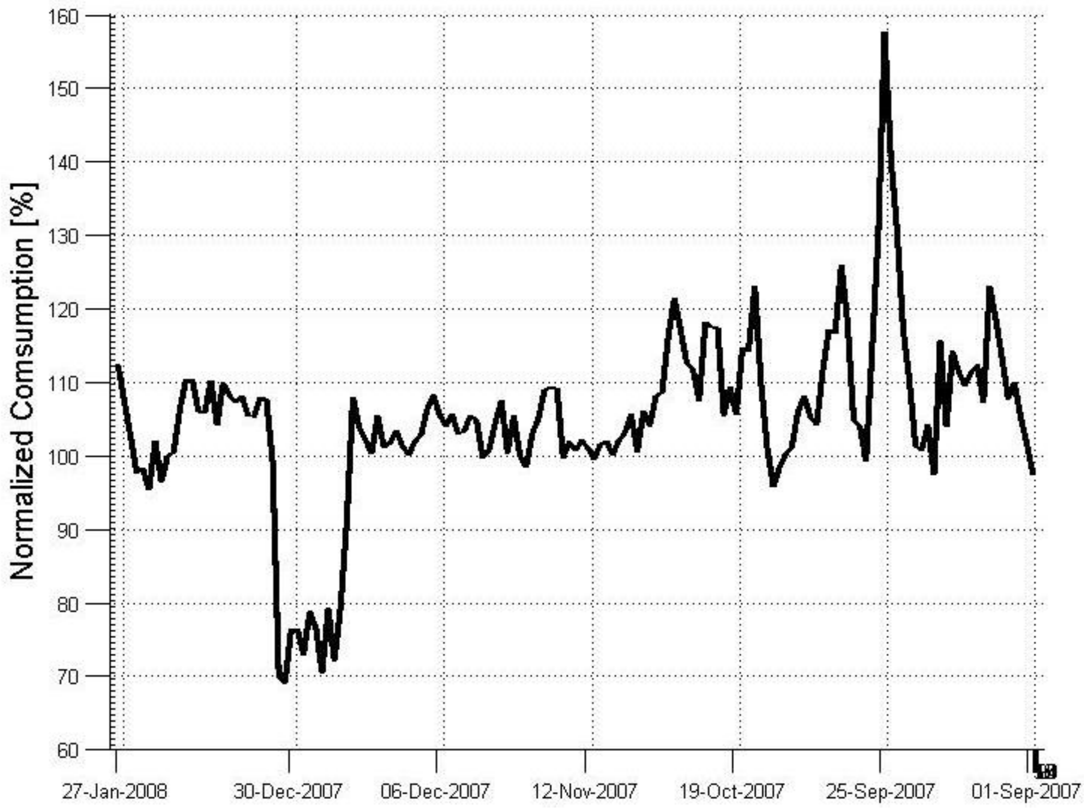

Figure 0.24 Normalized daily heat consumptions between 01.09.2007 and 27.01.2008

Berg

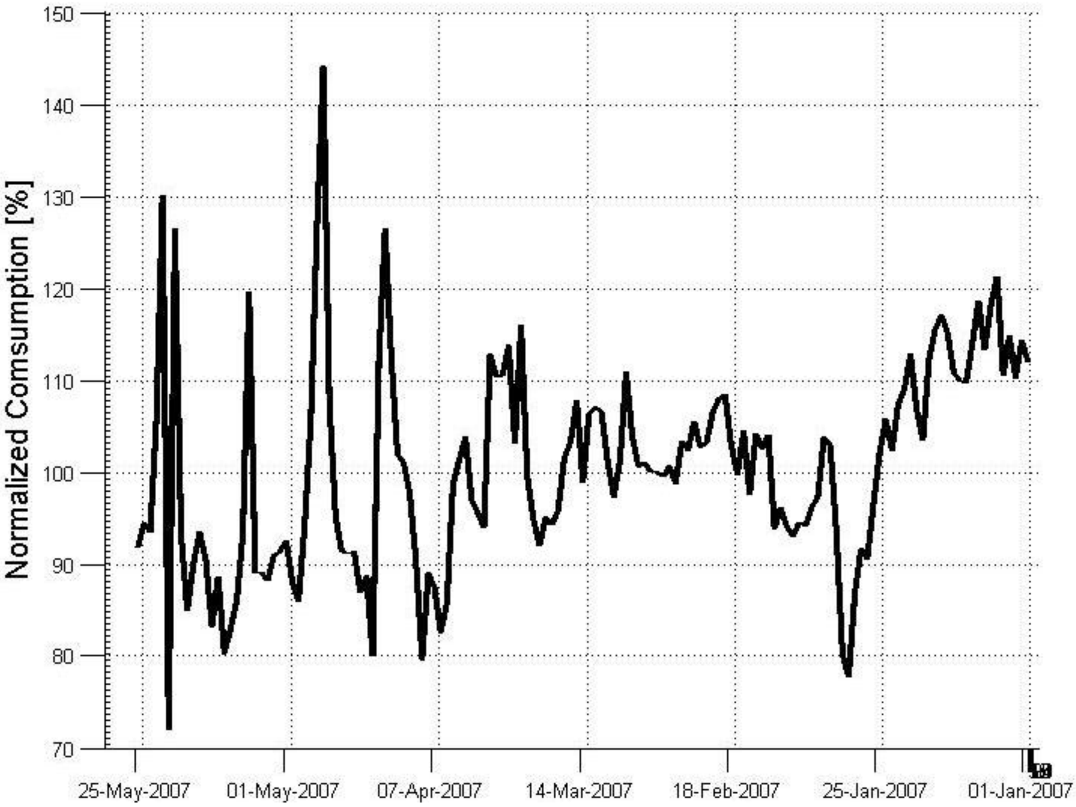

Figure 0.25 Normalized daily heat consumptions between 01.01.2007 and 25.05.2007

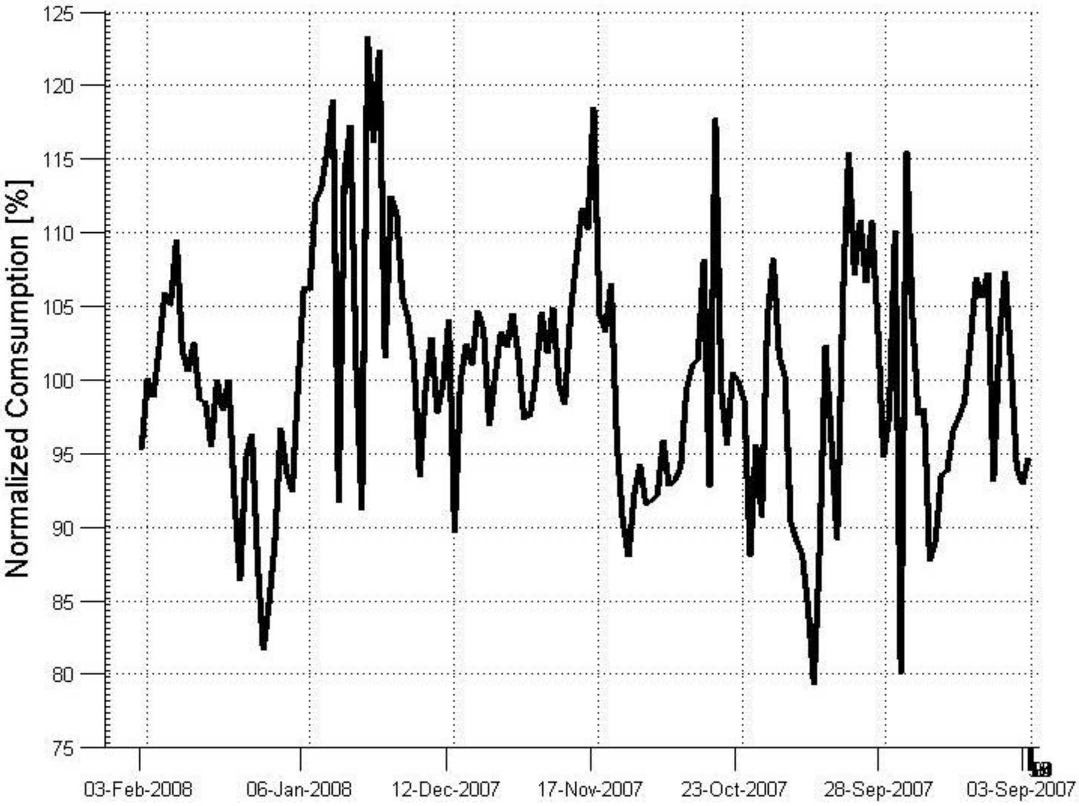

Figure 0.26 Normalized daily heat consumptions between 03.09.2007 and 03.02.2008

Gamle Kjemi

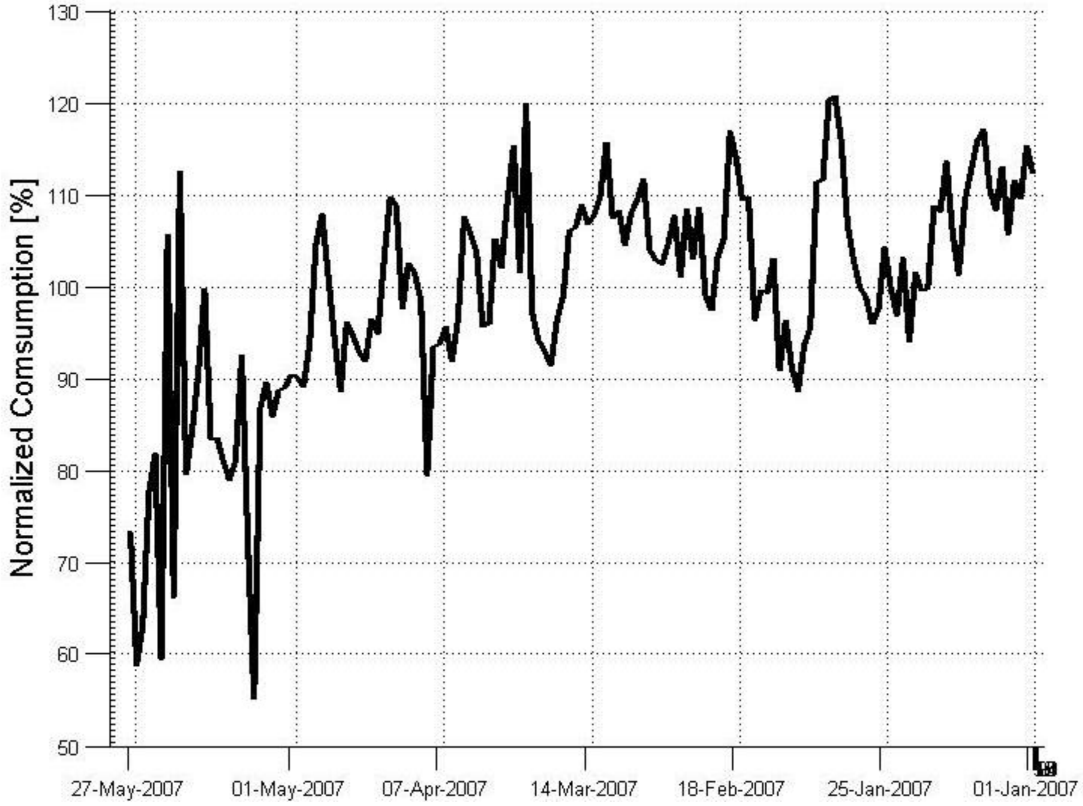

Figure 0.27 Normalized daily heat consumptions between 01.01.2007 and 27.05.2007

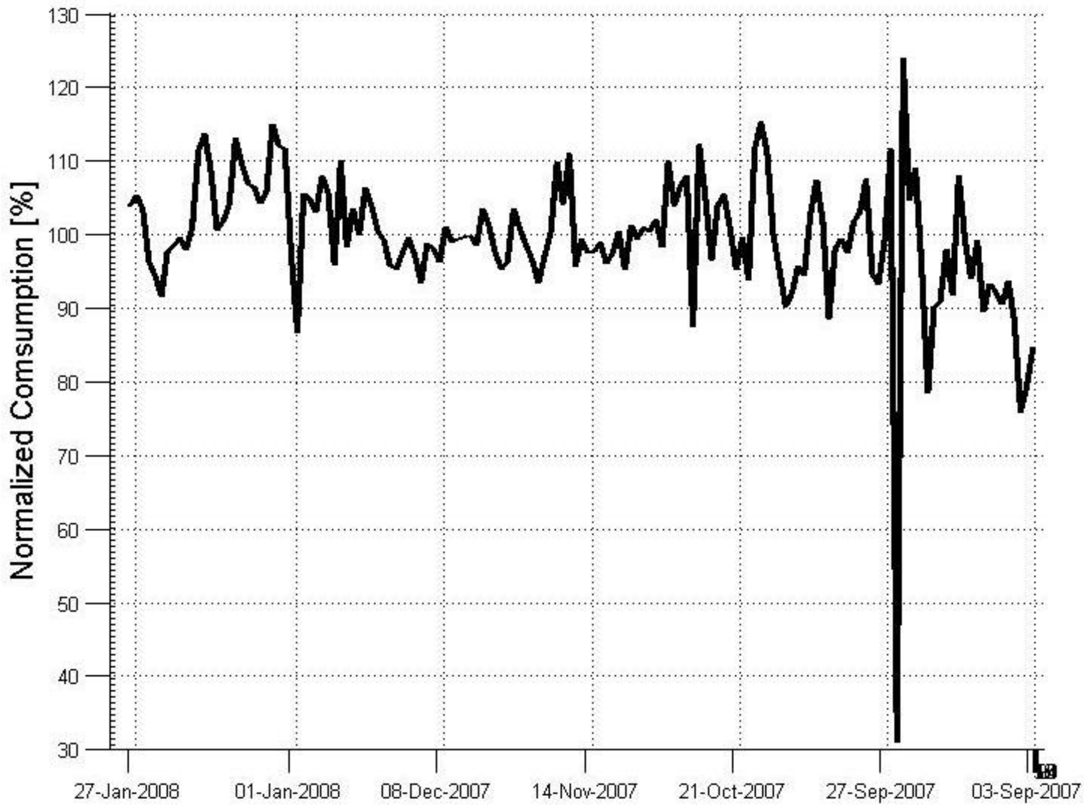

Figure 0.28 Normalized daily heat consumptions between 03.09.2007 and 27.01.2008

Sentral Bygg 2

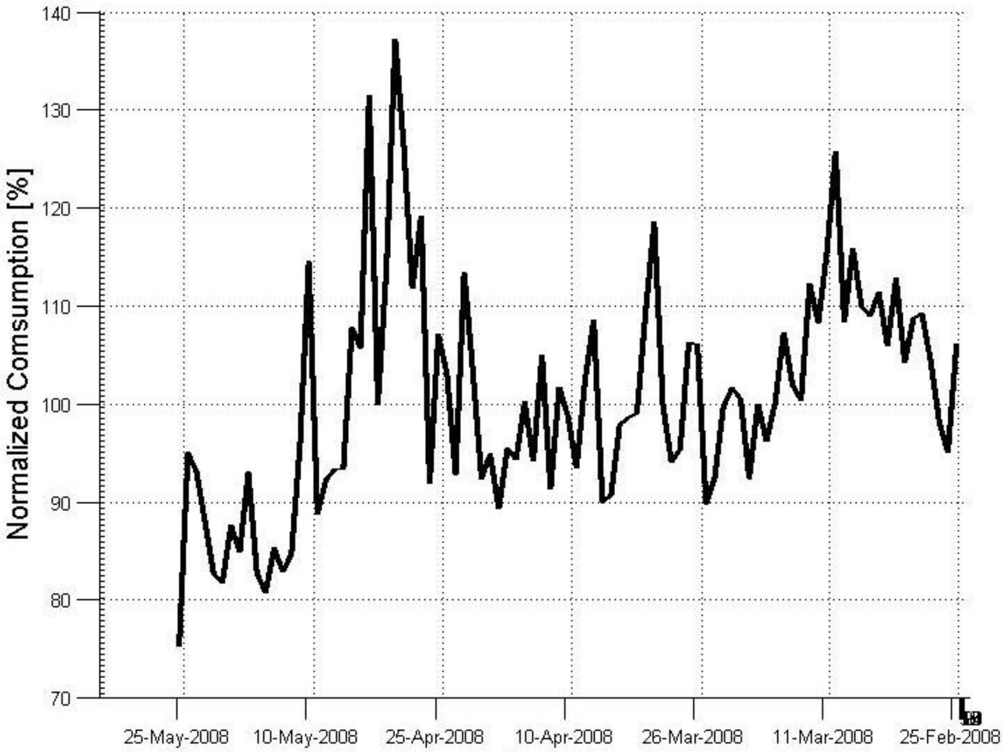

Figure 0.29 Normalized daily heat consumptions between 25.02.2008 and 25.05.2008

Elektro B

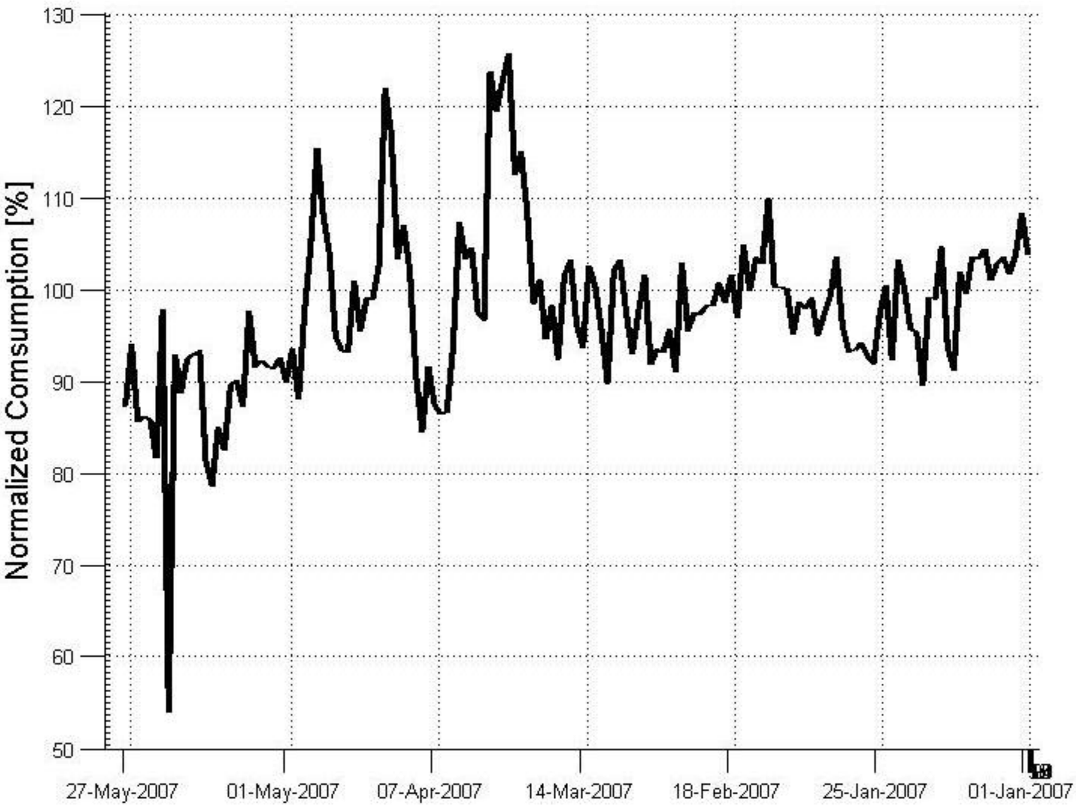

Figure 0.30 Normalized daily heat consumptions between 01.01.2007 and 27.05.2007

Figure 0.31 Normalized daily heat consumptions between 29.01.2007 and 27.05.2007

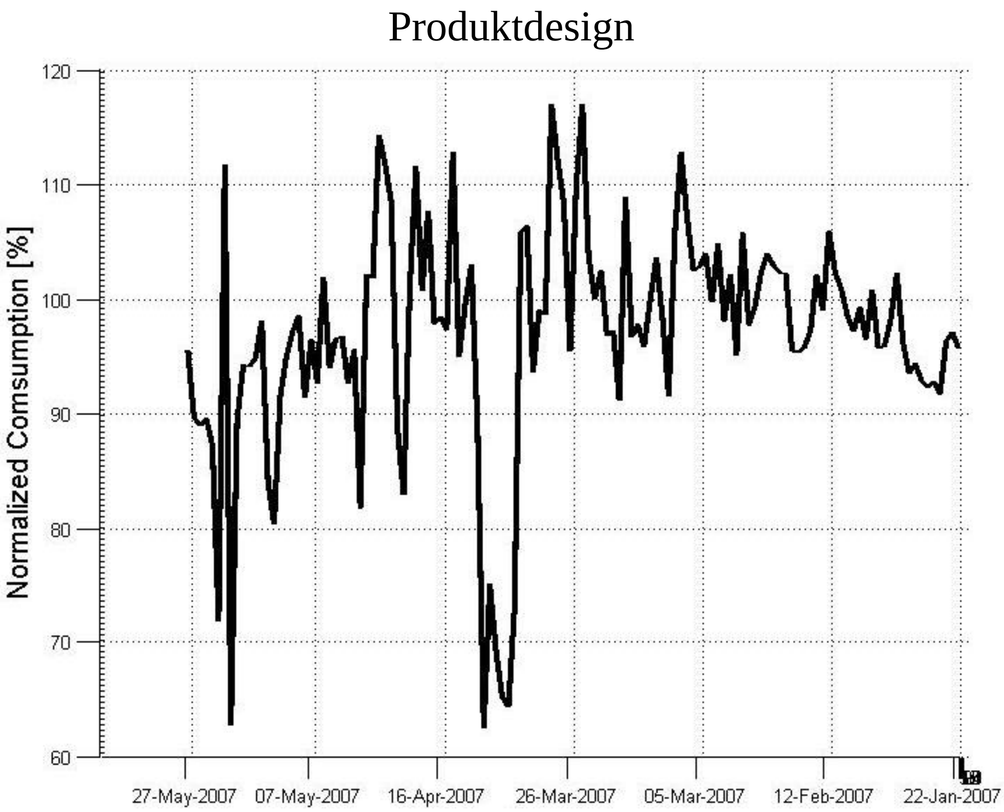

Figure 0.32 Normalized daily heat consumptions between 22.01.2007 and 27.05.2007

Elektro E and F

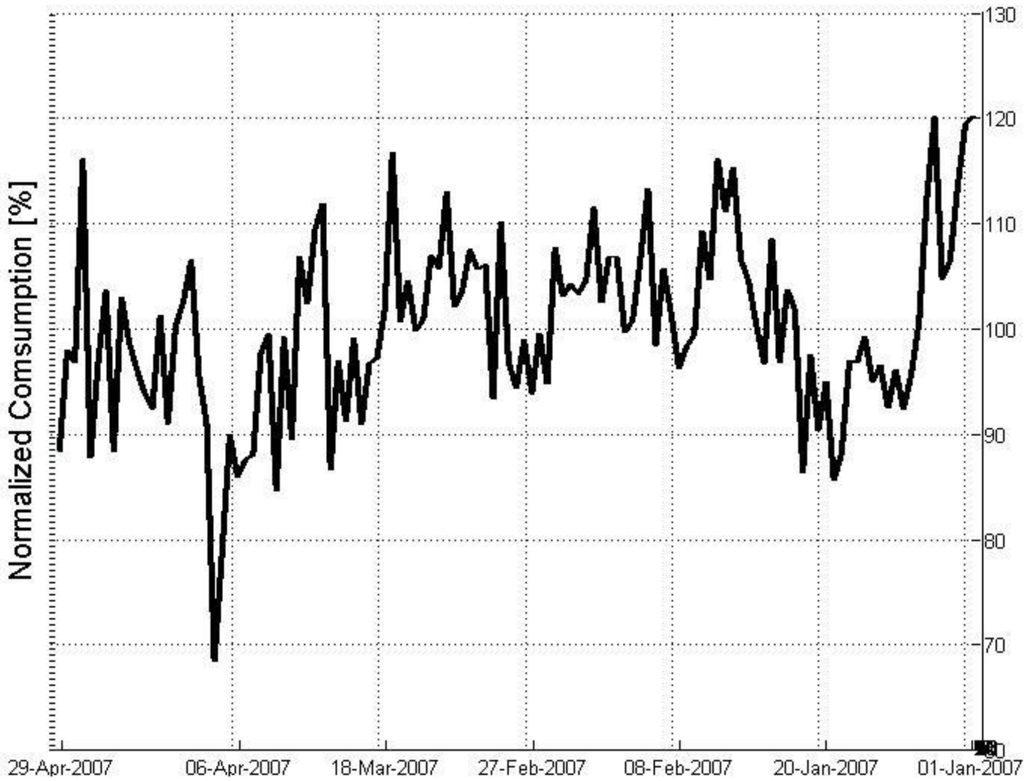

Figure 0.33 Normalized daily heat consumptions between 01.01.2007 and 29.04.2007

Metallurgi

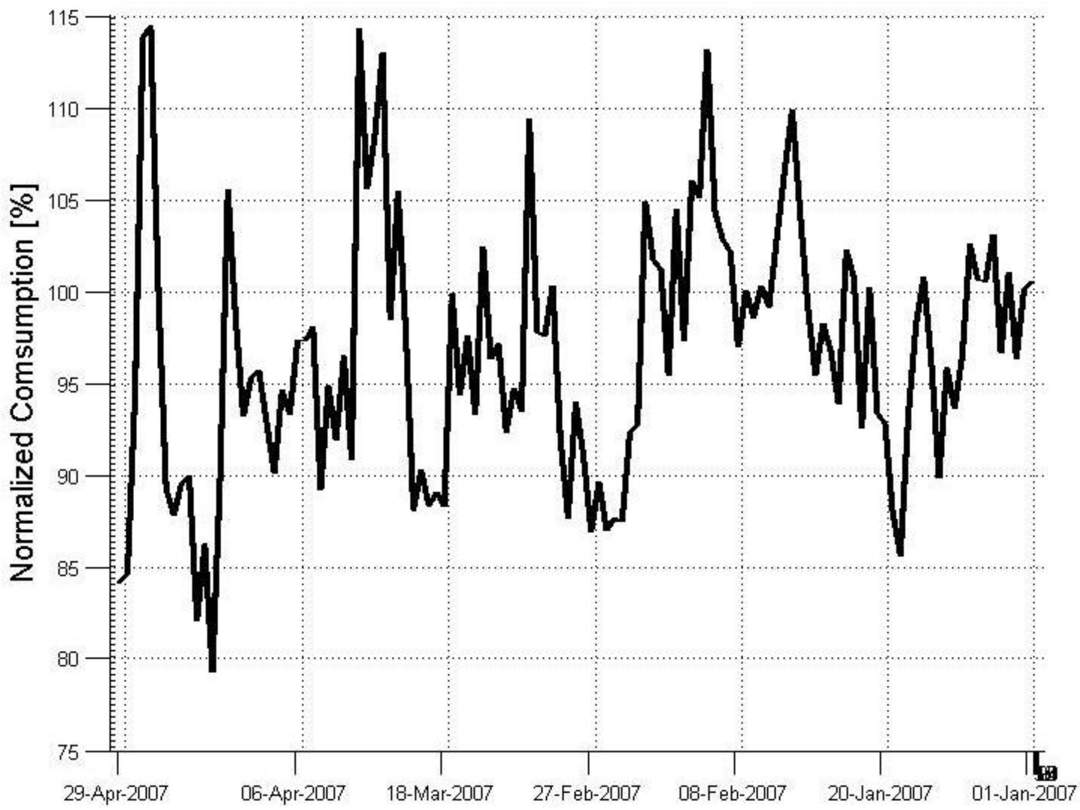

Figure 0.34 Normalized daily heat consumptions between 01.01.2007 and 29.04.2007

Oppredning – gruvedrift

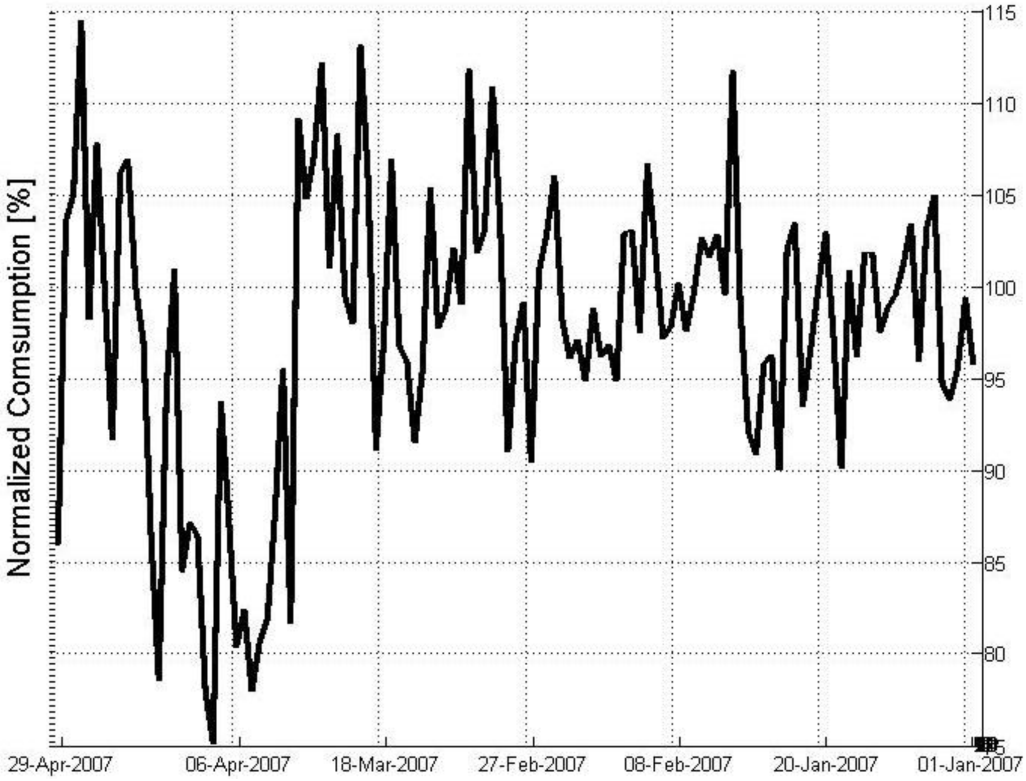

Figure 0.35 Normalized daily heat consumptions between 01.01.2007 and 29.04.2007

PFI

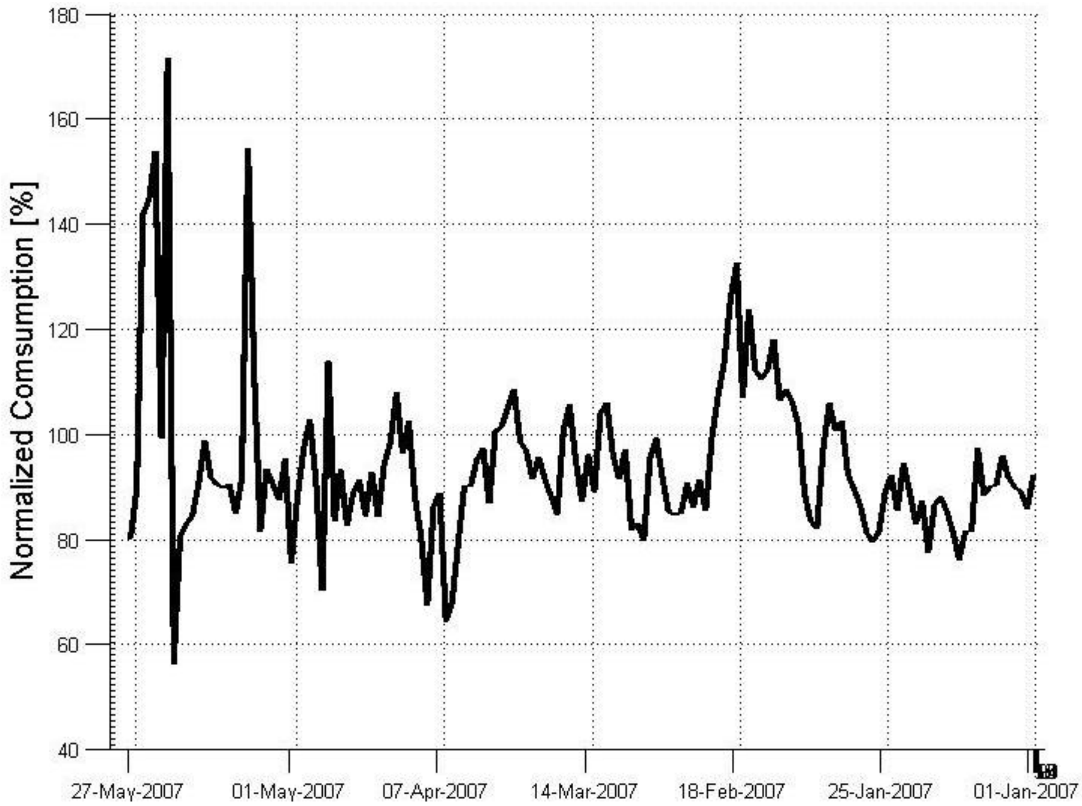

Figure 0.36 Normalized daily heat consumptions between 01.01.2007 and 27.05.2007

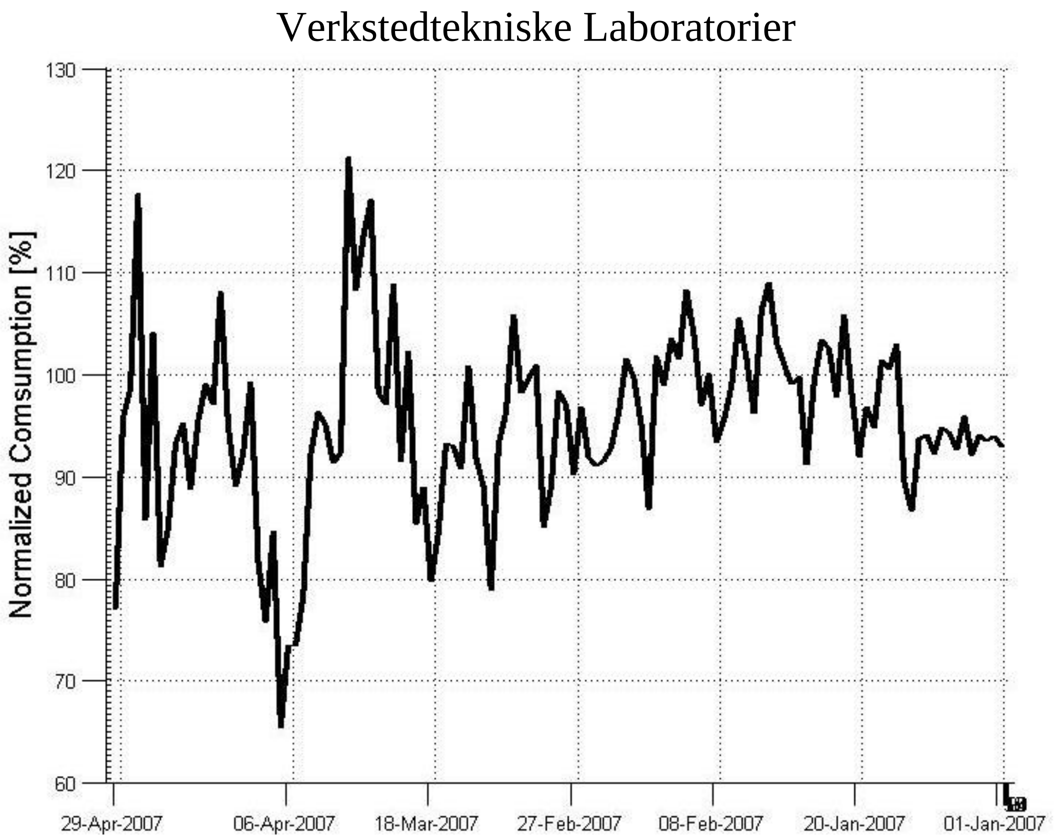

Figure 0.37 Normalized daily heat consumptions between 01.01.2007 and 29.04.2007

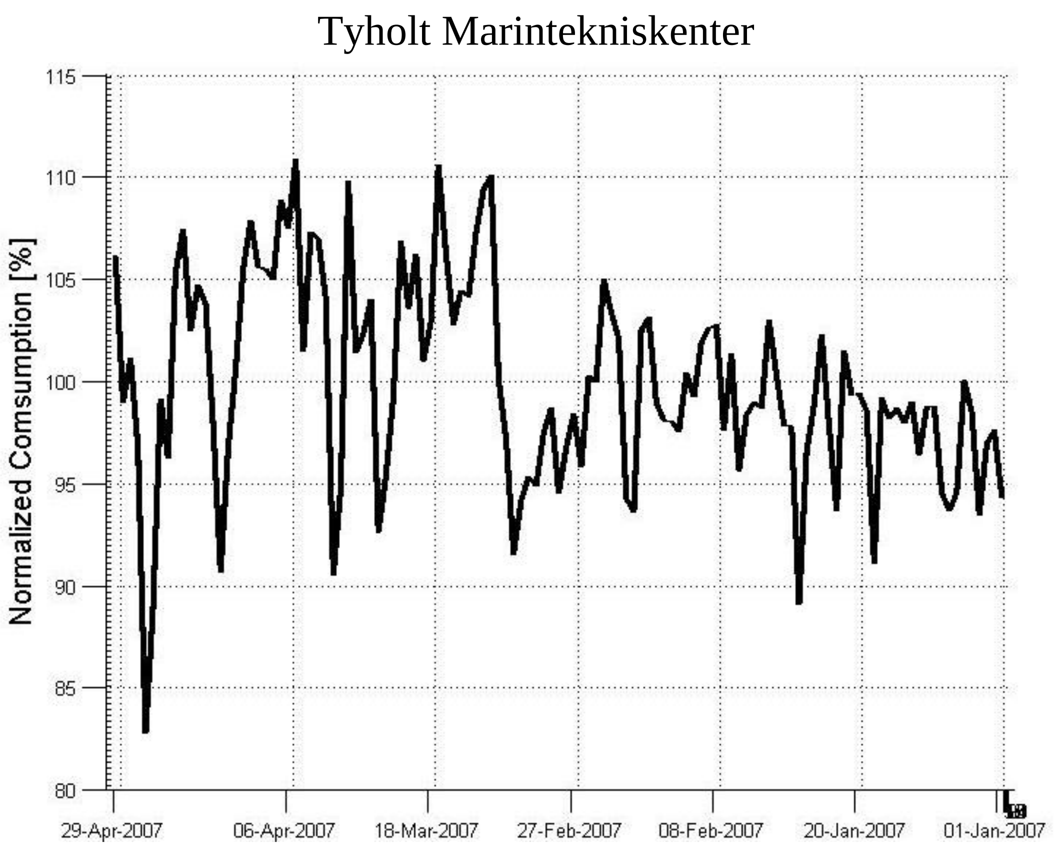

Figure 0.38 Normalized daily heat consumptions between 01.01.2007 and 29.04.2007

Appendix I.2 - Ventilation systems

Dragvoll 3

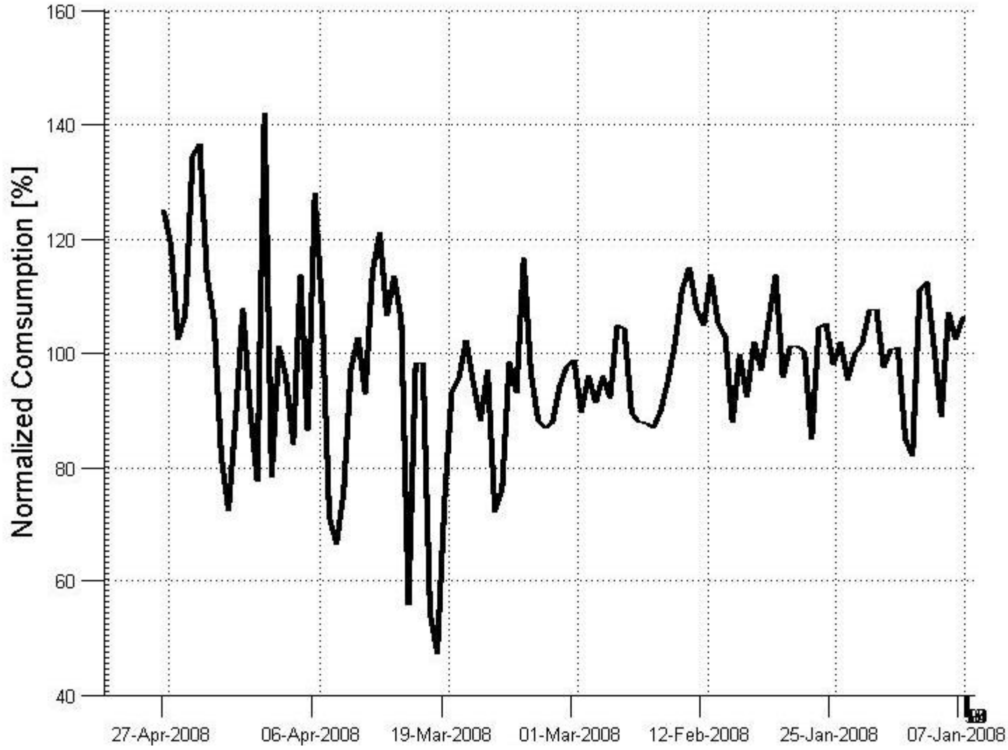

Figure 0.39 Normalized daily heat consumptions between 07.01.2008 and 27.04.2008

Dragvoll 8

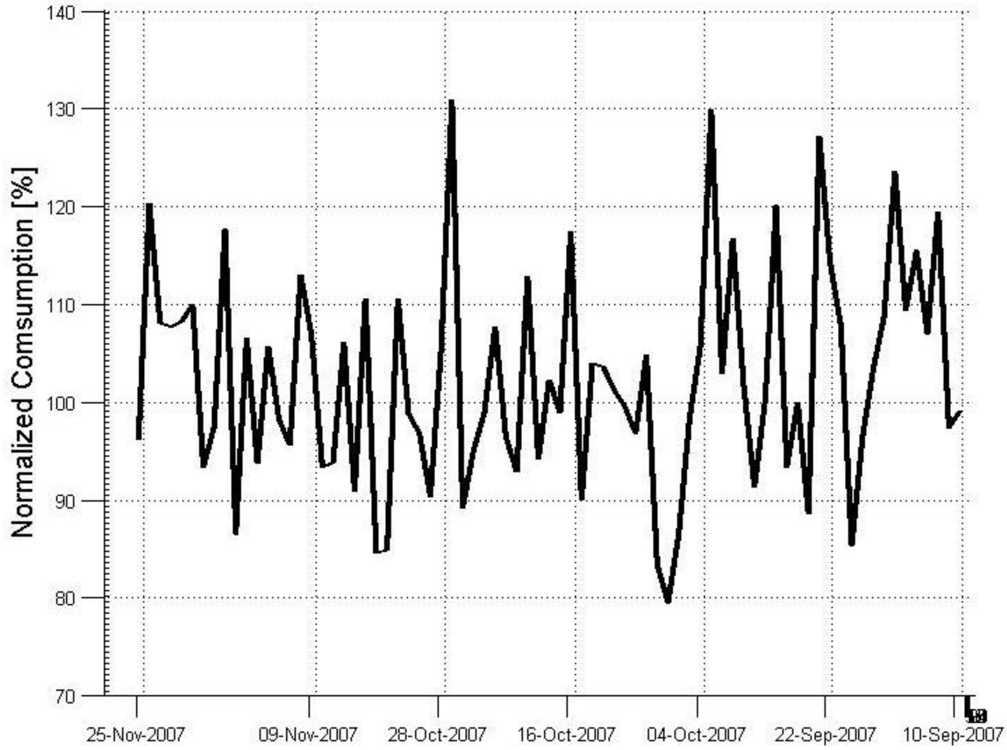

Figure 0.40 Normalized daily heat consumptions between 10.09.2007 and 25.11.2007

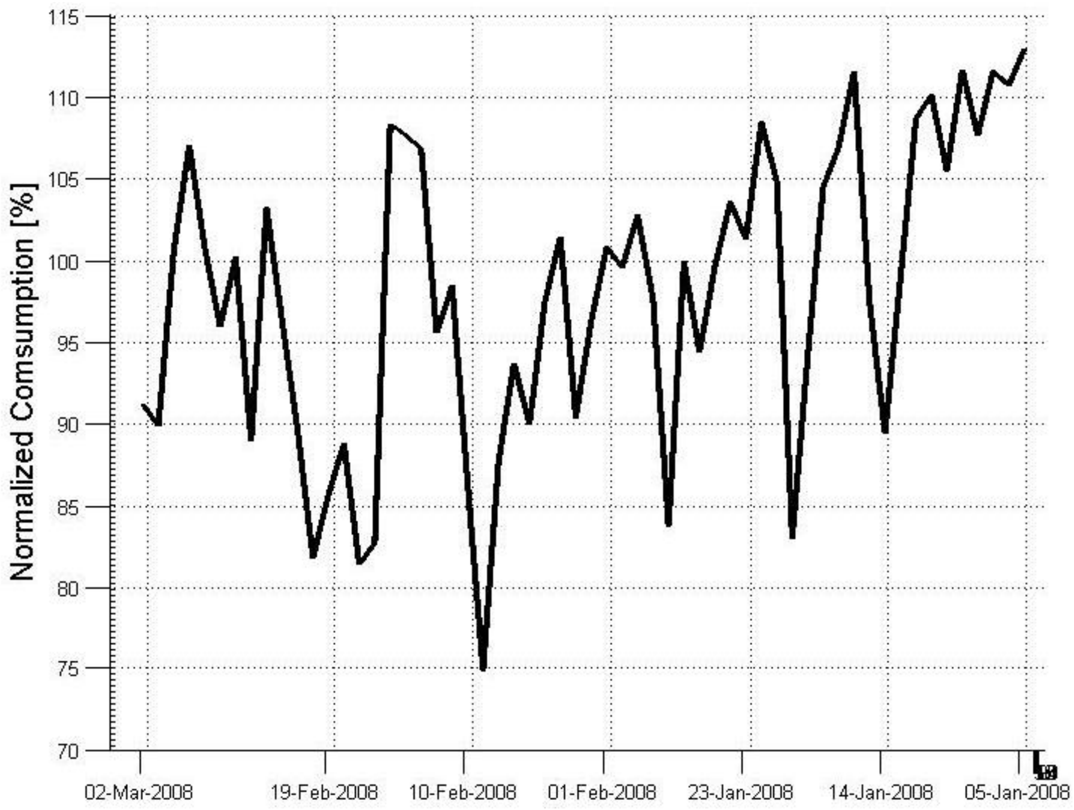

Figure 0.41 Normalized daily heat consumptions between 05.01.2008 and 02.03.2008

Dragvoll Idrettssenteret

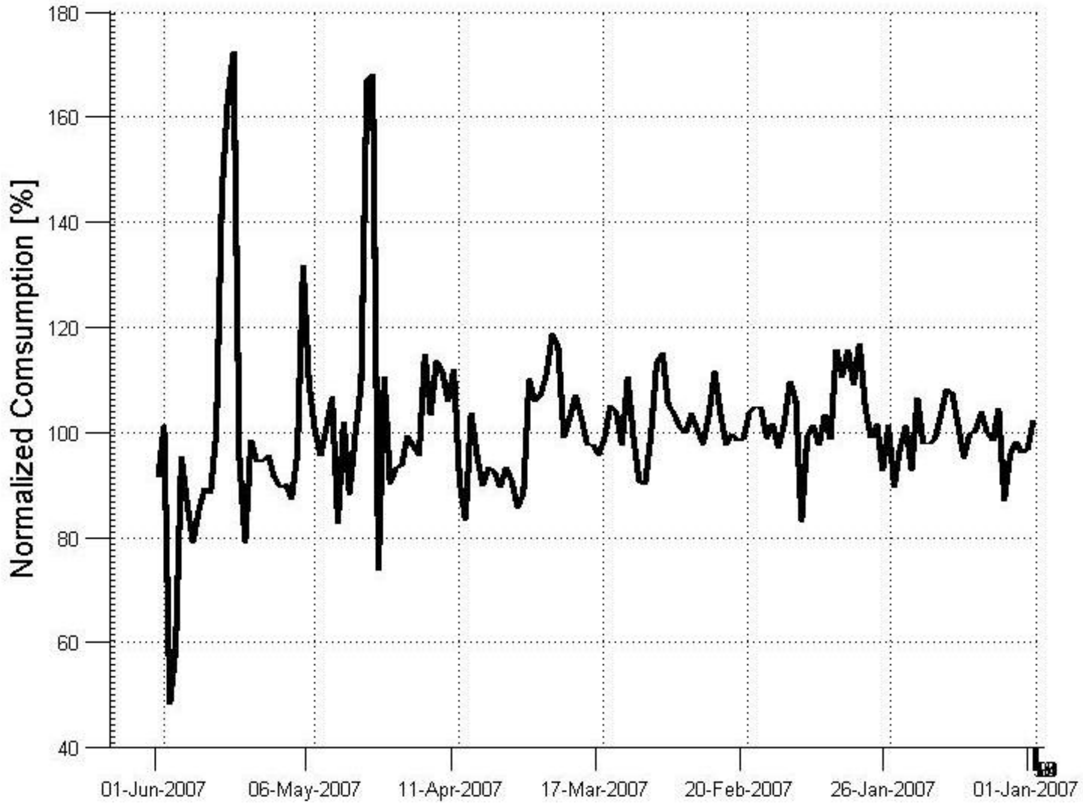

Figure 0.42 Normalized daily heat consumptions between 01.01.2007 and 01.06.2007

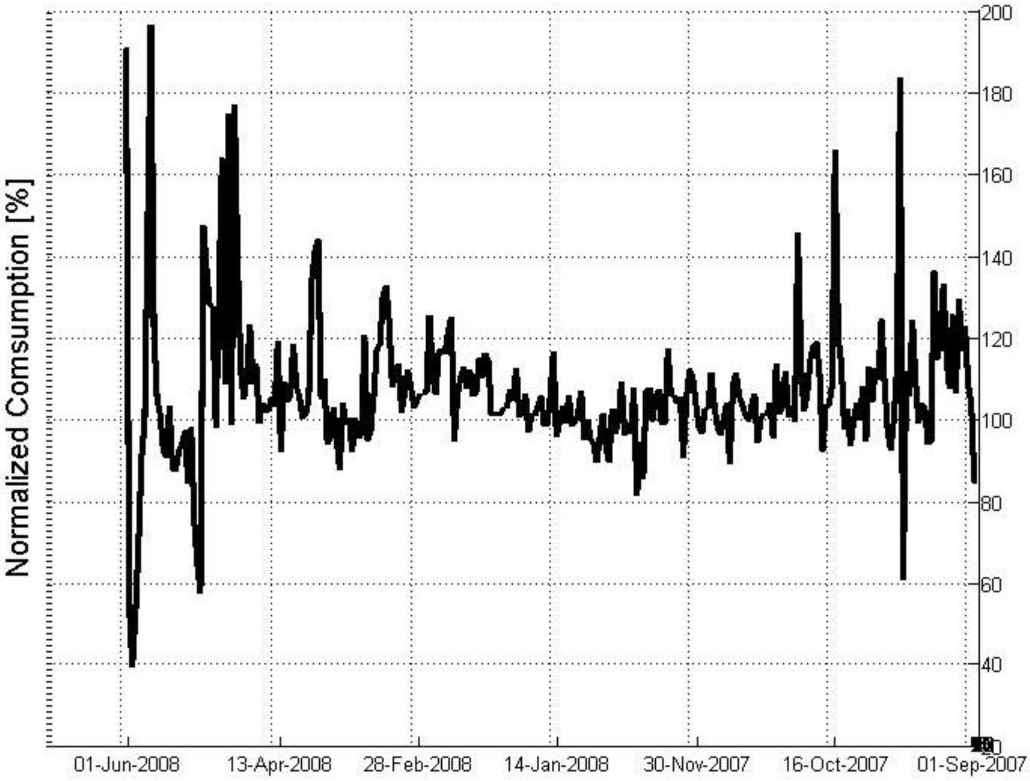

Figure 0.43 Normalized daily heat consumptions between 01.09.2007 and 01.06.2008

Dragvoll 2

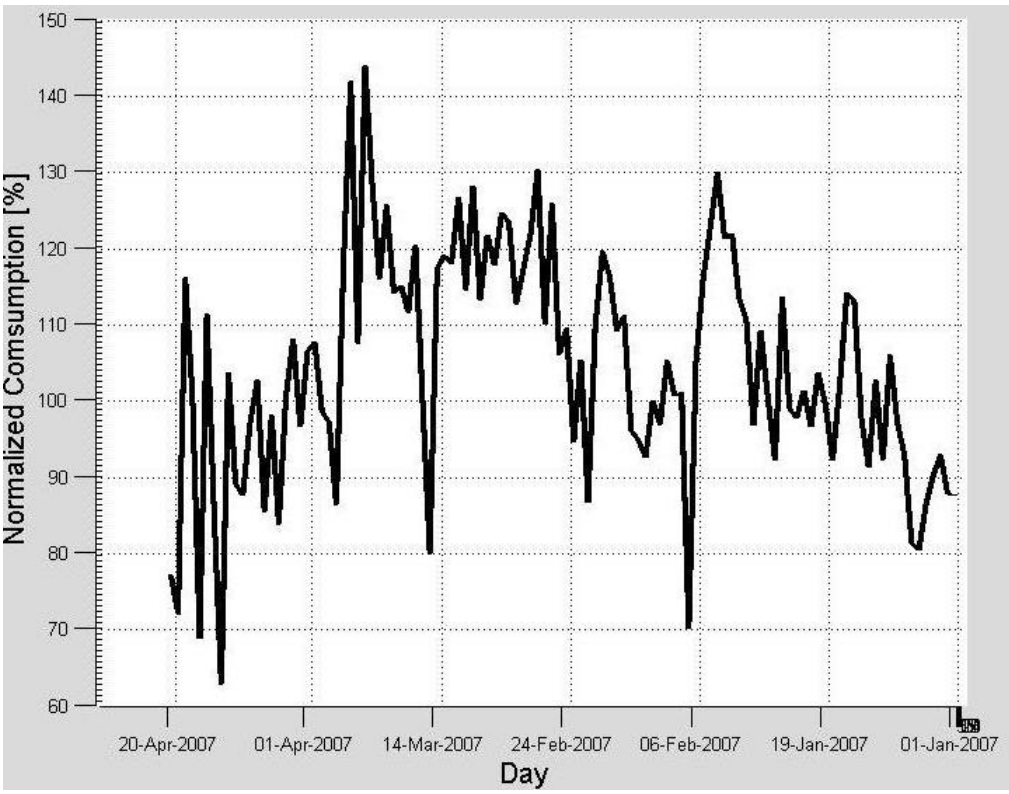

Figure 0.44 Normalized daily heat consumptions between 01.01.2007 and 20.04.2007