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Analysis of energy use at university campus

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Abstract

The study of the building energy demand has become a topic of great importance, because of the significant increase of interest in energy sustainability. University campuses represent specific groups of diverse buildings, with significant energy consumption. They consist of many different buildings, representing small-scale town for itself. Therefore, they provide an excellent testbed to characterize and understand energy consumption of group of „mixed use“ buildings. Suitable building database for University campus NTNU Gloshaugen is created, and available data of heating and electricity energy use are collected and organized.

Having correct and reliable data is essential, so data error analysis using statistical methods is performed. Heating energy use was modeled using Matlab statistical toolbox functions. Creating a model of energy use helps in future building planning; it can provide useful information about most probable energy consumption for similar buildings, or predict energy use in different conditions.

This assignment is realised as a part of the collaborative project “Sustainable Energy and Environment in Western Balkans” that aims to develop and establish five new internationally recognized MSc study programs for the field of “Sustainable Energy and Environment”, one at each of the five collaborating universities in three different WB countries. The project is funded through the Norwegian Programme in Higher Education, Research and Development in the Western Balkans, Programme 3: Energy Sector (HERD Energy) for the period 2011-2013.

1 Aim

The study of the building energy demand has become a topic of great importance, because of the significant increase of interest in energy sustainability, which has grown up after the emanation of the EPB European Directive [1]. According to the circumstances it can be possible to determine the energy performance of a building through a calculation model starting from building known features (forward approach) or to assess the energy use from energy meters (inverse approach).

Aim of this thesis is to analyze energy use at NTNU campus Gloshaugen, using inverse approach - measured data for electricity and heating consumption is used. Collected information of buildings, and electricity and heating consumption is used to create a model. Creating a model of energy use helps in future building planning; it can provide useful information about most probable energy consumption for similar buildings, or predict energy use in different conditions. Also these models can be used to show impacts of possible energy savings measures and help in finding optimal way of reducing energy costs.

It is also very important to have correct and reliable measured data. If a part of a building is leased to other users, there is necessity for calculating bills for each tenant. There is increased interest in data error analysis and developing methods that can point out possible meters malfunction. Also, without correct measured data it is not possible to monitor and prove benefits of applying energy saving measures for increasing energy efficiency.

1.1 Thesis organization

Chapter 2 is Introduction and it contains general information about thesis aim and main reasons for statistical analysis of total energy use in University campuses. Some limitation occurred during this analysis are explained.

In Chapter 3 it is discussed latest scientific research on real energy use in buildings, role of University campuses in sustainable development, and application of different statistical methods. Papers with most significant influence on this thesis are presented.

In Chapter 4 methodology for the thesis is presented. Database, its shapse used for different levels of analysis (individual buildings, large buildings stock or national level) are discussed. Most important statistical methods are presented.

Chapter 5 introduces Case study – NTNU University campus Gloshaugen, with some general description of campus.

In Chapter 6 collected heating and electricity energy use data are discussed. Issues and problems occurring during data collecting are pointed out.

Chapter 7 presents descriptive statistics for University campus NTNU Gloshaugen.

In Chapter 8 Principal component analysis (PCA) method is used to analyze collected data and discuss data errors (measurement faults).

In Chapter 9 Principal Component Analysis method is used to create a model of heating energy use in NTNU campus Gloshaugen.

2 Introduction

The study of the building energy demand has become a topic of great importance, because of the significant increase of interest in energy sustainability, which has grown up after the emanation of the EPB European Directive [1]. Considering constant increase of fuel prices, threats of global warming, implications of carbon emissions from traditional fuels, there is a growing interest in improving energy efficiency. One of the most important elements in ensuring a building's efficiency is energy management and monitoring. Energy monitoring is an energy efficiency technique based on the standard management axiom stating that "you cannot improve what you cannot measure". It implies the necessity of measurements and data organization.

According to the circumstances it can be possible to determine the energy performance of a building through a calculation model starting from building known features (forward approach) or to assess the energy use from energy meters (inverse approach). Scientists and engineers are lately moving from calculating energy demand toward analyzing the real energy consumption of buildings. One of the reasons is that non-calibrated models cannot predict well building energy use, so there is a need for real time image of energy use in buildings (using measured and analyzed data). Development of ICT technologies and improving of measuring and monitoring equipment, made it possible to collect and organize significant amount of data. Some of important questions are to determine which parameters should be monitored, define the optimal number and position of meters, choose suitable frequency of collecting data (annually, monthly, daily, hourly or sub-hourly). It is essential to identify main influencing factors in order to reduce number of monitored parameters. In order to properly analyze energy use of buildings, creating a suitable database is essential.

Energy management is the means to controlling and reducing buildings energy consumption, which enables building owners to:

- **Reduce costs** – this is becoming increasingly important as energy costs rise.
- **Reduce carbon emissions** and the environmental damage that they cause - as well as the cost-related implications of carbon taxes, every organization may be keen to

reduce its carbon footprint to promote a green, sustainable image. Not least because promoting such an image is often good for the bottom line, especially for educational organizations.

- **Reduce risk** – the more energy some building consumes, the greater the risk that energy price increases or supply shortages could seriously affect its functionality. With energy management every organization can reduce this risk by *reducing* demand for energy and by *controlling* it so as to make it more *predictable*.

In order to monitor and control energy consumption, adequate collecting data is primer issue. The old school approach to energy-data collection is to manually read meters once a week or once a month. This is quite a chore, and weekly or monthly data is not nearly as good the data that comes easily and automatically from the modern approach [2].

The modern approach to energy-data collection is to fit interval-metering systems that automatically measure and record energy consumption at short, regular intervals such as every 15-minutes, half-hour or hour.

Detailed interval energy consumption data makes it possible to see patterns of energy waste that it would be impossible to see otherwise. For example, there is simply no way that weekly or monthly meter readings can show how much energy is used at different *hours of the day*, or on different *days of the week*. Therefore more detailed energy use reading makes it much easier to find the routine waste in the building.

It is also very important to have correct and reliable measured data. If a part of a building is leased to other users, there is necessity for calculating energy consumption bills for each tenant. There is increased interest in data error analysis and developing methods that can point out possible meters malfunction. Also, without correct measured data it is not possible to monitor and prove benefits of applying energy saving measures. Creating a model of energy use helps in future building planning, it can provide useful information about most probable energy consumption for similar buildings. Also these models can be used to predict energy use in different conditions, show impacts of possible energy savings measures and help in finding optimal way of reducing energy costs.

2.1 Limitations

Majority of data was in Norwegian language, which required additional time to adequately translate and understand provided data. Also, for same buildings, there are different values found in various sources (significant differences in area and year of construction for some buildings). Data for some buildings could not be found.

One of the biggest issues in gathering energy use data was defining positions of meters, and their „leveling“ (is the meter responsible for part of building, one building, or group of connected buildings).

3 Background

3.1 University campuses and their role in sustainable development

University campuses are specific groups of diverse buildings, with significant energy consumption. They consist of many different buildings, with variety of use (offices, laboratories, classrooms etc.), representing small-scale town for itself. Therefore, they provide an excellent testbed to characterize and understand energy consumption of group of „mixed use“ buildings.

The specific importance of universities in promoting sustainable development has been highlighted in a number of significant declarations, including the Talloires Declaration (1990), the Halifax Declaration (1991), the Swansea Declaration (1993), the Kyoto Declaration (1993), the Copernicus Charter (1993) and Students for a Sustainable Future (1995) (IISD, 2002) [3]. At the policy level, a growing number of environmental, sustainable development and related policies have been promulgated by universities in many parts of the world (Keniry, 1995, Springett, 1995 and IISD, 2002). Policy content typically addresses both academic programs, for example the promotion of environmental courses plus the integration of environmental concepts into the wider curriculum and the practical, day to day, operational activities of the university as a community [4]. As institutions for research, teaching and policy development, with their influence and resources, universities and colleges play important role in promoting sustainable development [5]. The potential of educational institutions for contributions within this area, is now being recognised by various quarters, such as the United Nations, the European Union, Government policies, agreements, and numerous research reports.

In a time faced with increasing environmental challenges, the tertiary sector is being recognized as well suited to take on the leadership for environmental protection [5]. By greening their own campuses, higher educational (HE) institutions can teach and demonstrate the principles of awareness and stewardship of the natural world, as well as increasing the chances of clean and pleasant local and global environments for the future [6].

However, as the ‘greening of higher educational institutions’ is a complex and relatively new field of research, further studies are needed to analyze energy use in University campuses, and thereby help HE institutions realize that ‘going green’ has numerous advantages. Leal Filho [7] suggests ‘going into the specifics’, i.e. dealing with specific issues and themes such as energy use and waste management, as one possible way of addressing the task of transforming colleges and universities into green institutions. As Leal Filho [7] indicates, ‘such contexts have clear approaches and clear outcomes’.

As many of the people whose decisions will affect the future attend colleges and universities today, HE institutions have the potential of teaching environmental literacy to the politicians, teachers, and decision-makers of tomorrow [8]. Both in the classroom and by the example of its physical plant, a university can give students an understanding of the interrelationship between business decisions and the natural environment [6]. A green university can furthermore become a green model for the external community by gathering and sharing effective ideas on environmental issues and practices.

The greening of a college or university can also be cost effective. Eagan and Keniry [8], show that revenues and savings for 23 campus conservation projects in the USA came to more than $ 16 million in just one year. The possibilities of saving costs on campus greening has also been exemplified by the “50-50” pilot project, now widely spread in Germany [7]. Knowing that „you cannot improve what you cannot measure”, first step in “greening” campuses would be to analyze current energy use.

3.2 Large building stock

Considering that university campuses represent specific group of diverse buildings, recent research of large building stock is studied. As there is increase interest in this field of study, it was essential to gather and analyze results and conclusions made by scientists. Authors came to conclusions that can be applied for university campuses, or give an idea for similar analysis. S. P. Corgnati et al. [9] introduced energy index, that can be used for energy analysis and prediction of energy use. Chen, S., et al. [10] pointed out the importance of breakdown of energy use, and proposed a way of solving issues in lack of data or submeters for end users. It showed that other scientists and engineers also have some similar issues with missing or faulty data, and that it is important topic of research, which should be explored.

Statistical analysis of a large stock of buildings represent methods used to estimate the energy consumption and/or the peak demand of a building at a level of detail that is suited to apply to a number of buildings that is statistical significant (usually more than tens of buildings).

S. P. Corgnati et al. [9] carried out a filed survey in order to collect, elaborate and analyze data concerning the actual energy consumption for space heating of a sample of about 140 buildings (120 high schools) in the Province of Torino (Italy). Collected data for energy consumption were normalized and statistically analyzed in order to compare different buildings and different heating seasons.

A form was set up for the collection of the building data and of the amounts of energy consumption, and it is divided into three main sections:

- General data (which include identifying data, climatic data and the main features of the building)
- Monthly energy data (includes table of conventional quantities, measured quantities and corrected conventional quantities)
- A diagram comparing predicted and measured specific heat supply

With the purpose to have significant statistical data, climatic, users and energy data were collected for a period of at least three heating seasons and on a monthly basis.

In order to make data uniform and comparable, they introduced an energy index, derived from the collected data and named it *conventional specific energy supply for space heating* (QPs,c).

In order to characterize the building stock in terms of energy consumption, for the last three heating seasons, the following data were collected:

- seasonal and monthly billed fuel consumption for space heating;
- seasonal and monthly supplied thermal energy for space heating;
- seasonal and monthly operating periods of the heating plant.

Moreover, the seasonal and monthly actual degree-days of the analyzed sites were also evaluated. A preliminary analysis of the data was carried out, aimed at highlighting the main correlations among the data and the statistical values of the sample.

The results showed good correlation line between the annual billed fuel consumption and the gross heated volume. Also, the linear correlation between average monthly specific billed fuel consumption and monthly degree-day was verified.

One of their conclusions is that actions aimed at reducing the energy consumptions of the sample should be addressed firstly to few buildings with large volumes to have an immediate impact on the consumption decreasing.

A good agreement is shown between annual measured heat supply and assessed values for heat supply, for school buildings. On the contrary, the monthly heat supply data point out a strong discrepancy between measured and calculated energy use. This result can be explained by the uncertainty of monitoring periods, i.e. the meters can be read non-exactly at the end of each month.

Their methodology showed suitable for long period assessment and prediction of energy demand on large building stocks, rather than on a single building.

3.3 Regional/national level

Aim of this thesis is to analyze energy use of University campus, which represents group of buildings. If the need and benefits of statistical analysis are shown on example of group of buildings, the idea of expanding analysis to regional and national level can be promoted. It is useful to support energy planning and strategic energy policies in the middle and long term.

Chen, S., et al. [10] pointed out the need to establish a national statistical system of energy consumption in the residential building sector in China, so as to look into the actuality of residential energy consumption, and to provide sufficient data and energy efficiency countermeasures for building energy efficiency work in China. Different countries have different characteristics of energy consumption and influence mechanisms, so the statistical methods in different countries must suit the actual conditions of their own countries.

A statistical index system of residential energy consumption should not only reflect the actuality and specialty of residential energy consumption, but also incarnate the influencing factors. Monthly and annual consumption of various energy sources should be recorded in order to master residential energy consumption structures. Meanwhile, different end-use categories, such as space heating, air-conditioning, and lighting should also be recorded, to analyze their energy-saving potentials. Secondly, the thermodynamic property of enclosures directly affects the consumption of space heating and air conditioning, so the index system must cover housing unit characteristics. Finally, as performances and running schedules of energy consuming equipment are also the main ingredients affecting energy consumption, it should also be an important part of the index system.

They developed specific index system that consists of five kinds of indices:

- housing units characteristics (architecture structures, floor areas, characteristics of enclosures)
- household characteristics (age and vacation of members, domestic annual income)
- possession of energy consuming equipment in households (air-conditioning, space heating, cooking and water heating, lighting, domestic electrical appliances)
- running schedule of energy consuming equipment
- monthly and annual energy consumption of various energy sources consumed by different kinds of equipment

The analysis of real time measurement in a representative household reflect that energy consumption is closely related to the living schedules of households and the performance parameters of energy consuming equipment, and hence it proves that it is scientific to set down these indices to record performances of domestic appliances and their running schedules in the statistical index system.

One of main questions in energy analysis is the breakdown of end users. If there are submeters for each system or user installed, it is not a problem. But often, there are not enough submeters installed. It was important to study how have the scientists tried to resolve those issues.

The major difficulties in establishing the breakdown of different end users are the lack of energy sub-meters of individual appliances in households. To overcome this, authors tried to estimate energy use amount of each end user [10]. All of the end-use consumption can be divided into two categories. The first category is defined as the non-weather related energy use. Typical examples are artificial lighting, domestic electrical equipment, and cooking and water heating. The second category is the weather related energy use, namely space heating and cooling use. Assuming that other than space heating and cooling use, the monthly electricity use of all other electrical appliances would be uniform throughout the year, the annual electricity use for space heating and cooling can be estimated from the difference between the annual actual household electricity use and the annual electricity use if the monthly electricity use throughout the year would stay steady at the average level over the spring and autumn months. Unfortunately real time measurements showed that it is a very rough assumption that cooking and water heating are considered as the non-weather related energy. These results also pointed out necessity for real time measurements, with more installed submeters (even for simple household), because it is very hard to accurately predict breakdown of different energy sources and systems [10].

In [11] Caldera et al, it is presented methodology that can be applied to find out simplified correlations, which can be used for the assessment of the energy demand for space heating of the whole investigated population of buildings characterized by the same weather condition. A representative sample of 50 multy-family residential building was extracted from the investigated population of buildings, and the detailed calculations, aimed at finding the numerical value of the coefficients included in the correlations, was developed only on selected the sample of building. The methodology can represent a very useful tool to easily assess the energy performance for space heating of wide real estates.

The resulting analytical formulas defined the relationship between the energy performance of a building and its geometrical and thermal properties. Analysis also considered the age of the buildings.

The comparison between the calculated energy demand for space heating and the metered actual consumption is of great interest: it lets to value how much the occupants move away from standard conditions, in order to find measures for energy savings. On the other hand, it is important to verify how the modeled energy demand represents actual consumption.

To validate the model, the proposed correlations were compared to Standard deterministic equations, and correlation was very good (R^2>0,.99). The correlations that the authors found determine in a direct, easy and fast way the energy demand parameter, which otherwise would require an involved procedure, if calculated according to the Standards procedures.

4 Methodology

4.1 Energy data analysis

Effective data analysis is essential but is often not given appropriate priority. In fact, poor analysis of data can destroy the operation of an Energy Management System (EMS) and result in misleading messages. Energy data includes not only energy usage but key influencing factors as well. Data must be collected at an adequately high frequency.

The objectives of data analysis are to better understand energy use and costs and to model energy use. A range of techniques can be utilized, from simple to complex. These should be selected to suit the problems being addressed (rather than selecting an analysis technology and then finding a problem to suit).

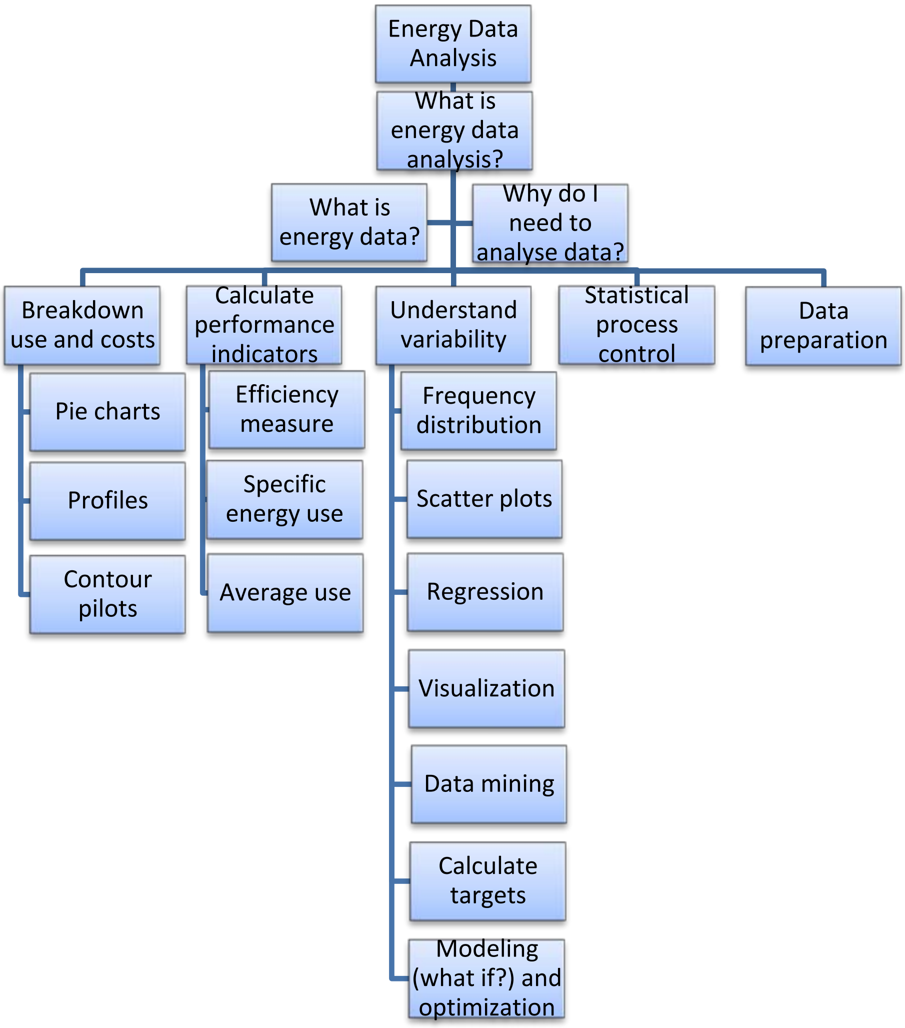

Figure 1. Block diagram showing elements of energy data analysis [12]

Figure 1 shows basic elements of energy data analysis. It can provide some guidance to energy analysis, giving main questions that researcher should ask, and steps to follow at the beginning of research. After that, data needed for energy use analysis should be adequately collected.

4.2 Collecting data

The old school approach to energy-data collection is to manually read meters once a week or once a month. This is quite a chore, and weekly or monthly data is not nearly as good the data that comes easily and automatically from the modern approach [2].

The modern approach to energy-data collection is to fit interval-metering systems that automatically measure and record energy consumption at short, regular intervals such as every 15-minutes, half-hour or hour.

Detailed interval energy consumption data makes it possible to see patterns of energy waste that it would be impossible to see otherwise. For example, there is no way that weekly or monthly meter readings can show how much energy is used at different *hours of the day*, or on different *days of the week*. And seeing these patterns makes it much easier to find the routine waste in the building. Interval of collecting energy use data and number of information depend on analyzed object.

When the study focuses on very large building stocks, useful analyses can be performed even if few information for each single building is available (annual energy consumption and some influencing parameters) but for a wide number of buildings; when the study focuses on individual buildings, the number of required information increases, at least because the data about energy consumptions (and the corresponding influencing factors) have to be collected at monthly level.

4.3 Building database

Database has the key role in applying „data driven“ approach of energy use analysis. Shape of the database, characteristics, its organization and required number of information depend primarily on the goal and the subject of the analysis. Subject of statistical investigation can be divided in three main categories [13]:

- Individual buildings

- Large building stocks
- Regional/national level analysis

Aim of this chapter is to provide information about possible shapes and organization of database, based on various authors` experience, which can be applied for University campus Gloshaugen. Depending on the aim of the analysis, there are different approaches.

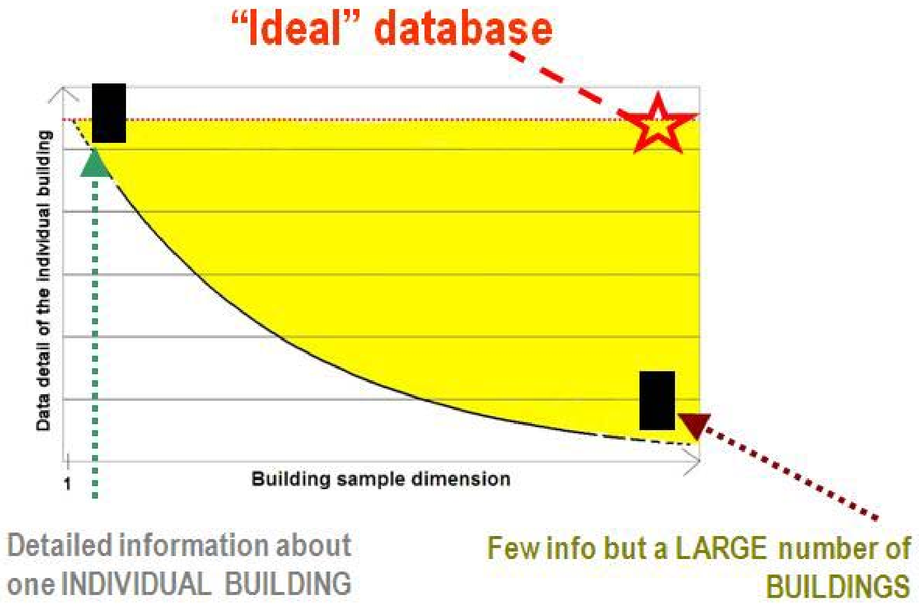

Figure 2. Diagram of databases information according to building sample dimension

If the goal is to analyze energy consumption for individual building, its behavior in several years, diagnosing some of installed systems, or planning of energy saving measure, then larger number of data is required (Figure 2). For such detailed energy diagnosis, gathering detailed building characteristics (high number of parameters). Also, collecting data for energy consumption and weather conditions on hourly or even sub-hourly level is requested.

Moving to large building stock, first goal is to have group of homogenous buildings, and to find out target values and main influencing factors. It is usually enough to collect data on monthly or annual level. It leads to idea of making statistical analysis to provide useful information for energy planning on national level. If analysis is performed at national level, a lots of building are used, but described by few parameters available (few information). This master thesis analyze group of buildings, but there is an idea to promote need for creating databases that could be expanded to national level.

4.4 Statistical analysis

With development of ICT technologies, it is now possible to gather and analyze significant amount of data, so there is increased interest in statistical analysis of energy use data (on annual, monthly, daily and hourly level).

Statistical analysis has many applications. Statistics can be used to describe the object of a study (individual building or larger stock), providing clear description of real energy use - descriptive statistics. Use of statistical parameters (mean value, standard deviation, etc) can help in getting useful information and create real-time image on building energy consumption. Then, using suitable database, it is possible to find relationship between targets (energy use – for example heating and electricity) and variables (most influencing factors). After that, mathematical model can be created, in order to predict energy use in different conditions (weather, operating schedules, etc.).

4.4.1 Descriptive statistics

Descriptive statistics provide summaries about the data samples and about the observations that have been made. Such summaries may be either quantitative (summary statistics), or visual (simple graphs).

The methods used in the energy consumption analysis for description are Descriptive Statistics and Exploratory Data Analysis. The Exploratory Data Analysis is an approach for data analysis that uses many techniques, mostly graphical, to provide insight in the data set, determine structure, distribution, extract most influencing factors and detect anomalies [14].

A **scatter plot** is a simple plot of one variable against another. It reveals relationship or association between two variables [15]. Such relationships manifest themselves by any non-random structure in the plot. It can be used for primer analysis of collected energy data [14].

When conducting a statistical study, the researcher must gather data for the particular variable under study. To describe situations, draw conclusions, or make inferences about events, the researcher must organize the data in some meaningful way. The most convenient method of organizing data is to construct a frequency distribution. After organizing the data, the researcher must present them so they can be understood by those who will benefit from reading the study. The most useful method of presenting the data is by constructing statistical charts and graphs.

A **frequency distribution** is a tool for organizing data. It is used to group data into categories and show the number of observations in each category. A frequency distribution is a graphical representation of how often something occurs. It is a way of organizing data so it can be easily understood and used [16]. A **cumulative frequency distribution** is a way to list how many values fit into the first class of data, the first 2 classes, the first 3 classes, etc., or the last class, the last 2 classes, etc.

The Standard Deviation (SD) of a data set is a measure of how spread out the data is.

Energy profiles show how much energy is being used at particular time-of-the-day and day-of-the-week. It can be useful also for finding energy waste. The patterns (or profiles) of energy usage contained within interval energy data are great for discovering where a building is wasting energy. If the profiles show energy being used on times or days when energy manager is not aware of a good reason for energy to be used, that is an indication that energy is possibly being wasted, and there is something that should be investigated.

a) Individual buildings

For analysis of individual buildings normally a large amount of information is collected, comprising detailed building characteristics, climatic data, energy uses and frequent timely energy consumption data with frequency ranging from several minutes to daily or monthly data. The objective of the studies usually is to analyze the energy consumption, to find the main influence factors in order to act over them and achieve energy savings. Another purpose of the analysis may be to model the building and to compare the expected with the observed behavior for detecting operational faults or predict savings. The data set should be reduced to some representative parameters in order to obtain conclusions.

When the energy consumption of individual building is studied, it is expected to provide some of these informations: a breakdown of the energy consumption by uses (heating, lighting, HVAC systems, etc), by energy sources, by periods of use (occupied/unoccupied), consumption normalized by number of users, volume, area, etc. Simple charts like pie charts or box plots can be used for visualization of preliminary analysis. **Frequency distributions** or **histograms** are used for estimation of the probability distribution of parameters (outside temperature, specific consumption, etc). **Scatter plots** show liner or nonlinear relation between parameters in datasets.

b) Building stocks

The objective of the analysis of large stocks of buildings is to discover common characteristics of building typologies and the main factors influencing their energy consumption. The available data is normally more reduced and with lower time frequency compared to individual buildings, but is available for large number of buildings of similar characteristics. The results of the studies are usually used for developing of design guides or recommendations and best practices aiming the reduction of the energy consumption in new or existing buildings. Therefore, the descriptive statistics are used for summarizing the data set parameters and properties like the range and the distribution within the data set. This permits to distinguish the most important variables and members of the set and to prioritize the measures.

Energy consumption parameters for large building stocks may be similar to those for individual buildings, but in that case the quantitative statistics for description are these characterizing the interval and the distribution: the mean, standard deviation, minimum and maximum values. Histograms and cumulative frequency distributions are used to plot or estimate the probability density of the variables of interest.

c) Regional/national level

The regional/national analyses of building energy consumption have principally the objective to support energy planning and strategic energy policies in the middle and long term. In order to perform the analyses the energy consumption should be structured and studied by building typologies, purpose of use and energy types.

4.4.2 Statistical analysis for energy use prediction and identification of the prediction model parameters

The classic approach to evaluate the building`s energy use is based on the application of a model with known system structure and proprieties as well as forcing variables (forward approach). This model can be more or less complex depending on the requested result accuracy and output time step. The forward approach requires a detailed knowledge of the physical phenomena (and their relative magnitude and interactions) affecting the system behavior, and the building system operating mode. ESP-r, BLAST, DOE-2 and Energy Plus are the most widespread simulation codes based on forward simulation models.

A different approach for building energy analysis is based on the so called inverse or **data-driven** models. In recent years, considerable attention has been given to data-driven based methods [17]. By a data driven approach (inverse modeling) an empirical analysis is carried out on the building energy behavior, and its relationship to one or more driving forces or parameters. To develop an inverse model, it is necessary to carry out a mathematical description of the building or system, and then identify the parameters of interest using statistical analyses. The input and output variables are known and measured, and the goal is to determine a mathematical description of the relationship between the independent variables and the dependent one. In contrast to the forward approach, the data-driven approach is useful when the "system" has been built (that is, the "system" exists and works) and actual performance data are available for model development and/or identification. The model parameters are evaluated from actual building performance and working conditions, so the data driven model is fine for the evaluation of as-built system performance, allowing more accurate prediction of future system under specific real boundary conditions.

The definition of the building energy analysis purposes is the fundamental step for the selection of the appropriate model approach. The approach must be able to match the analysis requirements with sufficient accuracy. The requirements of building energy analysis may include design optimization, energy audit, energy certification and so on. As mentioned, the different methods can be grouped into two main families, according to the goal of the analysis.

Forward approach: it is the classical presentation of any physical phenomena;. it starts with the definition of the energy model, then the collection of input variables and finally the simulation run to evaluate the output.

Data driven approach: it may be described as a bottom approach as it starts with the measure of the force driven variables and of the output variables then the evaluation of some building features called "system parameter" and the construction of the data driven model that will be used to assess the output for another set of force driven variables.

4.5 Principal Component Analysis – PCA

. Principal Component Analysis (PCA) [18] is a multivariate technique in which a number of related variables are transformed to a smaller set of uncorrelated variables.

$$PC_p = a_0 + a_{i1}X_1 + a_{i2}X_2 + \ldots a_{in}X_n \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\mathbf{(1)}$$

where PC is Principal Component.

The method of Principal Components is primarily a data-analytic technique that obtains linear transformations of a group of correlated variables such that the transformed variables are uncorrelated. It is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. PCA main use is as a descriptive technique, but it has numerous other applications, such as including missing data, data editing, discriminant and cluster analysis, analysis of variance, etc. Data are compressed by reducing the number of dimensions, without much loss of information [19].

Given a table of two or more variables, PCA generates a new table with the same number of variables, called the *principal components*. Each principal component is a linear transformation of the entire original data set. The coefficients of the principal components are calculated so that the first principal component contains the maximum variance (which we may tentatively think of as the "maximum information"). The second principal component is calculated to have the second most variance, and, importantly, is uncorrelated (in a linear sense) with the first principal component. Further principal components, if there are any, exhibit decreasing variance and are uncorrelated with all other principal components.

PCA is completely reversible (the original data may be recovered exactly from the principal components), making it a versatile tool, useful for data reduction, noise rejection, visualization and data compression among other things.

Some of possible applications of PCA are:

- data error analysis
- defining driving variables and creating model for energy use

$$Y = c_0 + c_1PC_1 + c_2PC_2 + \ldots c_pPC_p \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

4.5.1 Principal Component Analysis for creating model

In „data-driven“ approach the input and output variables are known and measured, and the goal is to determine a mathematical description of the relationship between the independent variables and the dependent one. Matrix **X** represents input variables (also called „predictors“, etc.). It is made out of parameters from previously created building database. Matrix **Y** represents output variables („target“ or „response“ variables). In energy use model, it is electricity and heating energy use.

Both of these matrices are known (collected or measured data), and PCA is used to find out main influencing factors and define relationships between input (building database) and output (energy use).

$$\text{buildings}\left\{\left[\overbrace{\begin{bmatrix} X_{11} & \dots & X_{1n} \\ \dots & \dots & \dots \\ X_{m1} & \dots & X_{mn} \end{bmatrix}}^{\text{building data}}\right]\right. \Rightarrow \begin{bmatrix} PC_{11} & \dots & PC_{1p} \\ \dots & \dots & \dots \\ PC_{m1} & \dots & PC_{mp} \end{bmatrix} \quad \overset{\text{energy use}}{\text{buildings}\left\{\left[\begin{bmatrix} Y_{1} \\ \dots \\ Y_{m} \end{bmatrix}\right] = f\left\{\left(\begin{bmatrix} PC_{11} & \dots & PC_{1p} \\ \dots & \dots & \dots \\ PC_{m1} & \dots & PC_{mp} \end{bmatrix}\right)\right\}\right.}$$

PCA "squeezes" as much information (as measured by variance) as possible into the first principal components. In some cases the number of principal components needed to store the vast majority of variance is shockingly small: a tremendous feat of data manipulation. This transformation can be performed quickly on contemporary hardware and is invertible, permitting any number of useful applications.

The first step in PCA is to *standardize* the data. Here, "standardization" means subtracting the sample mean from each observation, then dividing by the sample standard deviation. This centers and scales the data.

Partial Least Square Regression (PLSR) is an extension of the multiple linear regression model [20]. In its simplest form, a linear model specifies the linear relationship between a dependent (response) variable **Y**, and a set of predictor variables **X**, so that

$$Y = b_0 + b_1X_1 + b_2X_2 + \dots + b_pX_p \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (\ 3)$$

In this equation b_0 is the regression coefficient for the intercept and the b_i values are the regression coefficients (for variables 1 through p) computed from the data [20].

PLSR has been used in various disciplines such as chemistry, economics, energy use analysis where predictive linear modeling, especially with a large number of predictors, is necessary.

Partial Least Squares Regression (PLSR) and Principal Components Regression (PCR) are both methods to model a response variable when there are a large number of predictor variables, and those predictors are highly correlated or even collinear. Both methods construct new predictor variables, known as components, as linear combinations of the original predictor variables, but they construct those components in different ways. PCR creates components to explain the observed variability in the predictor variables, without considering the response variable at all. On the other hand, PLSR does take the response variable into account, and therefore often leads to models that are able to fit the response variable with fewer components.

Choosing the Number of Components with Cross-Validation

One method of choosing the number of extracted factors (components) is to fit the model to only part of the available data (the *training set*) and to measure how well models with different numbers of extracted factors fit the other part of the data (the *test set*). This is called *test set validation*. However, it is rare that there is enough data to make both parts large enough for pure test set validation to be useful. Alternatively, several different divisions of the observed data could be made into training set and test set. This is called *cross validation*

Cross-validation is a statistically sound method for choosing the number of components in either PLSR or PCR. It avoids overfitting data by not reusing the same data to both fit a model and to estimate prediction error.

The **Mean Squared Error of Prediction (MSEP)**, or its square root, is frequently used to assess the performance of regressions. It is also used for choosing the optimal number of components in principal components regression (PCR) [17] and partial least squares regression (PLSR) [21].

The **Root Mean Square Error (RMSE)** (also called the root mean square deviation, RMSD) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power [22].

The PLS weights are the linear combinations of the original variables that define the PLS components, i.e., they describe how strongly each component in the PLSR depends on the original variables, and in what direction.

4.5.2 Principal Component Analysis for data error analysis

Similar methodology can be used also for determining errors in measurements. In this case matrix **X** represents monthly meter (or submeter) data, and matrix **Y** monthly data for main electricity or heating energy use meter. Input and output are known (data are measured), and PCA can point out possible „faulty“ submeter data.

$$\text{month}\left\{\overbrace{\begin{bmatrix} X_{11} & \dots & X_{1n} \\ \dots & \dots & \dots \\ X_{m1} & \dots & X_{mn} \end{bmatrix}}^{\text{building meters}}\right. \Rightarrow \begin{bmatrix} PC_{11} & \dots & PC_{1p} \\ \dots & \dots & \dots \\ PC_{m1} & \dots & PC_{mp} \end{bmatrix} \qquad \text{month}\left\{\overset{\text{main electricity or heating meter}}{\begin{bmatrix} Y_{1} \\ \dots \\ Y_{m} \end{bmatrix}}\right. = f\left\{\begin{bmatrix} PC_{11} & \dots & PC_{1p} \\ \dots & \dots & \dots \\ PC_{m1} & \dots & PC_{mp} \end{bmatrix}\right\}$$

5 Case study – NTNU campus Gloshaugen

This master thesis has the aim to analyze energy use at NTNU campus Gloshaugen (Figure 3). NTNU campus Gloshaugen consists of 35 buildings, with total area of approximately 300,000 m^2. Depending on their purpose, building types are: office, educational, laboratory workshop and sport facilities. It includes the Faculties of Engineering Science and Technology, Natural Sciences and Technology, and Information Technology, Mathematics and Electrical Engineering. The first building (301 Hovedbygningen – Main building), which is also NTNU`s first building, was built in 1910, while the latest one (358 Hogskoleringen) was built in 2002. The biggest building, Realfagbygget, the natural science building, covers approximately 60,000 m$^2$, and is the largest building in Trondheim. The three of NTNU`s 11 libraries are located in Gloshaugen campus. The university`s student athletic association has a sport centre at this campus. Due to different building use and year of construction, various materials, insulation, and area under windows were used.

Figure 3. NTNU campus Gloshaugen

Building and Energy Management System (BEMS) and web-based Energy Monitoring System (Energy Remote Monitoring – ERM) are available at NTNU. Access to building system and operation data was provided via BEMS client installed on computer in university laboratory (Figure 4). There are 46 heating meters and 79 electricity meters installed in campus.

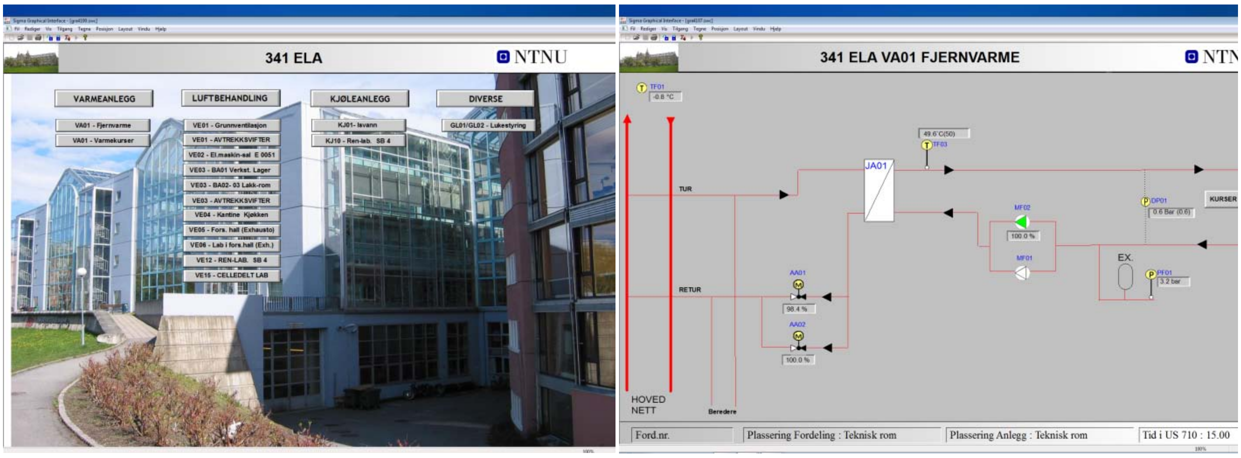

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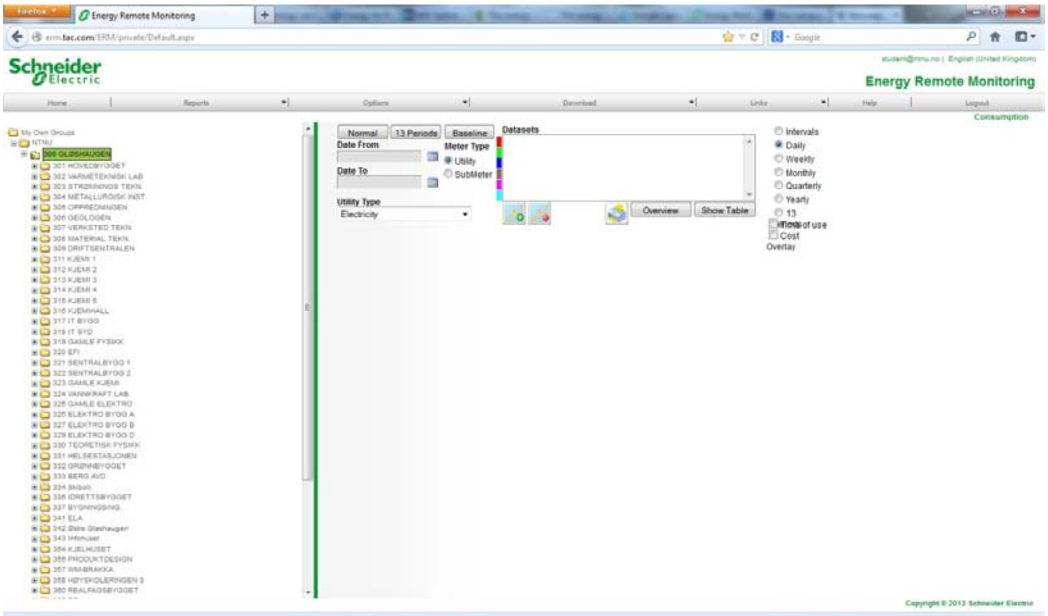
Figure 4. Building and Energy Management System (BEMS)

The Schneider Energy Remote Monitoring (ERM) system is an Automatic Monitoring and Targeting (aM&T) system with advanced analysis features, which receives main and submeter consumption data and provides system energy reporting, alarming, monitoring and analysis. Hourly heat and electricity consumption can be collected on ERM (http://erm.tac.com/erm/), which is shown in Figure 5. Total heating energy use in 2012 was 27,853 MWh, and electricity energy use was 62,405 MWh.

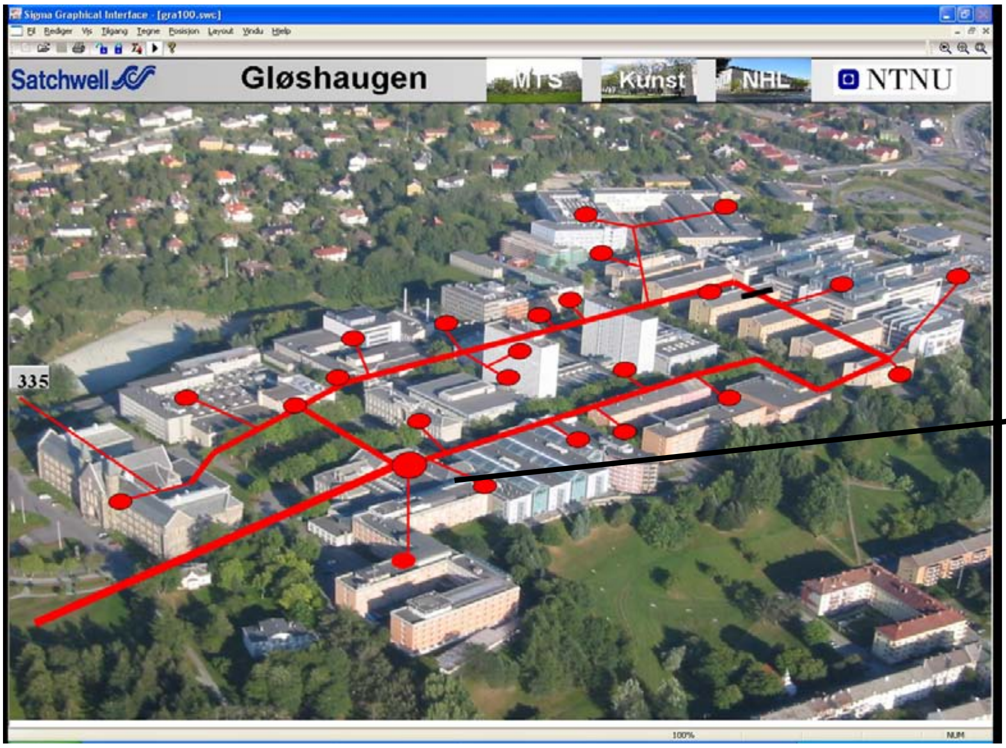


Date From
Date To
Meter Type
● Utility
○ SubMeter
Utility Type
Electricity
○ Intervals
● Daily
○ Weekly
○ Monthly
○ Quarterly
○ Yearly
○ 13
☐ Time of use
☐ Cost
Overlay

Figure 5. Web - based Energy Remote Monitoring (ERM)

Main challenges during data collecting refer to missing data from some meters or submeters. Reasons for that are various: malfunction of measurement devices, lost data due to system upgrading, different producers of monitoring equipment (different protocols), etc.

District heating net in University campus Gloshaugen is shown in Figure 6. Supply is organized in form of a ring, while the main heat exchanger is installed in building 325 Gamle Elektro (Old Electric Building).



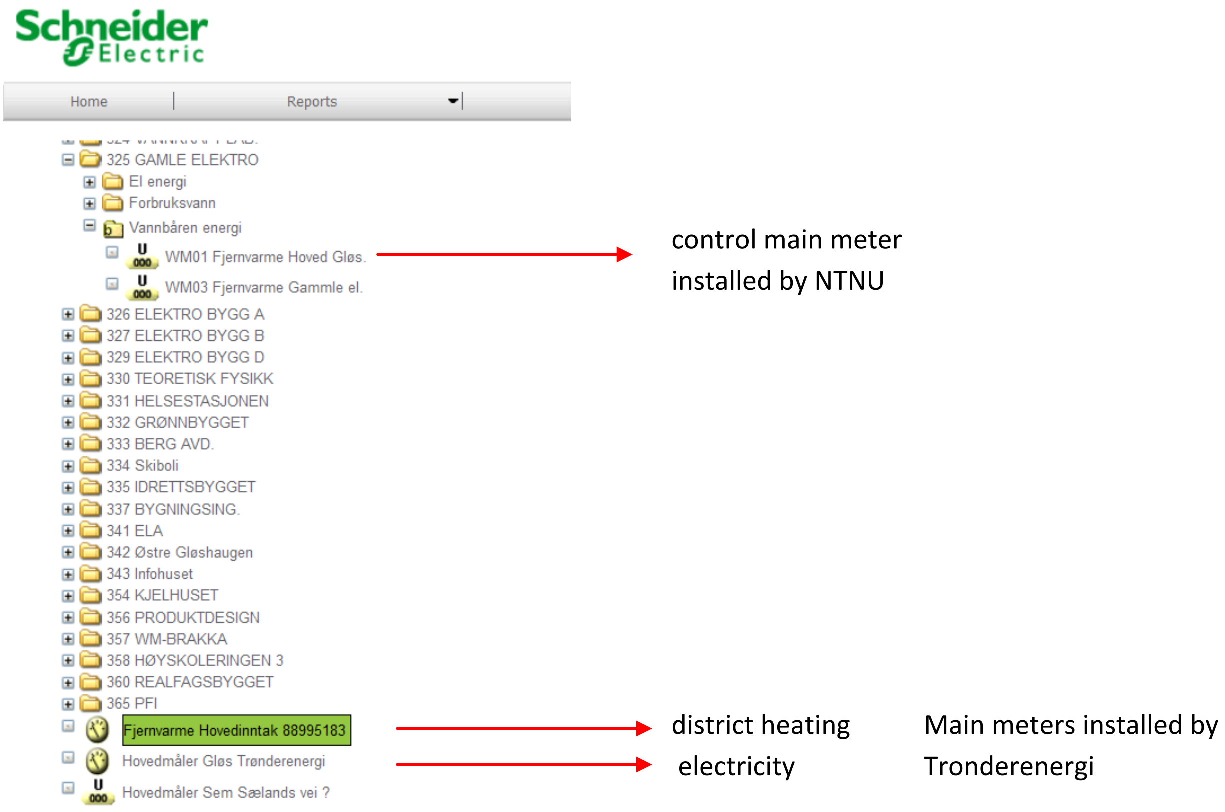
building 325 Gamle elektro
(Old Electric Building)
– main heat exchanger

Figure 6. District heating net in Gloshaugen

For main meters, consumption data is available for last four to five years, but some of the submeters are additionally installed, so those data are available for shorter period.

Meters in NTNU campus Gloshaugen

There are several meters installed in NTNU campus Gloshaugen. The bills for heating for campus are defined by the main meter, that is installed by district heating supplier Tronderenergi,. It is taken as reference, and in further text it is named the **Main meter Tronderenergi** (Fjernvarme Hovedinntak in Figure 7). The NTNU has installed its own, control main heating meter, which is placed in building 325 Gamle elektro (Old Electric Building). The main meter for electricity use, which measurements are relevant for billings, is installed by electricity supplier Tronderenergy, and it is named **Main electricity meter Tronderenergi** (Hovedmaler Tronderenergi).



325 GAMLE ELEKTRO
El energi
Forbruksvann
Vannbåren energi
WM01 Fjernvarme Hoved Gløs.
WM03 Fjernvarme Gammle el.
326 ELEKTRO BYGG A
327 ELEKTRO BYGG B
329 ELEKTRO BYGG D
330 TEORETISK FYSIKK
331 HELSESTASJONEN
332 GRØNNBYGGET
333 BERG AVD.
334 Skiboli
335 IDRETTSBYGGET
337 BYGNINGSING.
341 ELA
342 Østre Gløshaugen
343 Infohuset
354 KJELHUSET
356 PRODUKTDESIGN
357 WM-BRAKKA
358 HØYSKOLERINGEN 3
360 REALFAGSBYGGET
365 PFI
Fjernvarme Hovedinntak 88995183
Hovedmåler Gløs Trønderenergi
Hovedmåler Sem Sælands vei ?

control main meter installed by NTNU

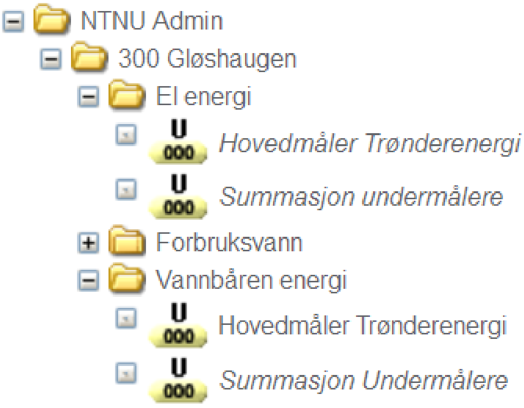
district heating

electricity

Main meters installed by Tronderenergi

Figure 7. Main meters in NTNU campus Gloshaugen

NTNU administrator has created a program for automatic sum of all installed submeters in campus („Summasjon undermalere” in Figure 8). That sum is compared with measurements of Main meters (“Hovedmaler Tronderenergi” in Figure 8), and in case of malfunction of some submeter, data are corrected. Energy use data from that source are further named as **Admin submeter sum**.



- NTNU Admin
  - 300 Gløshaugen
    - El energi
      - *Hovedmåler Trønderenergi*
      - *Summasjon undermålere*
    - Forbruksvann
    - Vannbåren energi
      - Hovedmåler Trønderenergi
      - *Summasjon Undermålere*

Figure 8. NTNU administrator meters

5.1 Creating building database

As it is mentioned in Chapter 4.3, database has a key role in proper analysis of energy use. The shape of database and information provided, depend on purpose of analysis. If more parameters are collected and used, energy use model will better predict energy use in buildings.

For creating buildings database for University campus Gloshaugen, different sources of information are used:

- Information about HVAC systems in buildings were found in BEMS Sigma client
- Data for building envelope, transmission coefficients, heated volume, etc. were found in Energy efficiency certificates
- Building maintenance staff provided tables containing useful information about number of systems, capacities of heat exchangers, etc. (source: System list – anleggsoversikt)

BEMS Sigma client provides information about HVAC systems, consumers, hydraulic schemes. Preview of BEMS installed in NTNU campus Gloshaugen is shown in Figure 4.

Energy efficiency certificates provided useful information about building envelope, surfaces, volume, walls, windows, doors, and also about systems (district heating share in total heating consumption, efficiency of systems, cooling and ventilation rewuirements, etc)

Majority of data was in Norwegian language, which required additional time to adequately translate and understand provided data.

Also, one of main issues is finding different values for same building in different sources. Summary of information regarding building surface and year built is shown in 0.. Part of the table with some most significant differences is shown in Table 1.

Table 1. Building area and year of construction found in different sources

	Data from Maintenance staff		Data from Energy Efficiency Certificate			Data from System list (anleggsoversikt)
Building	area	Year built	total area	heated area	Year built	area
	[m^2]		[m^2]	[m^2]		[m^2]
301 HOVEDBYGNINGEN	17,285.2	1910	17,360.0	-	1910	17,400.0
302 VARMETEKNISK NORD	15,191.3	1962	15,026.0	15,026.0	1962	14,720.0
305 OPREDNINGEN	3,954.8	1960	7,598.0	7,598.0	1960	3,806.0
307 VERKSTED TEKNISK	12,310.5	1966	11,400.0	11,400.0	-	11,778.0
308 MATERIAL TEKNISK	15,363.4	1958	12,600.0	12,600.0	1958	12,633.0
311 KJEMI 1	4,969.3	1954	6,067.0	6,067.0	-	3,801.0
312 KJEMI 2	5,236.7	1955	3,988.0	3,988.0	-	5,591.0

Finding other sources of information about buildings can help in detecting correct values for surfaces.

In **Table 2** is shown part of the created building database for University campus NTNU Gloshaugen (database is presented in Appendix B). It provides building parameters:

- Building areas (walls, windows, roof, floor area, heated area and volume)
- Thermal characteristics of building envelope (U-values for walls, windows, etc.)
- System characteristics (efficiency of district heating, system numbers, ventilation requirements, sanitary hot water, installed lighting, etc)
- weather data (heating degree days)

Table 2. Part of Building database for University campus NTNU Gloshaugen

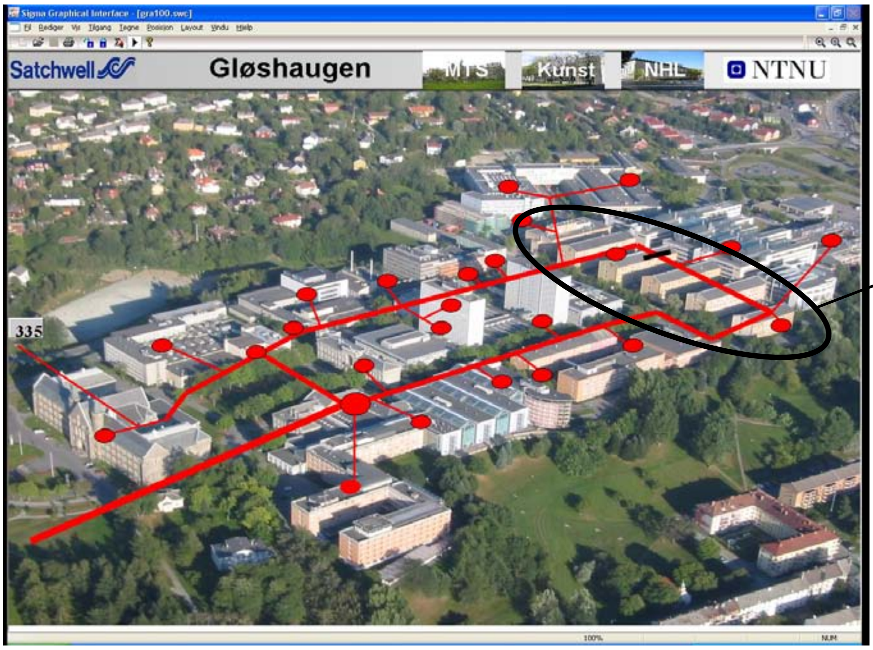
Building	outside walls area	roof area	floor area	windows, doors and glass area	heated area	heated air volume	U-value for exterior walls
	[m^2]	[m^2]	[m^2]	[m^2]	[m^2]	[m^3]	[$W/(m^2K)$]
302VARMETEKNISK NORD	5,504.0	4,315.0	4,824.0	2,293.0	15,026.0	73,600.0	0.35
303 STROMNINGSTEK.	1,632.0	1,098.0	1,098.0	354.0	3,030.0	12,520.0	0.87
304 METALLURGI	1,572.0	1,315.0	1,315.0	294.0	2,215.0	6,867.0	0.56
305 OPREDNINGEN	1,812.0	1,113.0	1,257.0	493.0	7,598.0	23,554.0	0.56
307 VERKSTED TEKNISK	2,592.0	3,064.0	3,214.0	1,830.0	11,400.0	39,000.0	0.43
308 MATERIAL TEKNISK	4,038.0	5,480.0	5,640.0	1,032.0	12,600.0	48,570.0	0.82
311 KJEMI 1	2,407.0	1,566.0	1,566.0	390.0	6,067.0	20,455.0	0.34
312 KJEMI 2	2,058.0	797.0	800.0	526.0	3,988.0	12,363.0	0.33
313 KJEMI 3	1,686.0	1,080.0	930.0	607.0	5,050.0	13,130.0	0.49
314 KJEMI 4	2,386.0	1,064.0	1,052.0	590.0	4,510.0	15,560.0	0.28
315 KJEMI 5	1,935.0	1,175.0	1,175.0	651.0	4,837.0	15,237.0	0.38
316 KJEMI 6 Kjemihallen	1,819.0	1,338.0	231.0	473.0	4,440.0	15,400.0	0.56

6 Energy use measurements

Hourly heat consumption for all meters and submeters can be collected on ERM (http://erm.tac.com/erm/), which is shown in Figure 5.

There are some cases that group of buildings is supplied with energy from the same substation. One of the first issues was to define what does specific submeter measure. Is the submeter in charge only for the building in which it is installed, or it measures heat consumption for part of building, or for several buildings? To answer that question, analysis of heating systems in whole campus was required.

In NTNU campus Gloshaugen there are Chemistry buildings: 311 Kjemi 1 (Chemisrtry 1), 312 Kjemi 2 (Chemistry 2), 313 Kjemi 3 (Chemistry 3), 314 Kjemi 4 (Chemistry 4), 315 Kjemi 5 (Chemistry 5) and 316 Kjemihall (Chemistry hall), shown in Figure 9.



Chemistry Buildings (311 to 316)

Figure 9. Chemistry Buildings in NTNU campus Gloshaugen

Some of those buildings have common meters, and also some systems (radiator heating, ventilation, etc.) have separate submeters installed. The position of submeters was hard to define.

For example, district heating for buildings 311, 312 and 313 is provided from the building 311 (Chemistry 1), so the first one is meter (it measures heat consumption for several buildings), and for 312 it is submeter, which was not clear from the start (Figure 10)

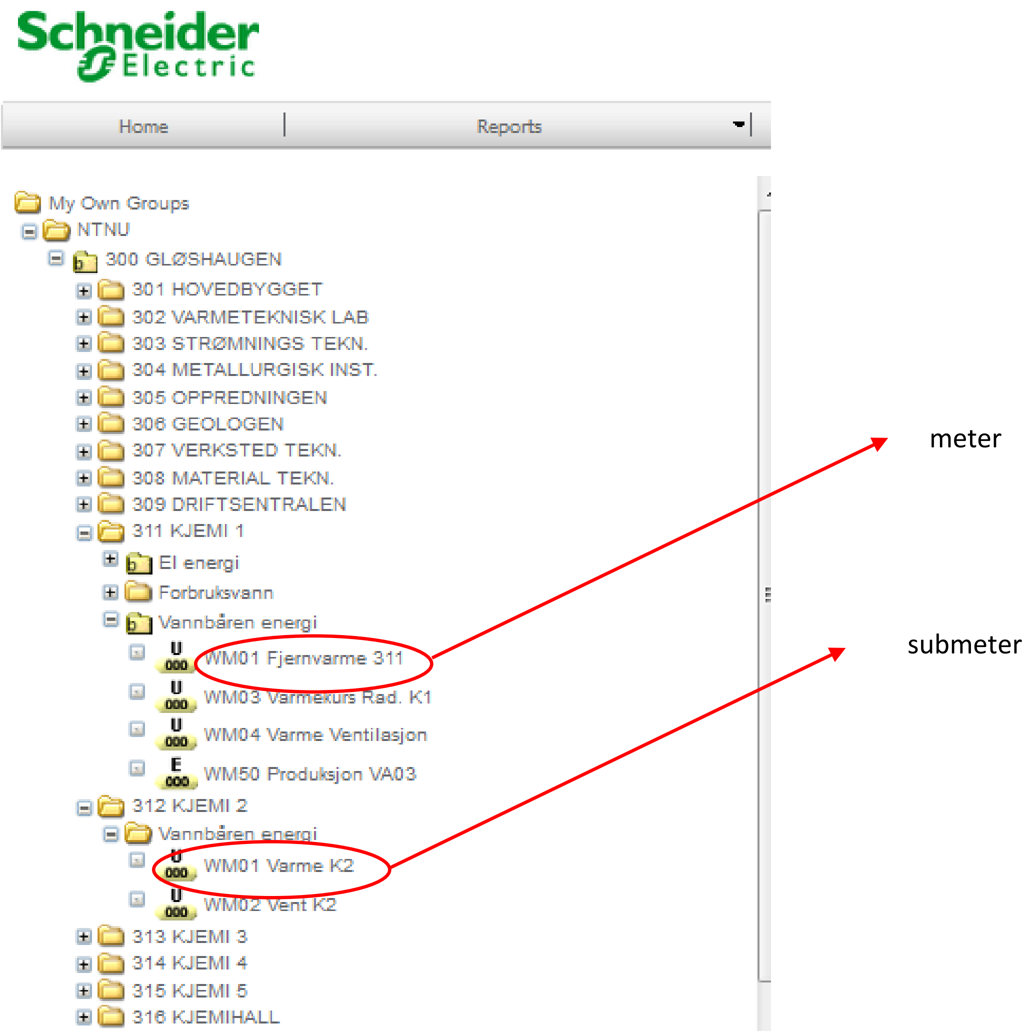


Figure 10. Example of issues with meters and submeters

Over the past years, submeters have been continuously installed, so some buildings have measured data since 2007, and some from 2010. One of the reasons for installing submeters, besides energy monitoring, is also for billing the tenants of the rented University space. Some buildings also have additional submeters for ventilation, and different heating zones.

Increasing the number of submeters provides better image of real energy consumption and shows possible „weak points” in heating system. It can improve the ability to accurately track energy use. Additionally installed submeters can be used to track loads of individual buildings, providing valuable information about the energy costs associated with specific functions, such as the operation of laboratories. The submetering can help distinguish different loads in buildings. The performance of energy efficiency projects in each building will be measurable through the meters and the persistence of savings can be documented by monitoring the ongoing energy use at each meter.

Part of table with all currently available data for Heating energy use from meters and submeters in NTNU campus Gloshaugen is shown in

Table **3**. Whole table is presented in Appendix C.

Table 3. Part of available data for all Heating meters and submeters in NTNU Gloshaugen

ANNUAL HEATING CONSUMPTION IN NTNU GLOSHAUGEN				
Building	Area [m^2]	Meter/Submeter	year	Eh [kWh]
301 HOVEDBYGNINGEN	17,285.2	WM01 FJERNV 301	2012	2,526,708
			2011	2,347,731
			2010	3,194,500
			2009	3,160,953
			2008	2,695,199
			2007	3,040,020
302 VARMETEKNISK	15,191.3	WM02 FJERNV 302	2012	929,209
			2011	385,714
			2010	1,048,847
			2009	959,938
			2008	1,121,850
			2007	1,522,071
		WM50 Heat pump KJ01	2012	341,712
			1/2 2011	82,138
		WM51 Heat pump KJ02	2012	299,182
			1/2 2011	227,006
309 DRIFTSSENTR.	2,017.0			NO DATA
311 KJEMI 1	4,969.3	WM01 FJERNV. 311	2012	3,148,733
			2011	3,413,600
			2010	4,527,775
			2009	3,663,100
			2008	3,356,000
			2007	3,524,422
		WM03 VARMEKURS. RAD K1	2012	144,985
			2011	172,750
			2010	148,060
			1/2 2009	109,100

There are more submeters installed for electricity (79 submeters) than heating energy use (46 submeters). Part of table with all currently available data for Electricity energy use from meters and submeters in NTNU campus Gloshaugen is shown in Table 4. The data is provided also for CO2 emission. Whole table is presented in Appendix D.

Table 4. Part of available data for all Electricity meters and submeters in NTNU Gloshaugen

ANNUAL ELECTRICITY CONSUMPTION AND CO2 EMISSION IN NTNU GLOSHAUGEN					
Building	Meter/Submeter	year	Eel [kWh]	CO2 [Tonnes]	Carbon [Tonnes]
301	RE01 230 V	2012	1,374,586	744.48	203.04
		2011	1,175,706	636.76	173.66
		2010	1,217,981	659.66	179.91
302	RE01 230 V	2012	1,539,099	833.58	227.34
		2011	936,725	507.33	138.36
		2010	258,875	140.21	38.24
		2009	560,655	303.65	82.81
		2008	159,120	86.18	23.50
		2007	147,389	79.80	21.76
	RE03 400 V	2012	452,555	245.10	66.85
		2011	257,721	139.58	38.07
		2010	51,773	28.04	7.65
		2009	112,137	60.73	16.56
		2008	31,824	17.24	4.70
		2007	29,451	15.95	4.35
303	RE01 400V	2012	263,994	142.98	38.99
		2011	214,683	116.27	31.71
		2010	199,752	108.19	29.51
304	RE01 230V	2012	240,263	130.13	35.49
		2011	236,941	128.33	35.00
		2010	245,639	133.04	36.28
	RE01 400V	2012	248,596	134.64	36.72
		2011	132,688	71.86	19.60
		2010	83,430	45.19	12.32
MAIN METER		2012	62,405,546	33,798.84	9,217.87
		2011	61,286,821	33,192.94	9,052.62
		2010	60,839,328	32,950.58	8,986.52
		2009	57,495,284	31,139.45	8,492.58
		2008	55,621,396	30,124.55	8,215.79

Figure 11 shows contribution of each building in total electricity consumption of university campus. It can point out what buildings have the biggest influence on total energy use, and also what is energy consumption for most of buildings. Biggest consumer is building 360 Realfagbygget (Natural Science Building, which is the building with biggest surface), and building 337 Byggteknisk (Building Technology) while majority of buildings use less than 1MWh of electricity per year.

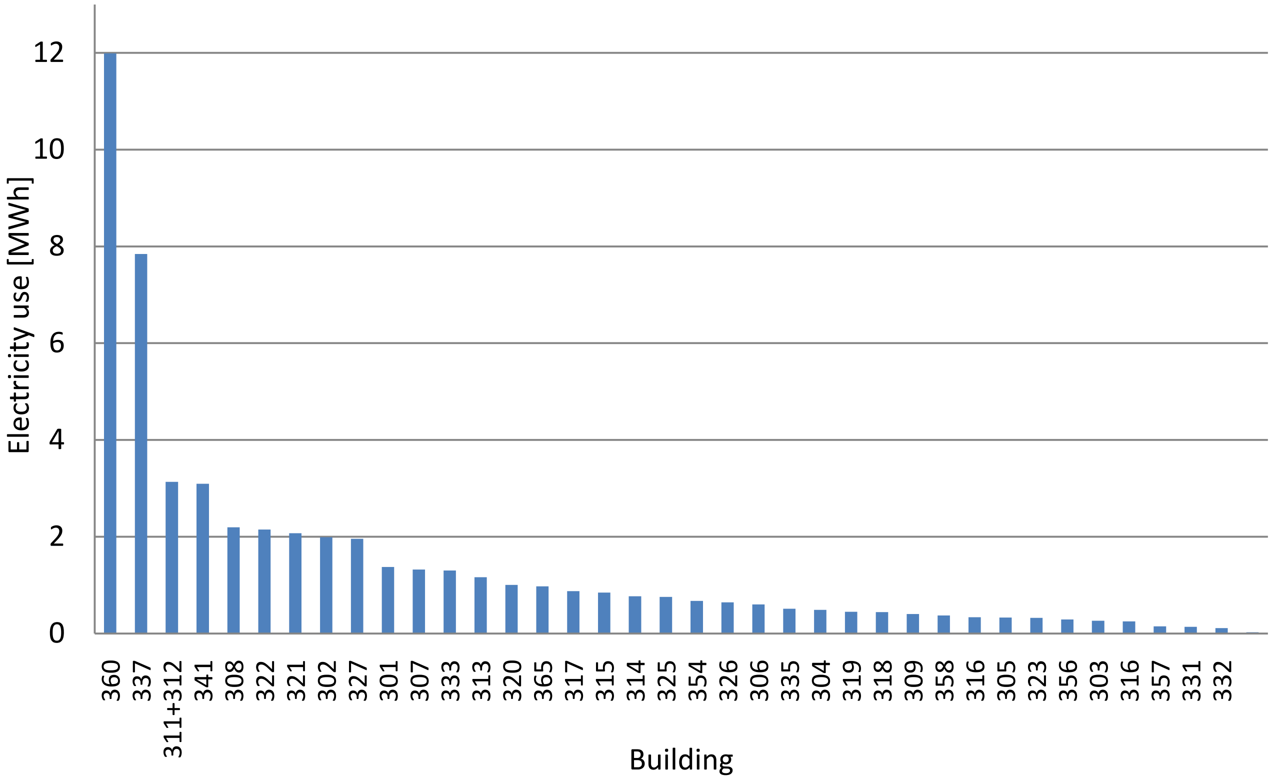


Figure 11. Contribution of each building in total electricity consumption of NTNU campus Gloshaugen for year 2012

6.1 Issues in creating building database and collecting energy use data

The most useful information for creating building database are collected from Energy reports (Energy certification of buildings). Some of those reports are missing, so there is lack of data for buildings:

- 301 Hovedbygning (it is the Main building, which is the oldest, built in 1910 year, so there is limited amount of data)
- 320 EFI
- 325 Gamle elektro (Old Electric Building) Del 2 (building information are found only for Del 1)
- 354 Kjelhuset
- 365 PFI

Since the submeters have been successively added, it was not always possible to separate energy use for each building. Also, if the data are available only for one year, there is no possibility to create a model (based on energy use for that year), which can be calibrated or evaluated using data for some previous year.

Heating energy use:

- Building 332 Gronnbygget is supplied with district heating net from building 308. Submeter for building 332 is probably installed in 2011 year, because data for heat consumption are available only for year 2012, and for part of year 2011. It is not possible to evaluate model using heating energy use of some other year.
- Building 315 Kjemi 5 and 316 Kjemihall have a common district heating meter, so it is not possible to determine exact consumption for each building.
- District heating for building 317 IT bygg and 318 IT bygg sud is provided from building 318. There is a submeter for heat consumption for building 317 IT bygg, but data are available only since july 2011.
- Building 325 Gamle elektro is supplied from building 341 ELA, and it is not possible to separate consumption for each building
- There is not consumption data for Building 328 Elektro C
- Building 327 ELEKTRO B supplies with district heating buildings: 326 Elektro A, 327 Elektro B, 328 Elektro C (no data for that building), 329 Elektro D and 330 Teoretisk fysikk (Theoretic Physics). There are submeters for buildings 326, 329 and 330, but data are available only from July 2011. Whole ELEKTRO complex should be considered together, if data could not be separated by some method
- Data for building 358 Hoyskolergingen are available only for year 2012.

There are more electricity submeters (79 submeters for electricity 230V and 400V) installed in University campus Gloshaugen, than heating energy use submeters (46 submeters).

Electricity energy use:

- Building 332 Gronnbygget has no installed submeter for electricity. It is supplied from Building 308 Material teknisk, so it was not possible to determine consumption for that building.

- Buildings 311 Kjemi 1 (Chemistry 1) and 312 Kjemi 2 (Chemistry 2) have some individual submeters (Figure 12), but a key submeter (311M4) is common for both buildings. Buildings should be considered together, or some method for separating electricity consumption should be proposed.

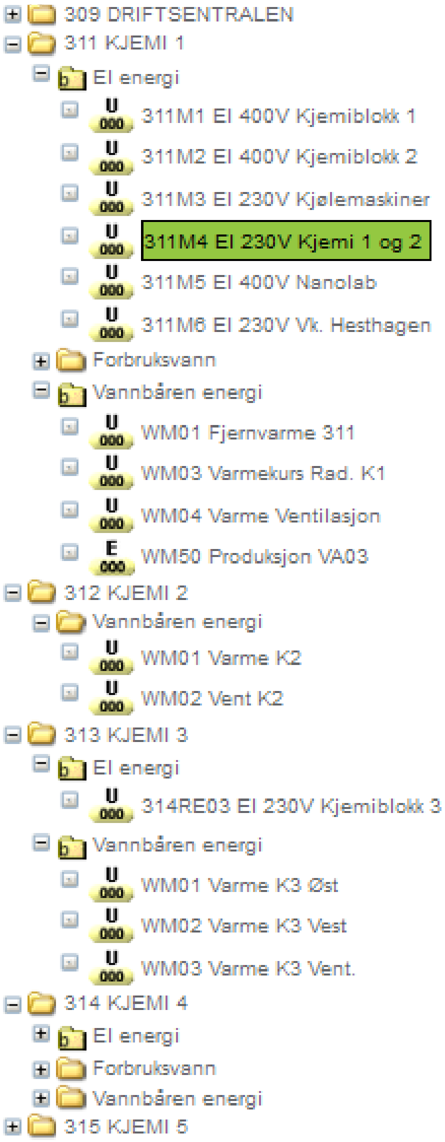


Figure 12. Submeters for buildings 311 Kjemi 1 (Chemistry 1) and 312 Kjemi 2 (Chemistry 2)

Some buildings have individual (their own) submeter for heating energy use, and „shared“ submeter (common submeter for a group of buildings) for electricity energy use, and vice versa. Buildings 315 Kjemi 5 supplies district heating for 314 Kjemi 4, 315 Kjemi 5 and 316 Kjemihall. There is no submeter for district heating for building 316 Kjemihall, but submeter for building 314 Kjemi 4 is installed. Electricity submeters are available for each building separately (314, 315 and 316). It makes it harder to accurately define energy use for each individual building, which will be most useful for creating model of energy use.

7 Energy use analysis for NTNU Gloshaugen

Detailed analysis was first performed for entire 2012 year, because those are the newest data, and they are available for all meters.

7.1 Energy use profiles

The patterns (or profiles) of energy usage contained within interval energy data are useful for discovering where buildings are wasting energy. The key is to try to link the patterns of energy use with the operations of the building.

Energy profiles show how much energy is being used at particular times-of-the-day and days-of-the-week. These profiles can indicate wasted energy, and point out possible points for energy savings.

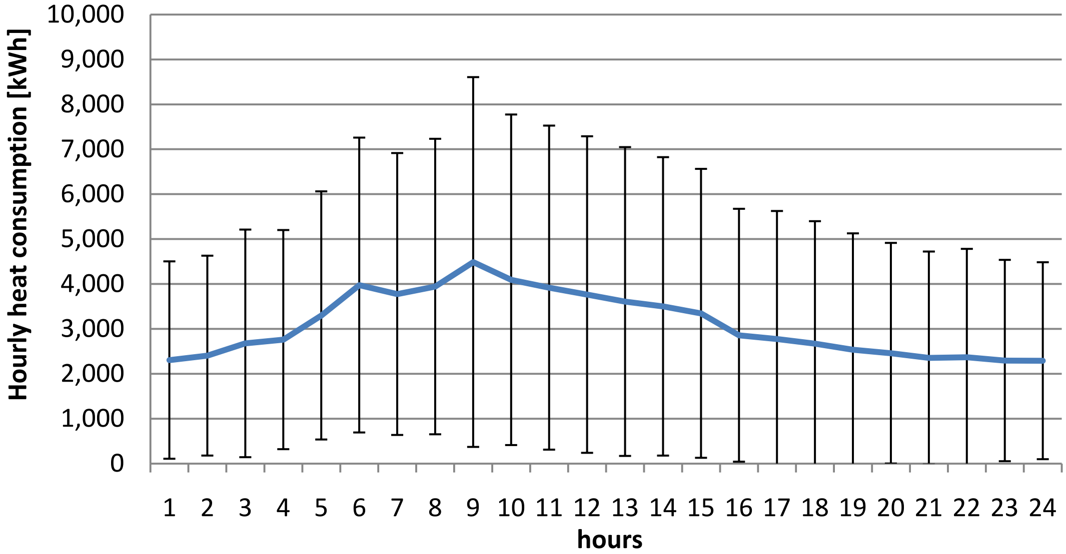


Figure 13. Hourly heating energy use profile for working day

The hourly load profiles with standard deviation of the Main meter Tronderenergi are presented in Figure 13 (working day) and Figure 14 (weekend). Heat consumption on working day is almost constant during night (after 18h), but it is still higher than 2,000 kWh. Maybe that is place where it is possible to make some energy savings (explore possibility to lower temperature during non-operating hours in campus). Peak of consumption is usually in

9 a.m., with big deviation (which is expected, due to significantly different outside temperatures during year).

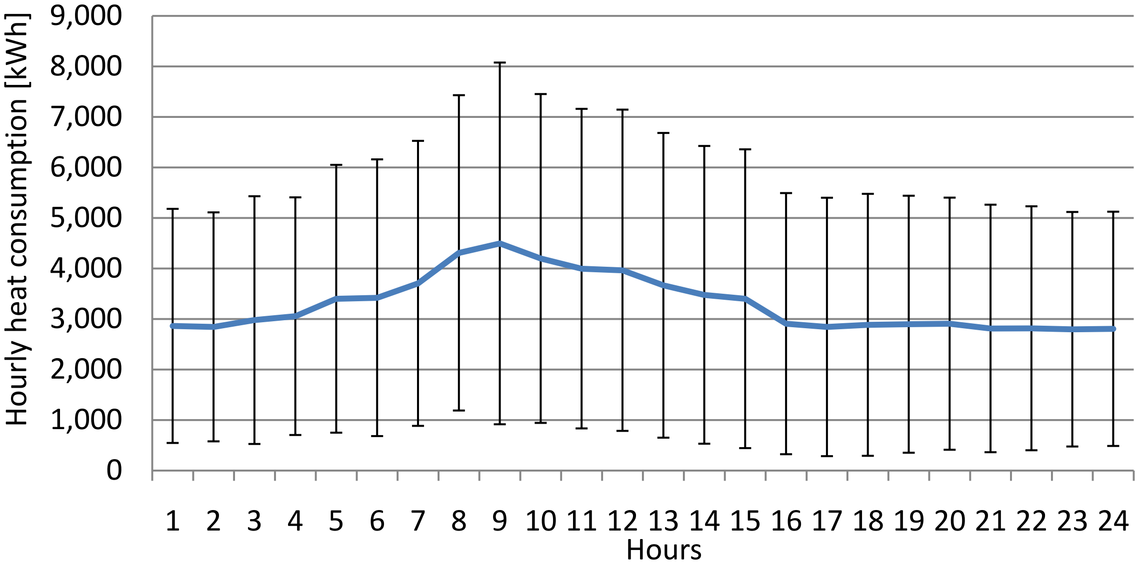


Figure 14. Hourly heating energy use profile for weekend

Heating energy use profile in weekend is more constant, with small peak usually around 9am (Figure 14). Also, heating consumption during night is nearly 3,000 kWh, so it should be considered improving energy efficiency by lowering that consumption.

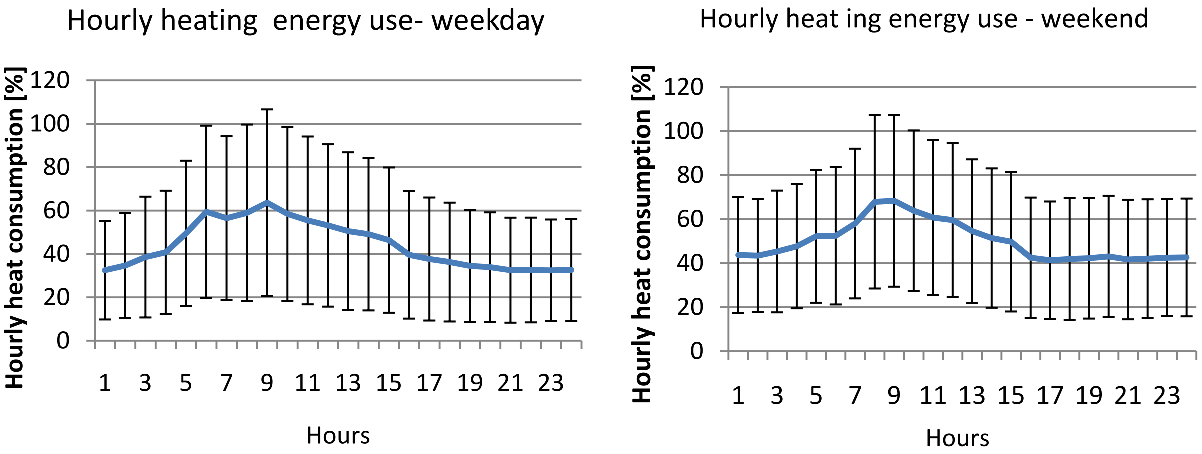


Figure 15. Hourly heating energy use profiles shown in percentage

The hourly electricity energy use profile with standard deviation of the Main meter is presented in Figure 16.

The campus has a broad peak, lasting from 11am to 3pm approximately during working days. The load is relatively flat at night, with loads coming on around 6am. The night-time loads drop at their minimum around midnight. The working day peak loads are about 4 MWh above the night-time load.

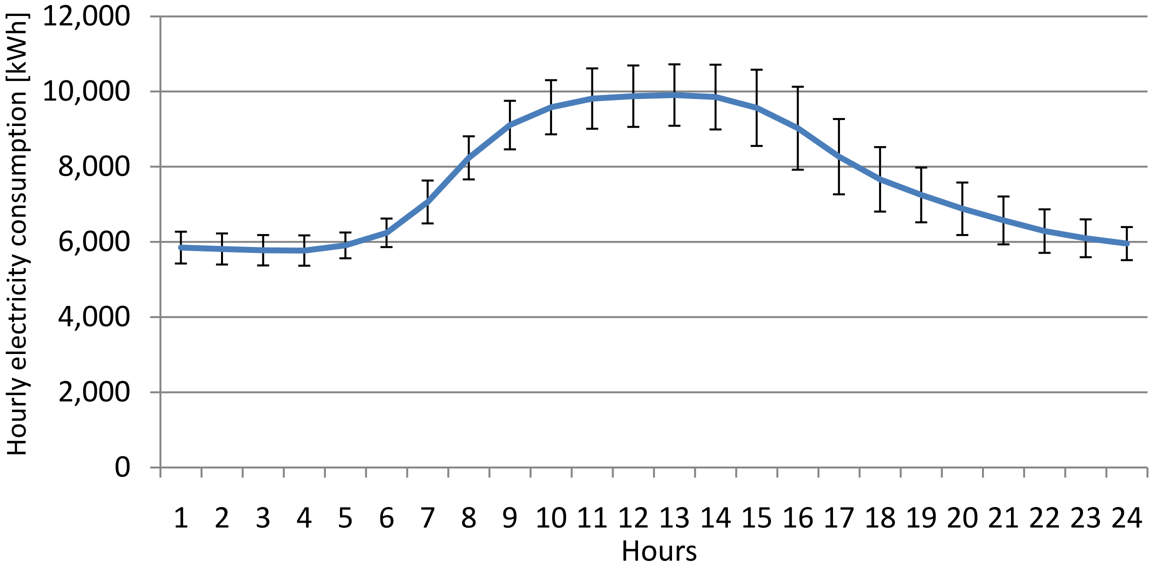


Figure 16. Hourly electricity energy use profile for working day

The level of activity on campus is relatively low at night, yet the electricity energy use profile is almost always above 6MWh. There are certainly loads at night that cannot be avoided, but this night load can present opportunity for savings (lighting project in order to reduce night lighting loads when buildings are not used).

Night-time electricity use is at around 60% of daytime peak load (Figure 18), with less deviation than during daytime. The weekend daytime peak loads are about 0.7 MWh above the nighttime load (Figure 17).

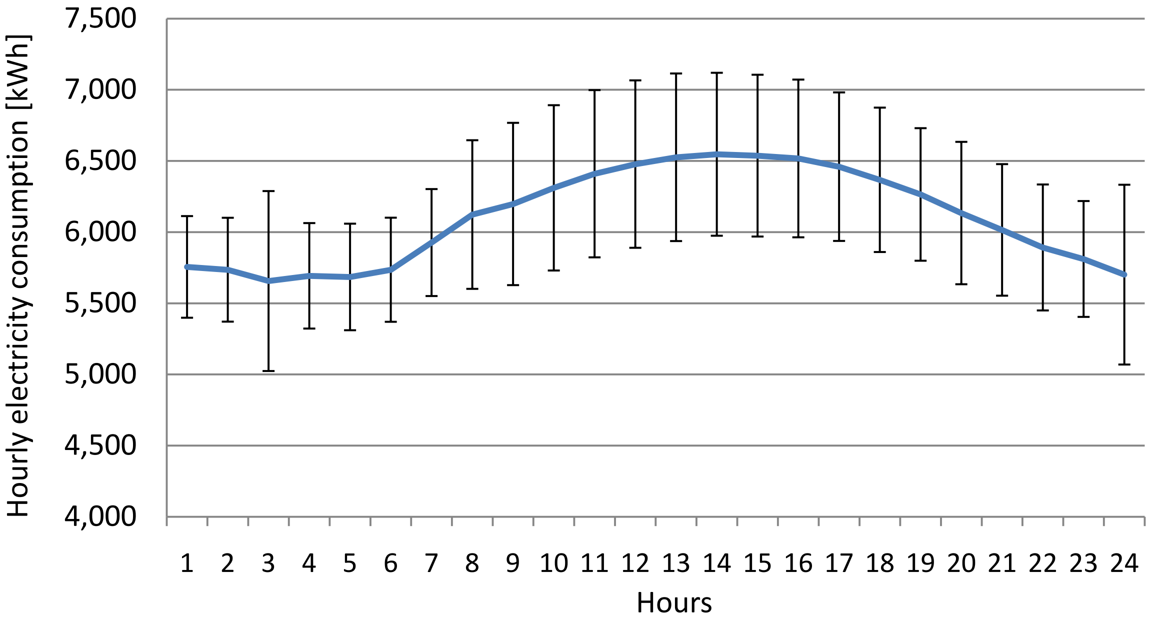


Figure 17. Hourly electricity energy use profile for weekend

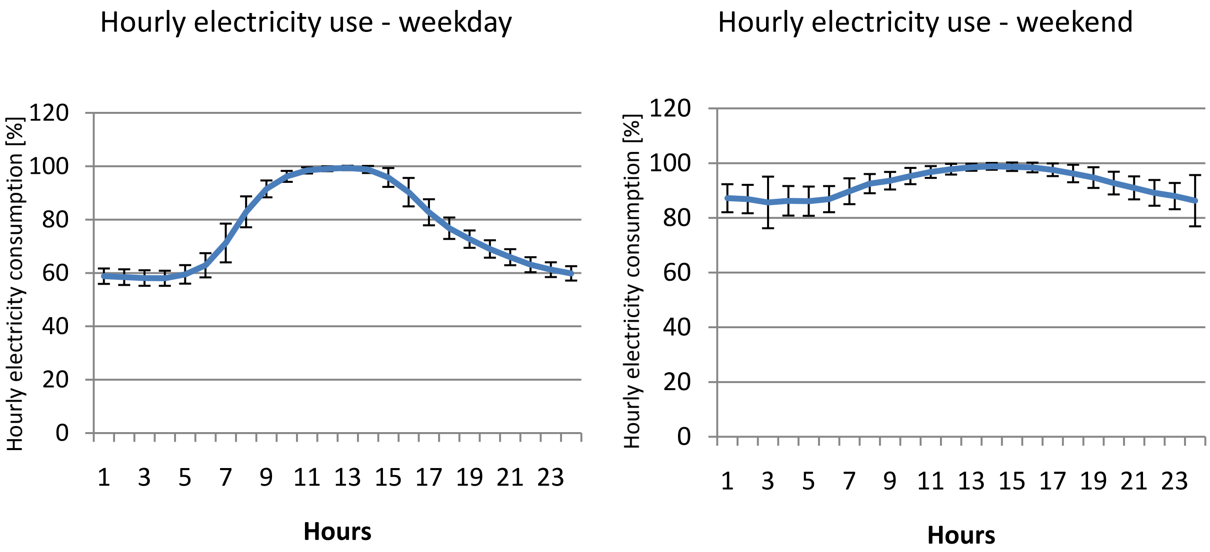


Figure 18. Hourly electricity energy use profiles shown in percentage

7.2 Specific energy use

For preliminary analysis of collected data Scatter plots (4.4.1. Descriptive statistics) are used.

The most common indicator used to benchmark performance for space heating for EU countries is the energy consumption per m^2 (to correct for differences in dwelling size) and degree-day (to correct for differences in climate).

Specific energy use is an important index for evaluating the state of energy management. It is calculated using the formula based on energy consumption per total floor are, heated floor are, etc. [23].

$$\text{Specific energy use} = \frac{\text{Energy use (MWh, calorific value, etc)}}{\begin{array}{c}\text{Amount closely related to energy use}\\ \text{(total floor area, heated volume, number of employees, etc.)}\end{array}}$$

As shown in Figure 19, majority of buildings in University campus Gloshaugen have area under 20,000 m^2, and their specific heating energy use (per m^2) is smaller than 200 kWh/m^2. These informations are useful for energy planning of University campus; they provide data for expected consumption if there is plan for expanding existing campus (adding more buildings) or building a new campus.

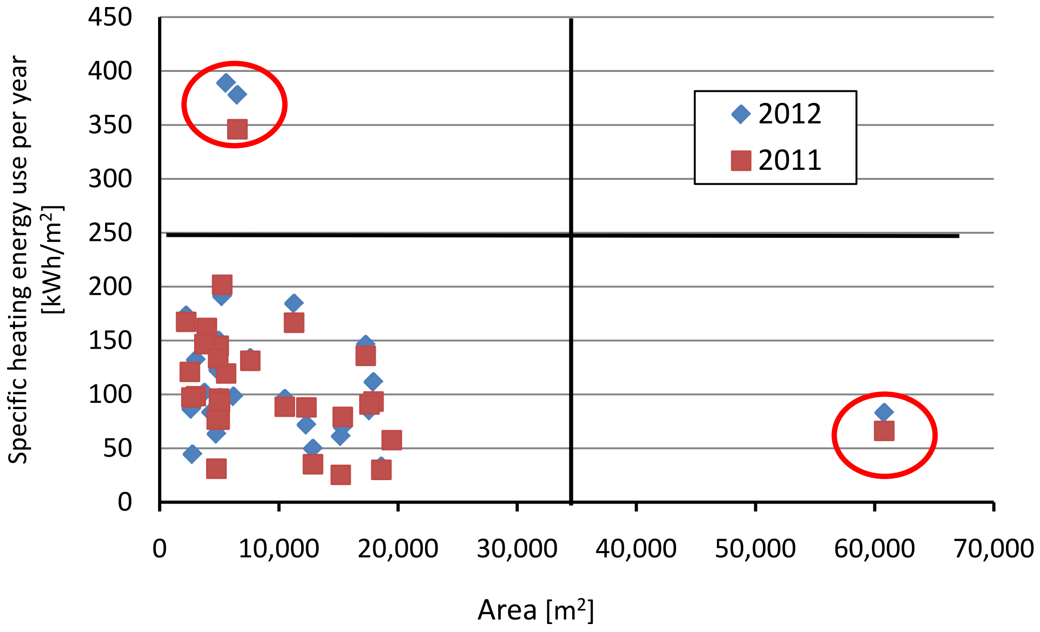


Figure 19. Specific heating energy use

Buildings that are in upper left quadrant of the diagram, the ones with higher specific heating energy use per year, are buildings with more laboratories. That result was expected, because of increased capacities for ventilation and sanitary hot water demand, which are typical for laboratories. This can provide some basics for energy planning of campus.

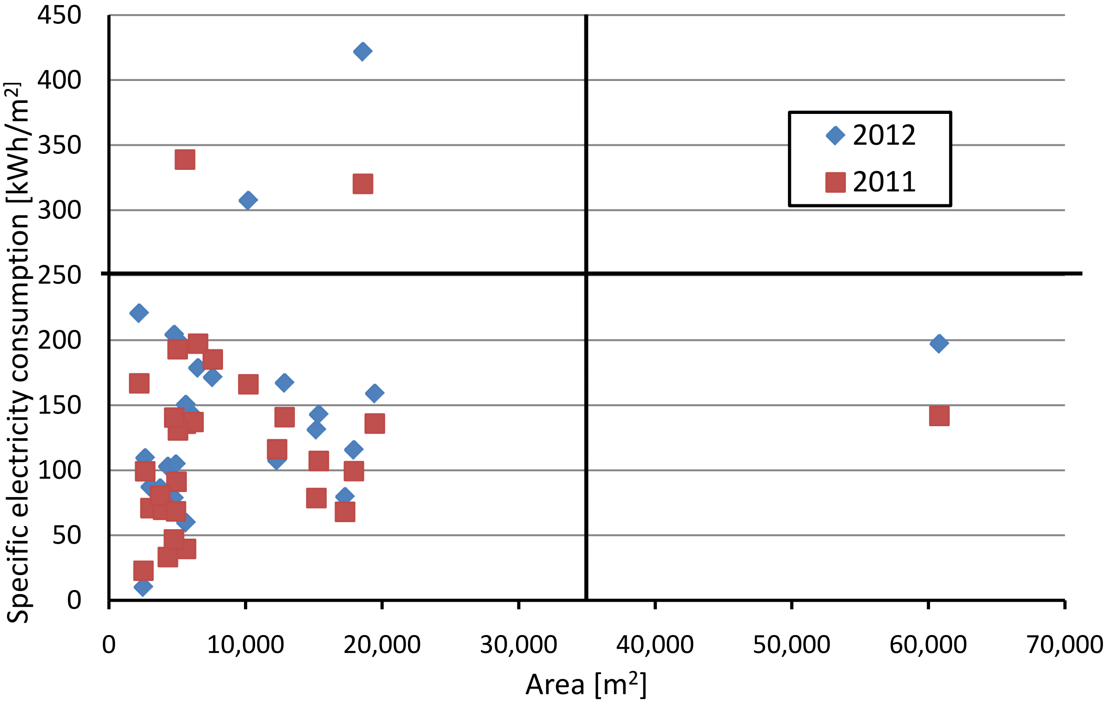


Figure 20. Specific electricity energy use

. A frequency distribution is a graphical representation of how often something occurs. It is a way of organizing data so it can be easily understood and used [16].

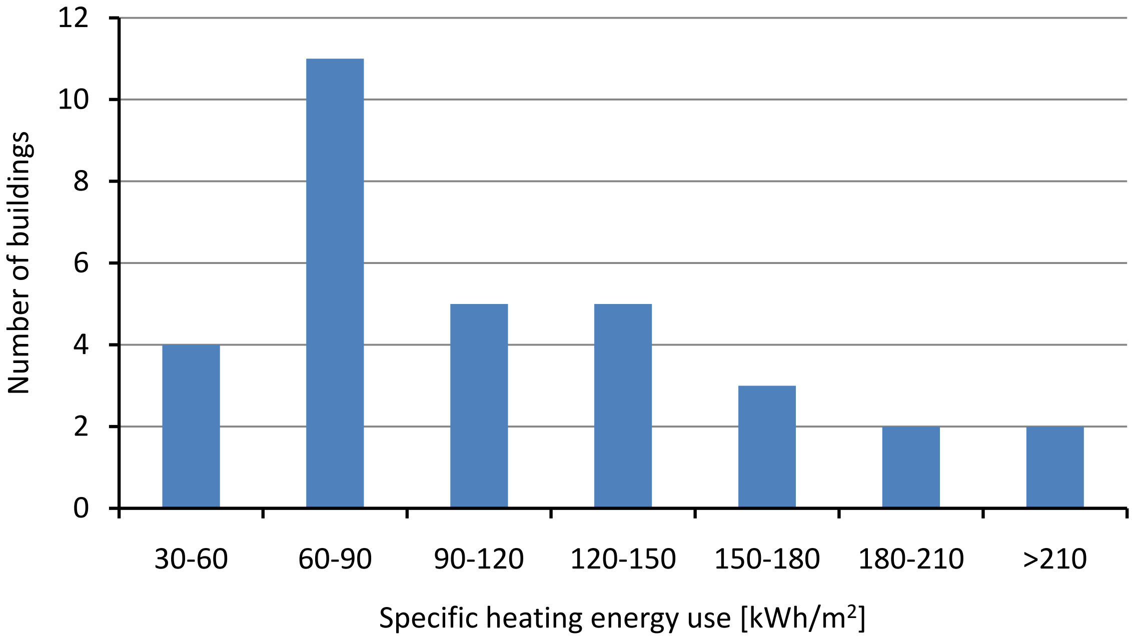


Figure 21. Frequency distribution for specific heating energy use for 2012

Analysis showed that majority of buildings (which have mostly offices and classrooms), use 60 to 90 kWh/m^2, while buildings that have many laboratories (Chemistry buildings) are the ones with highest values for specific heating energy use (180 to 390 kWh/m^2), as it is shown in Figure 21. These informations can be useful for energy planning of University campuses. It can also point out problem if some building is significantly „standing out“ from „most common“ energy use for that type of buildings.

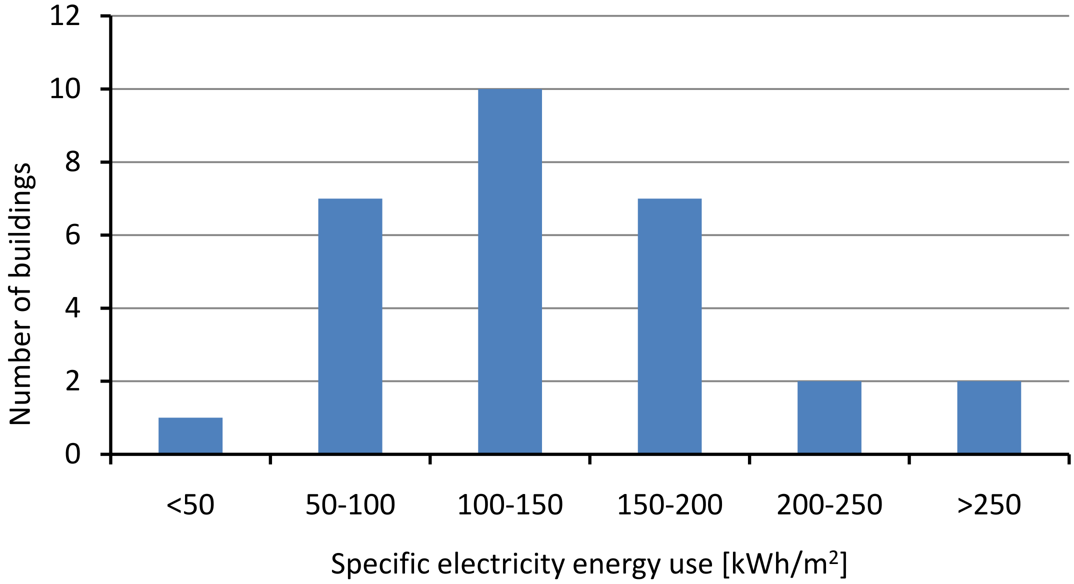


Figure 22. Frequency distribution for specific electricity consumption for 2012

Most of the buildings have specific electricity energy use 100 to 150 kWh/m^2. Specific electricity consumption is higher than specific heating energy use, for majority of buildings.

7.3 Total campus energy use analysis

Person responsible for ERM, NTNU administrator has programmed sum of all buildings submeters, which should represent total heat consumption for NTNU university campus Gloshaugen. Analysis on annual basis showed significant differences in measurement for Main meter and submeters sum. In order to find answers for those differences, daily analysis has been done. Comparison of measurement for Main meter Tronderenergi and Admin submeter sum for chosen winter month (January 2012) is shown in Figure 23.

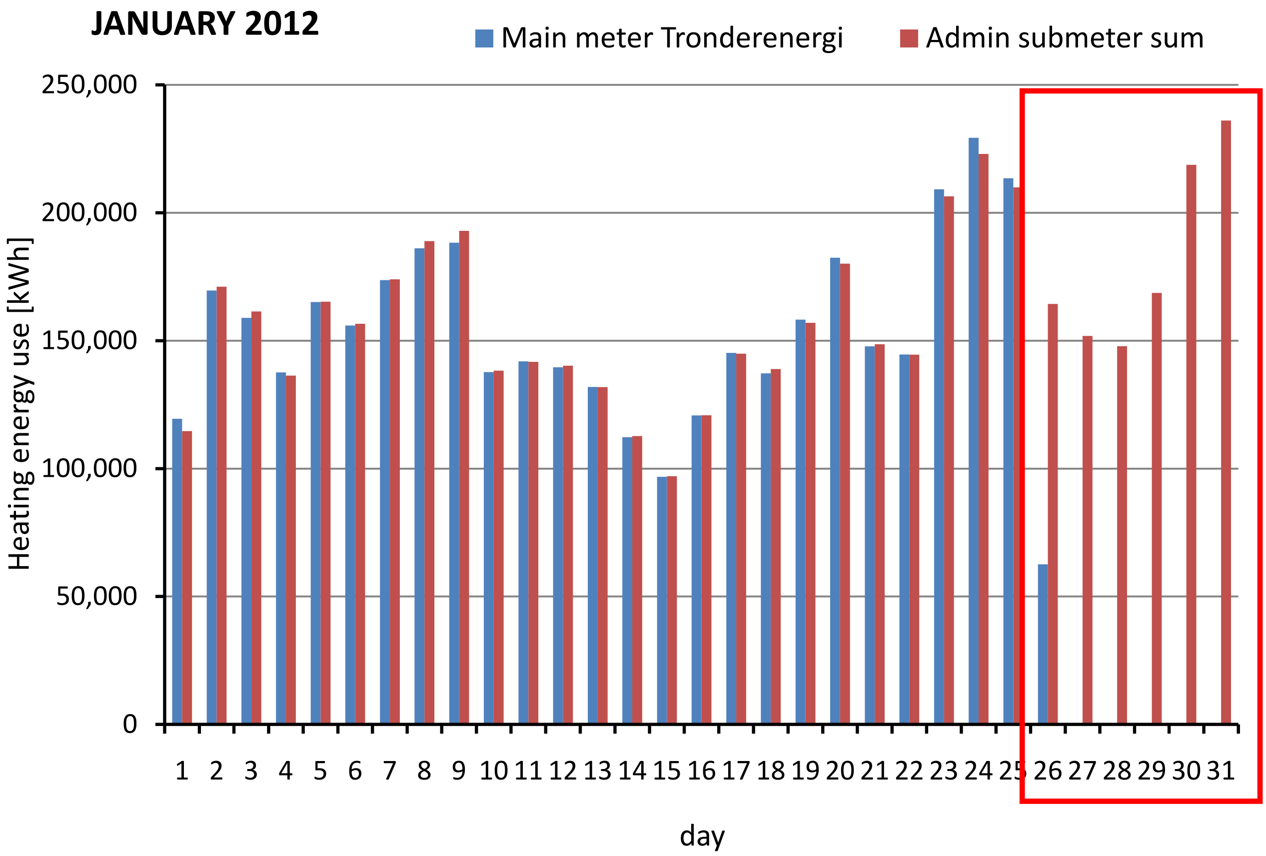


Figure 23. Comparison of heating energy use for Main meter Tronderenergi and Admin submeter sum

The diagram showed some differences in measured data. It is obvious that the main meter was not working properly since January 26th (recorded data are zeros). Since it is not possible that consumption for those days (working day with low outside temperature) is zero, one possible solution to correct non-logical data is to use Admin submeter sum for that period.

For finding source of differences between data, days with biggest deviation were observed on hourly basis.

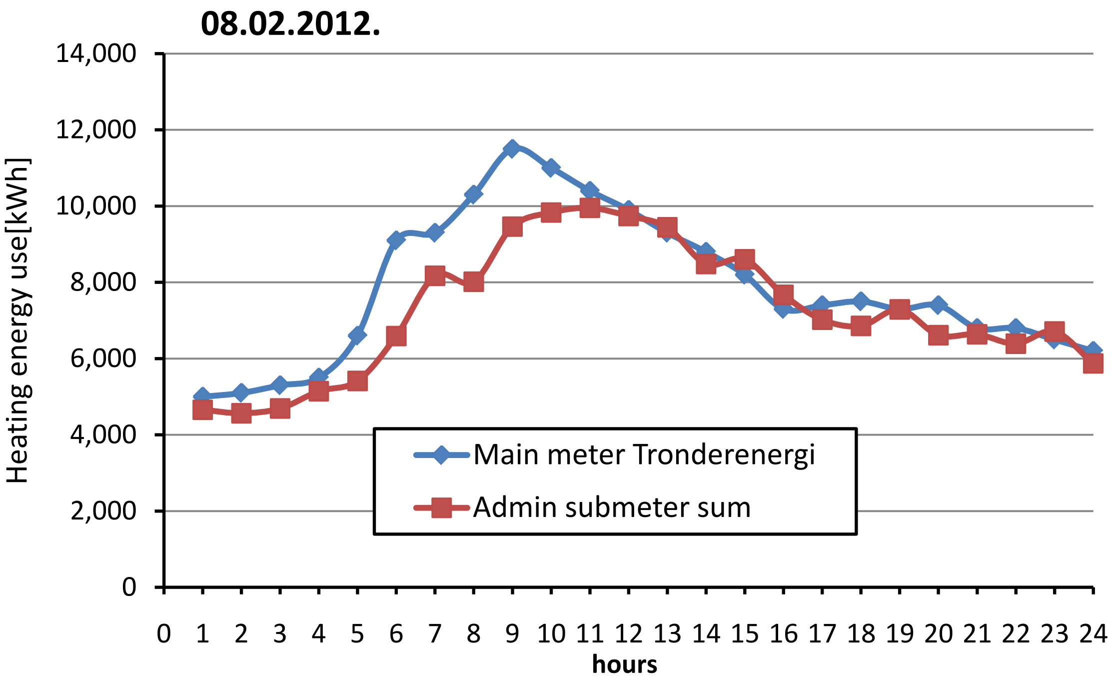


Figure 24. Hourly heating energy use for Main meter and Submeters sum on February 8th (working day)

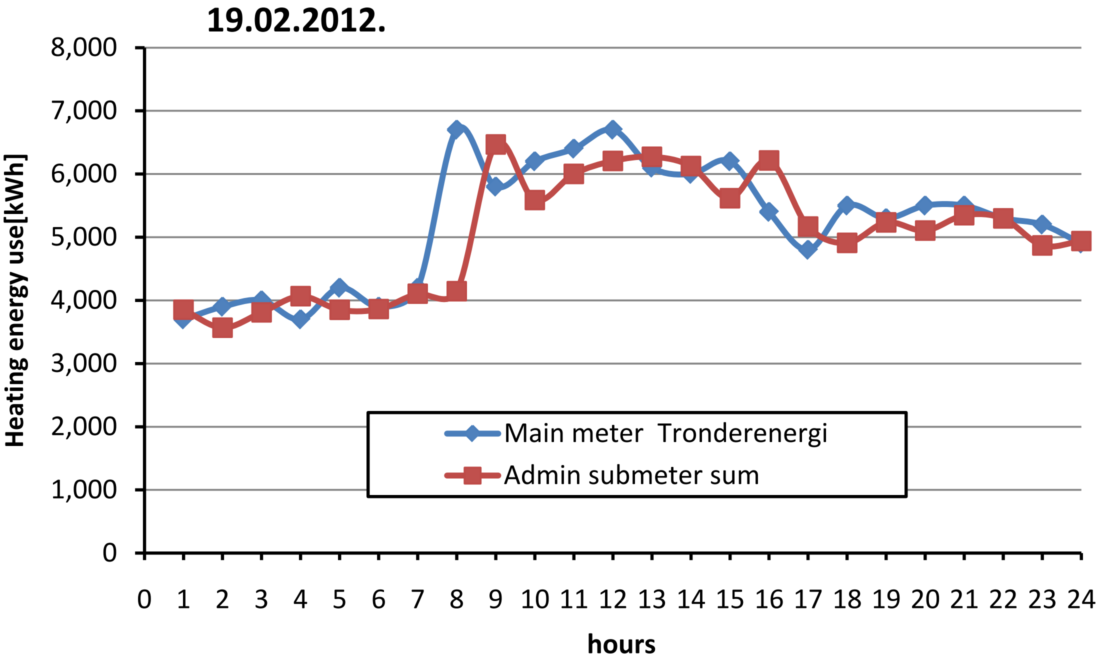


Figure 25. Hourly heating energy use for Main meter and Submeters sum on February 19th (Sunday)

In Figure 24 and Figure 25, we can see that Admin submeter sum shows very similar consumption curve like Main meter Tronderenergi, but with an hour delayed. It appears logical, since there is a time delay between collecting and transferring data.

Unfortunately, there are some days that have significant differences in values, and also in shape of consumption curve (Figure 26).

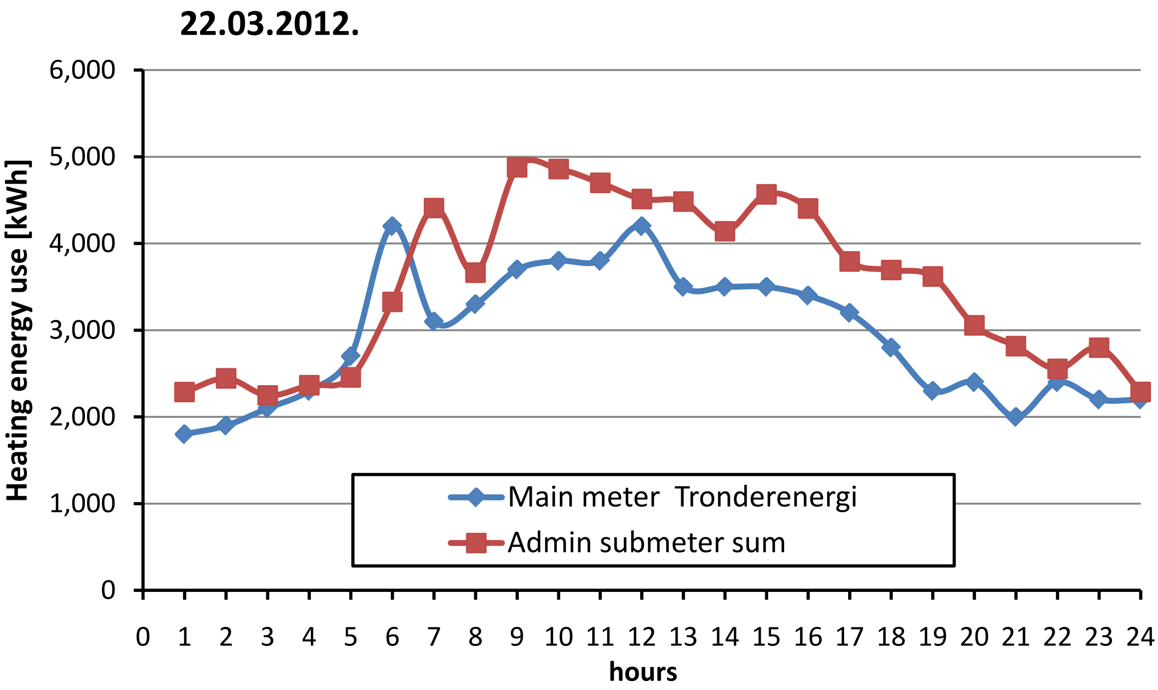


Figure 26. Hourly heat consumption for two meters on March 22nd (working day)

Even after observation of hourly profiles, it was not possible to get the answer to question why there is a difference in those data. If a submeter measured data are missing for some reason, NTNU administrator estimates consumption for that period, but there are no information about applied methodology.

Data correction

After analysis of hourly consumption, energy use data were corrected. First, for the period of obvious Main meter Tronderenergi malfunction, data with zero values were replaced with Admin submeter sum values. After that, points with larger deviation and zero values (during summer months) were excluded. Correlation with mean daily temperature was investigated.

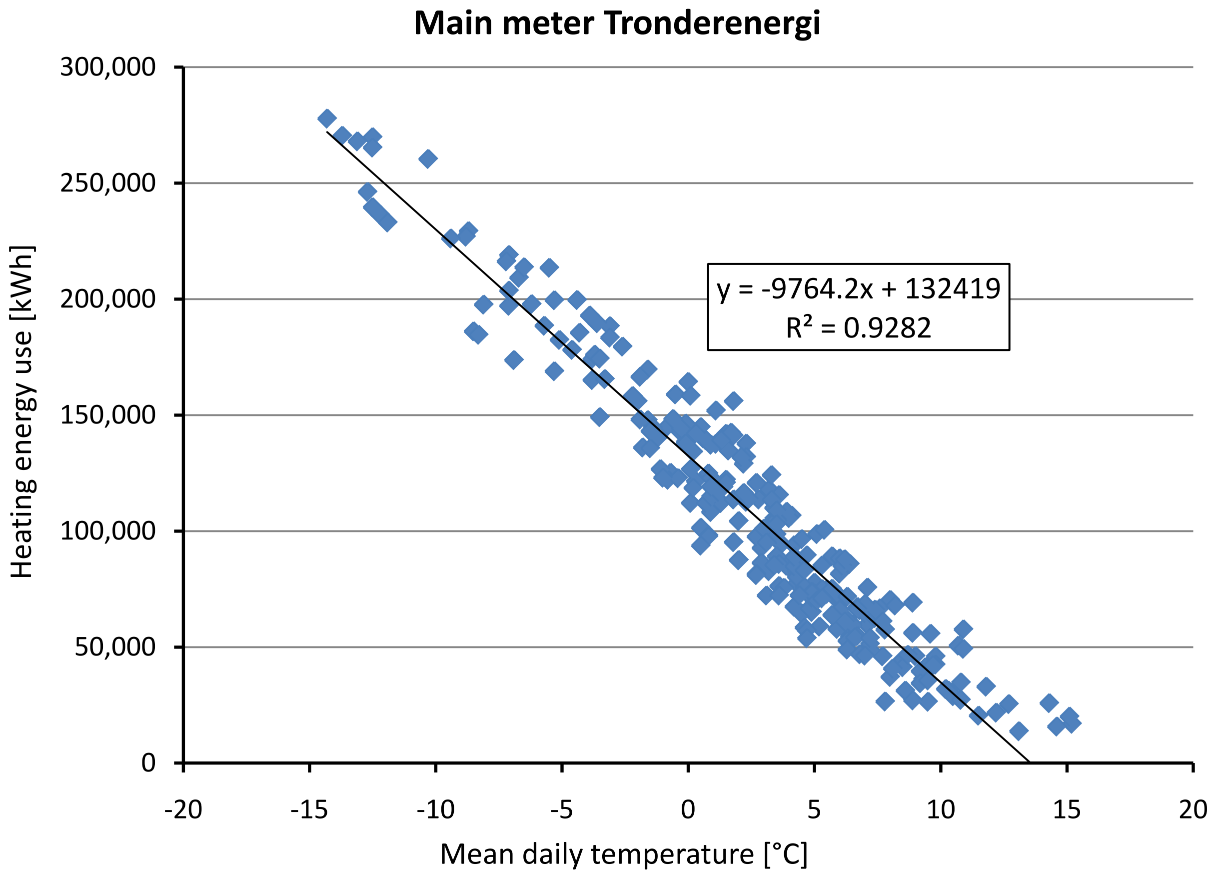


Figure 27. Analysis of Main meter Tronderenergi after data correction

The ‘goodness of fit’ is indicated by the R^2, which would be equal to 1 in the case of a perfect fit. The scatter plot for the Main meter Tronderenergi vs. mean daily temperature shows good correlation ($R^2>0.92$). It indices that data are corrected adequately, and that probably there are no significant errors in collected data for the Main meter.

Then, holidays and weekends were excluded from data. It is obvious that they have different patterns and energy profiles than working days (space is not occupied, less requirements for sanitary hot water, etc). Scatter plot after excluding weekends and holidays is shown in Figure 28.

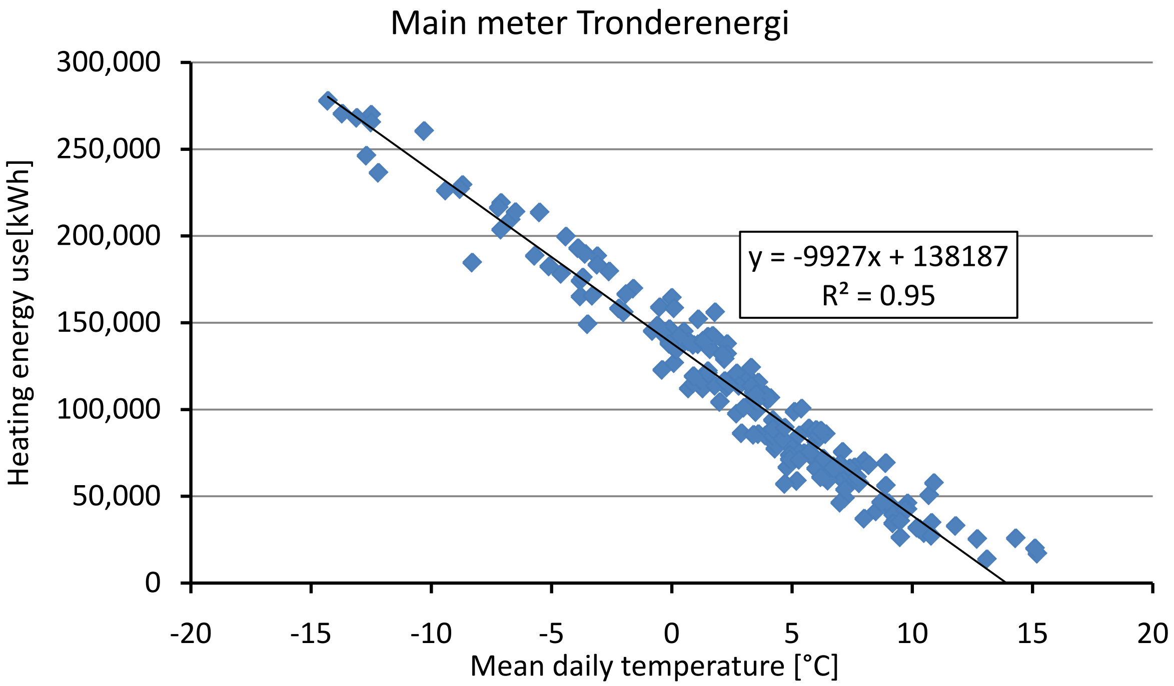


Figure 28. Analysis of Main meter Tronderenergi after data correction for working days

The „goodness of fit" is increased, R^2 is changed from 0.9282 (Figure 27) to 0.95 (Figure 28). Data considering working days show better correlation with mean daily temperature. That result was expected, considering that weekends and holidays have different operating mode.

Same analysis was done for Admin submeter sum (Figure 29).

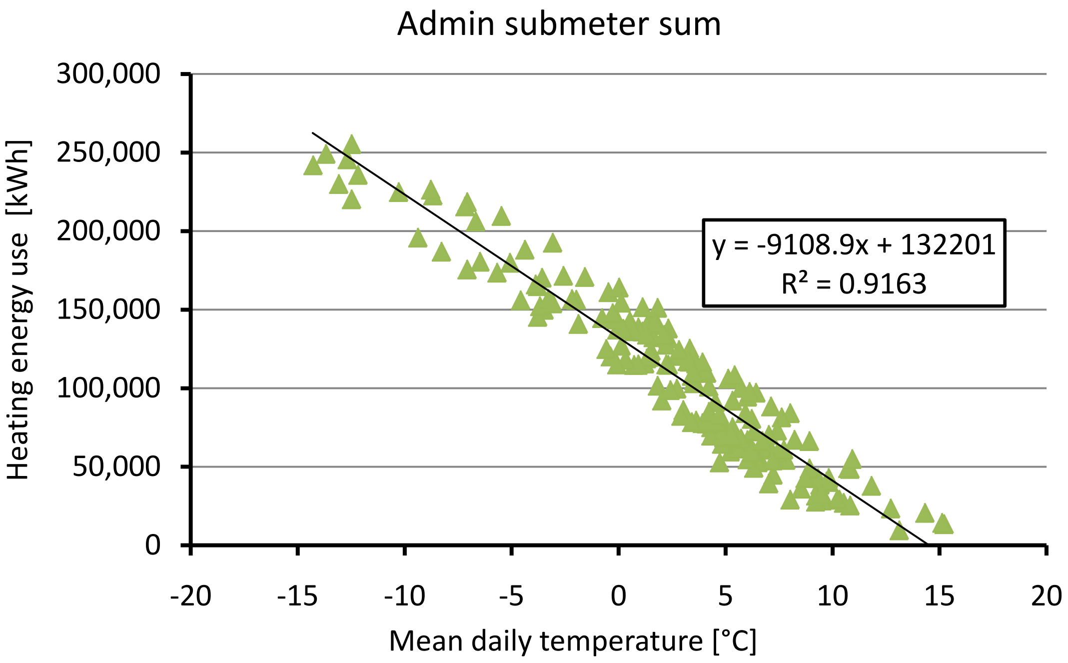


Figure 29. Analysis of Admin submeter sum after data correction for working days

Both Main meter Trondenergi and Admin submeter sum showed good correlation with mean outside daily temperature (Figure 28 and Figure 29). These kinds of plots represent simple, primer analysis of collected data. Better correlation of the Main meter Tronderenergi than Admin submeter sum indicates that it is more likely that more faulty data are found for submeters than for the Main meter. Therefore, the Main meter Tronderengi corrected data are considered as „true“ and relevant for further analysis.

8 Data error analysis

Why is it important to have correct data from submeters?

In University campus Gloshaugen area of 30,000 m^2 is leased to other users. NTNU pays the bills for electricity and district heating consumption by the measurements from Main meter installed by the energy distributor. Therefore, this meter should be taken as the relevant. Further, bills for each tenant should be calculated. Exact calculation of energy use expenses is in everybody`s interest. If there is a building submeter with incorrect measured data there is a possibility that some tenants pay more than they have spent in that period, in order to compensate the difference. If the simple approximation of consumption (based, for example, on leased area) is done, there is no interest in applying energy saving measures. Also, without correct measured data it is not possible to monitor and prove benefits of applying energy saving measures.

8.1 Data error analysis using Principal Component Analysis

Principal Component Analysis (PCA) [18] is a multivariate technique in which a number of related variables are transformed to a smaller set of uncorrelated variables.

The method of Principal Components is primarily a data-analytic technique that obtains linear transformations of a group of correlated variables such that the transformed variables are uncorrelated (4.5).

$$\text{month}\left[\overbrace{\begin{bmatrix}X_{11} & \dots & X_{1n}\\ \dots & \dots & \dots\\ X_{m1} & \dots & X_{mn}\end{bmatrix}}^{\text{building meters}} \Rightarrow \begin{bmatrix}PC_{11} & \dots & PC_{1p}\\ \dots & \dots & \dots\\ PC_{m1} & \dots & PC_{mp}\end{bmatrix}\right] \qquad \text{month}\left[\overset{\substack{\text{main electricity}\\ \text{or heating meter}}}{\begin{bmatrix}Y_{1}\\ \dots\\ Y_{m}\end{bmatrix}} = f\left\{\begin{bmatrix}PC_{11} & \dots & PC_{1p}\\ \dots & \dots & \dots\\ PC_{m1} & \dots & PC_{mp}\end{bmatrix}\right\}\right]$$

8.2 Heating energy use analysis

Considering there were some differences found in measurements, statistical methods were used to analyze collected data.

Bills are paid based on measurements of district heating supplier Main meter Tronderenergi, so it was taken as reference. Measured data for Main meter installed at NTNU and Submeter sum was compared to data for heating energy use form Main meter Tronderenergi for years 2012 (Figure 30), 2011 (Figure 31), and 2012 (Figure 32). Data shows high correlation (R^2>0.9), which indicates that there are probably not significant errors in measurements on annual level.

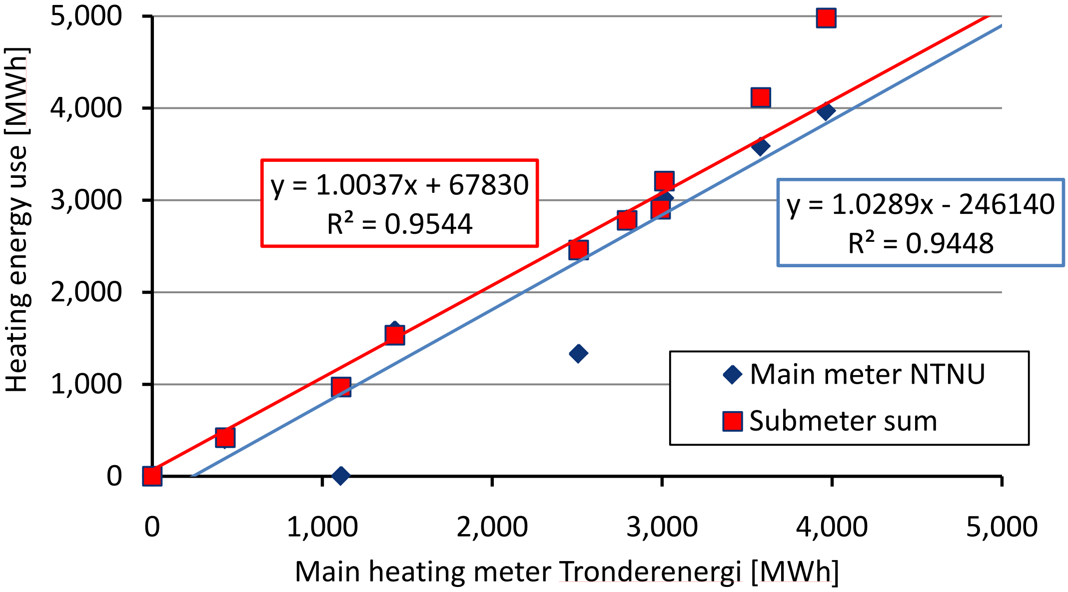


Figure 30. Comparing heating energy use measurements for Main meter Tronderenergi, Main meter NTNU and Submeter sum for year 2012

Data collected for year 2011 (Figure 31) showed best correlation, so those results were taken as „true“ and chosen for training the model.

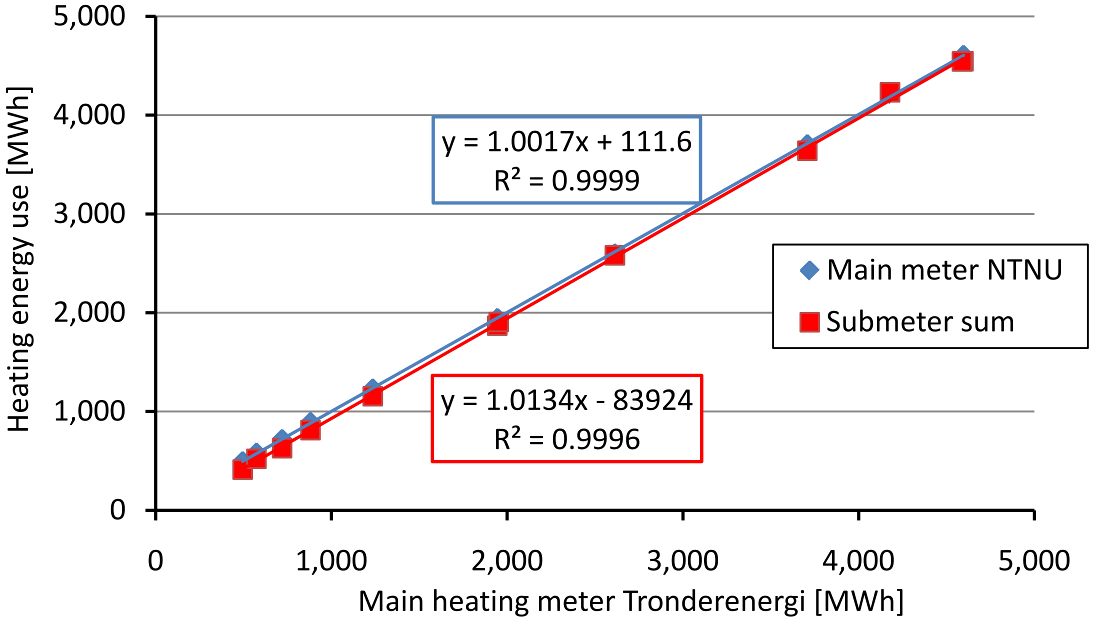


Figure 31. Comparing heating energy use measurements for Main meter Tronderenergi, Main meter NTNU and Submeter sum for year 2011

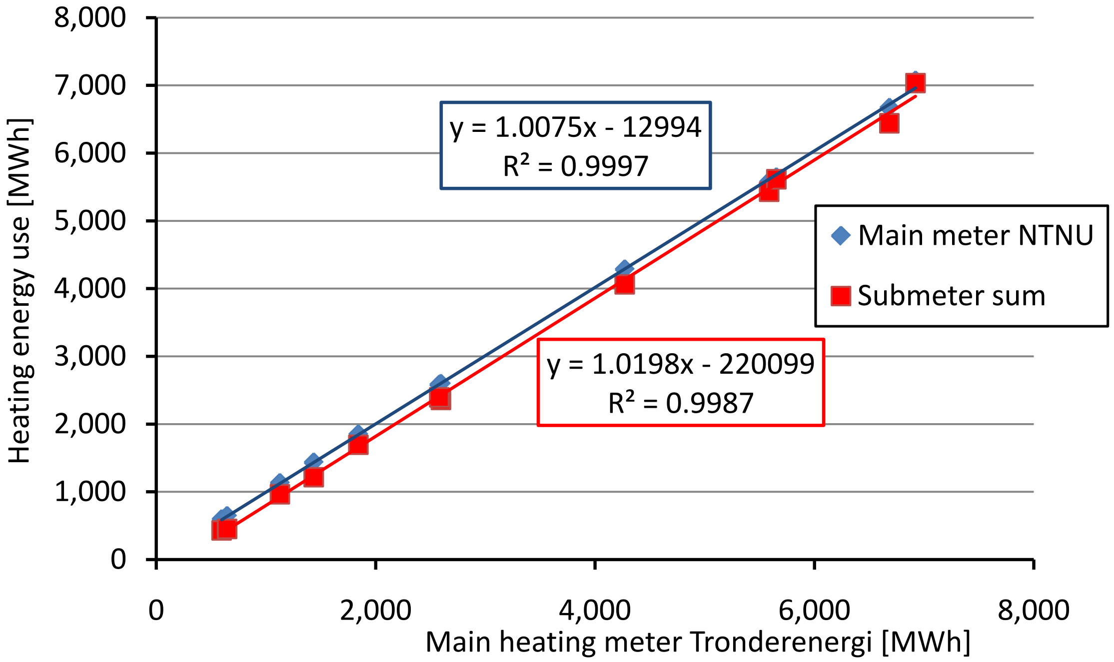


Figure 32. Comparing measurements for Main meter Tronderenergi, Main meter NTNU and Submeter sum for year 2010

Analyzing data for these meters using PCA (4.5.2) can help in defining faulty meters, specify the building and the month in which biggest error is recorded. Further work can be done in order to develop mathematical model that can help to correct data that are considered as faulty.

In this case input (predictors) were submeters for each building, and output (response) are the measurements of the Main meter Tronderenergi, the Main meter NTNU (controlled meter installed by NTNU), and Submeter sum.

PCA generates a new table with the same number of variables, called the principal components. The first principal component contains the maximum variance ("maximum information"). The second principal component is calculated to have the second most variance, and, importantly, is uncorrelated (in a linear sense) with the first principal component.

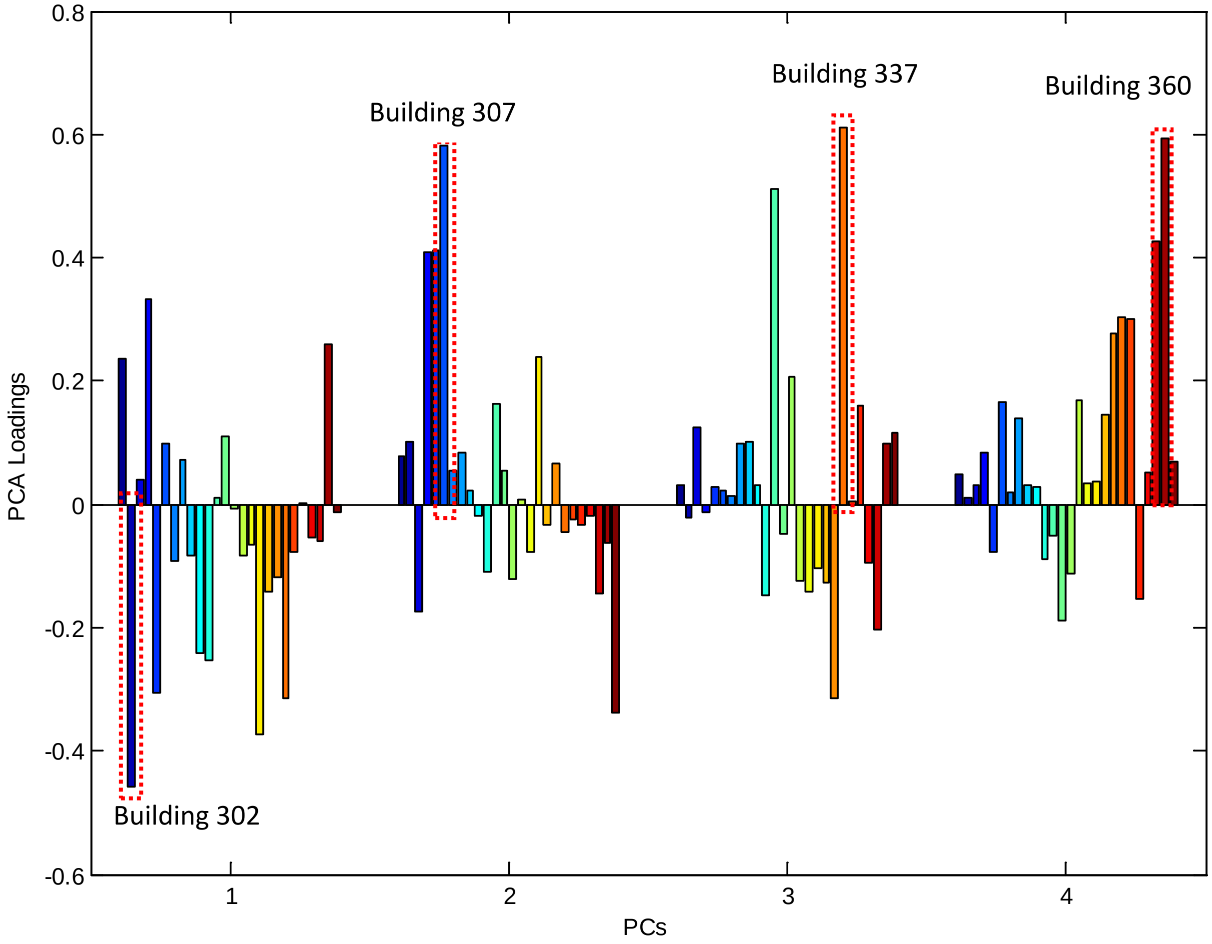


Figure 33. PLS weights for Heating energy use of the four most important Principal components

Each principal component is a linear transformation of the entire original data set. In Figure 33 the importance (weight) of an original variable is presented for the four most important PCs by showing the PLS weights. By using procedure based on PLS weights, it was found that the most important „share” in main principal components have buildings 307 Verksted Teknisk (Materials Engineering Laboratory), 337 Byggteknisk (Building Technology), 360 Realfagbygget (Natural Science Building) and 302 Varmeteknisk (Thermal Energy Building).

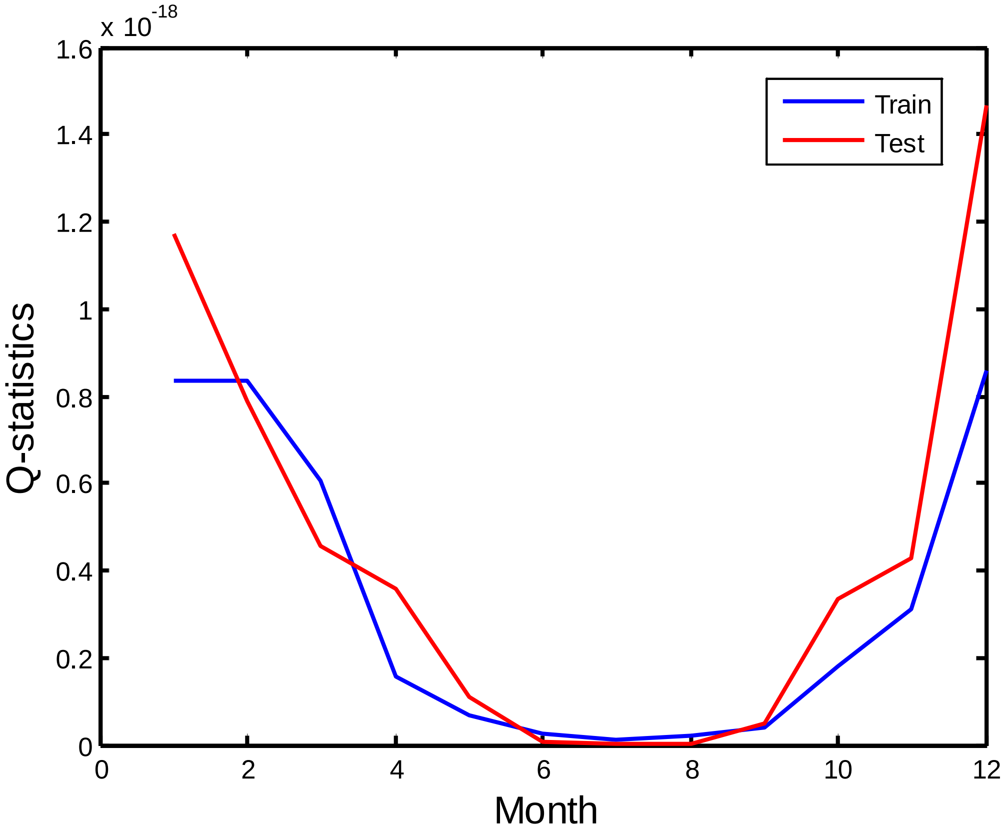


Figure 34. Q-statistics for train year (2012) and test year (2011)

Q-statistics is used for error analysis. Measured data for year 2011 were used as „train year“. Data for heating energy use for year 2011 were used as „test year“. In Figure 34 is shown that the curves are pretty similar, with some differences in 4th month (April), and 12th month (December). Results from Matlab identified that months with biggest error are 1st (January) and 12th (December); in both months biggest influence on error has building 301 Hovedbygningen (Main building); it is most probable faulty submeter.

8.3 Electricity energy use analysis

Electricity bills are paid based on measurements of electricity supplier - Main meter Tronderenergi, so it was taken as reference. After collecting data from all submeters installed in University campus Gloshaugen, it was summarized and that result is called **Submeter sum.**

Comparison was made between:

- The main electricity meter installed by Tronderenergi (Main electricity meter Tronderenergi
- Sum of submeters programmed by the NTNU administrator, which is shown in Figure 8 (Admin submeter sum)
- Sum of submeters manually made after collecting all available electricity use data (Submeter sum)

These three values should actually be the same, but they are not, so it showed that there were probably some faulty data. Maybe some of the submeters is responsible only for one system, all for the group of buildings. Comparison for these three values was done for year 2012 (Figure 35), year 2011 (Figure 36) and year 2010 (Figure 37).

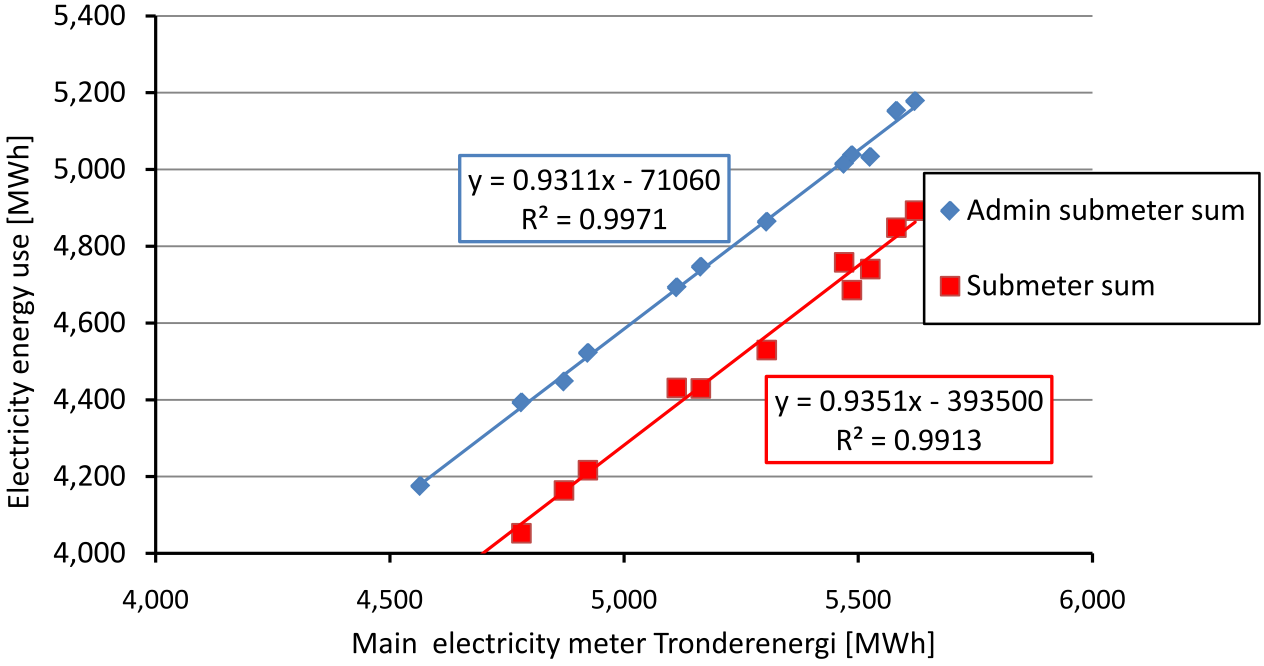


Figure 35. Comparison of electricity energy use measurements for Main electricity meter Tronderenergi, Admin submeter sum and Submeter sum for year 2012

Data for 2012 showed best correlation, so there were used for training the model.

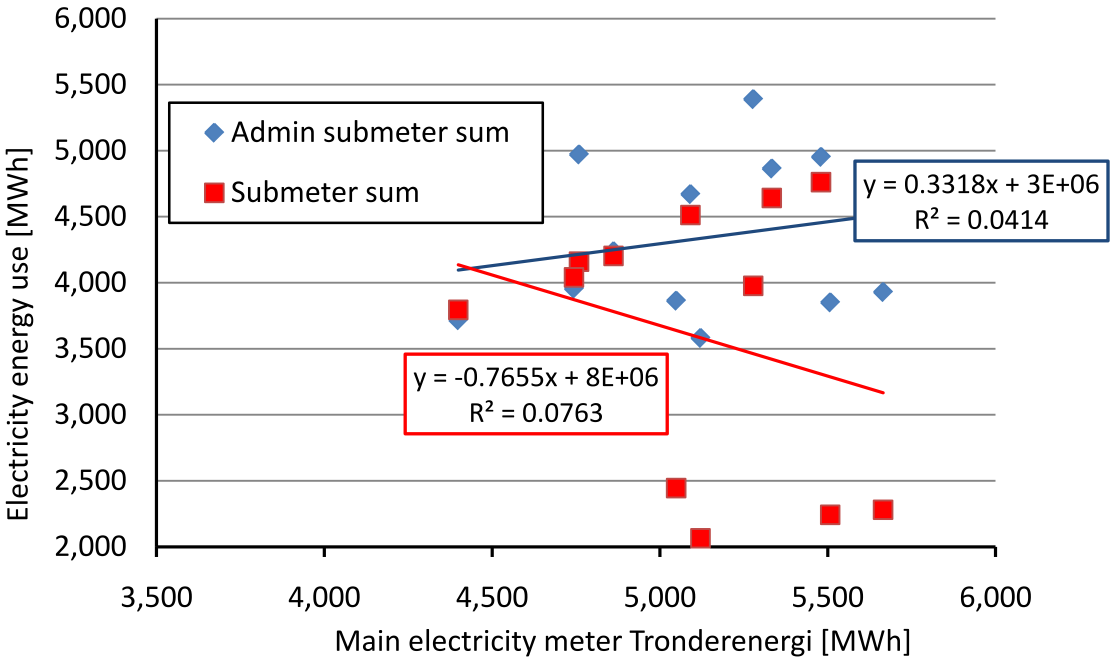


Figure 36. Comparison of measurements for Main electricity meter Tronderenergi, Admin submeter sum and Submeter sum for year 2011

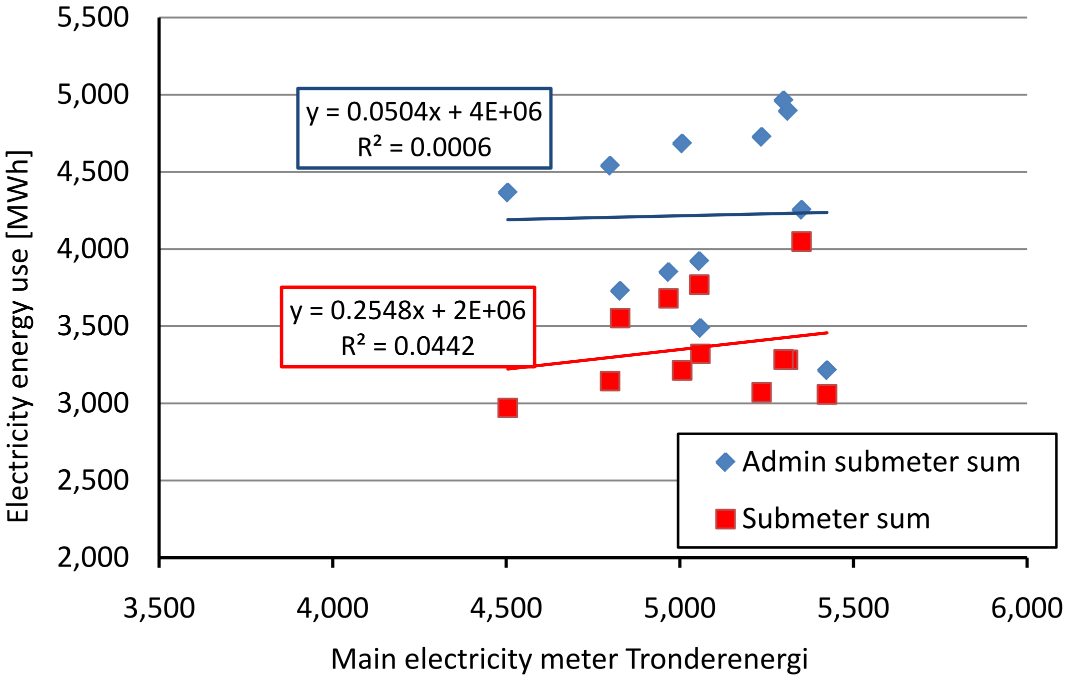


Figure 37. Comparison of measurements for Main electricity meter Tronderenergi, Admin submeter sum and Submeter sum for year 2010

Really poor correlations for year 2011 and 2010 ($R^2<0.1$) indicate significant errors in measurement. Principal Component Analysis was used to analyze errors for electricity energy use in year 2011 and 2010.

Partial Least Squares Regression (PLSR) and Principal Components Regression (PCR) are both methods to model a response variable when there are a large number of predictor variables, and those predictors are highly correlated or even collinear. Both methods are applied for electricity energy use analysis (Figure 38).

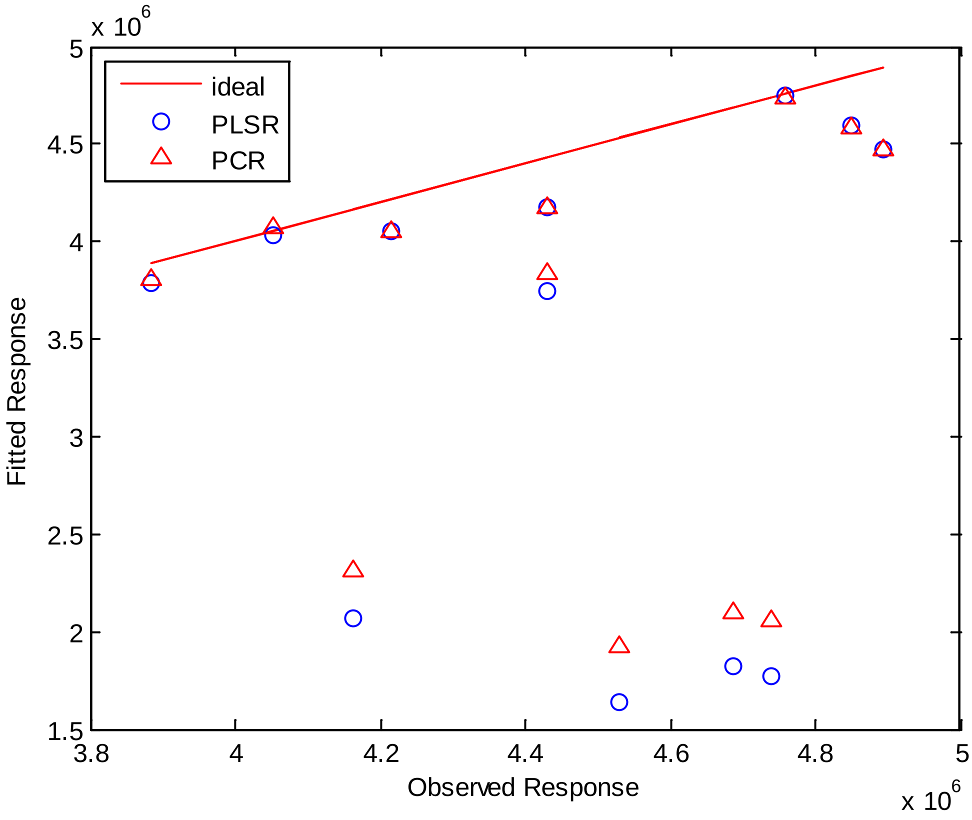


Figure 38. Fitted vs. observed response for the PLSR and PCR fits for electricity energy use data errors for year 2011

Figure 38 showed that PCR makes a slightly more accurate fit (closer to ideal). Some data are correct (on line representing ideal case), some are close to it, and some points are significantly far from ideal fit.

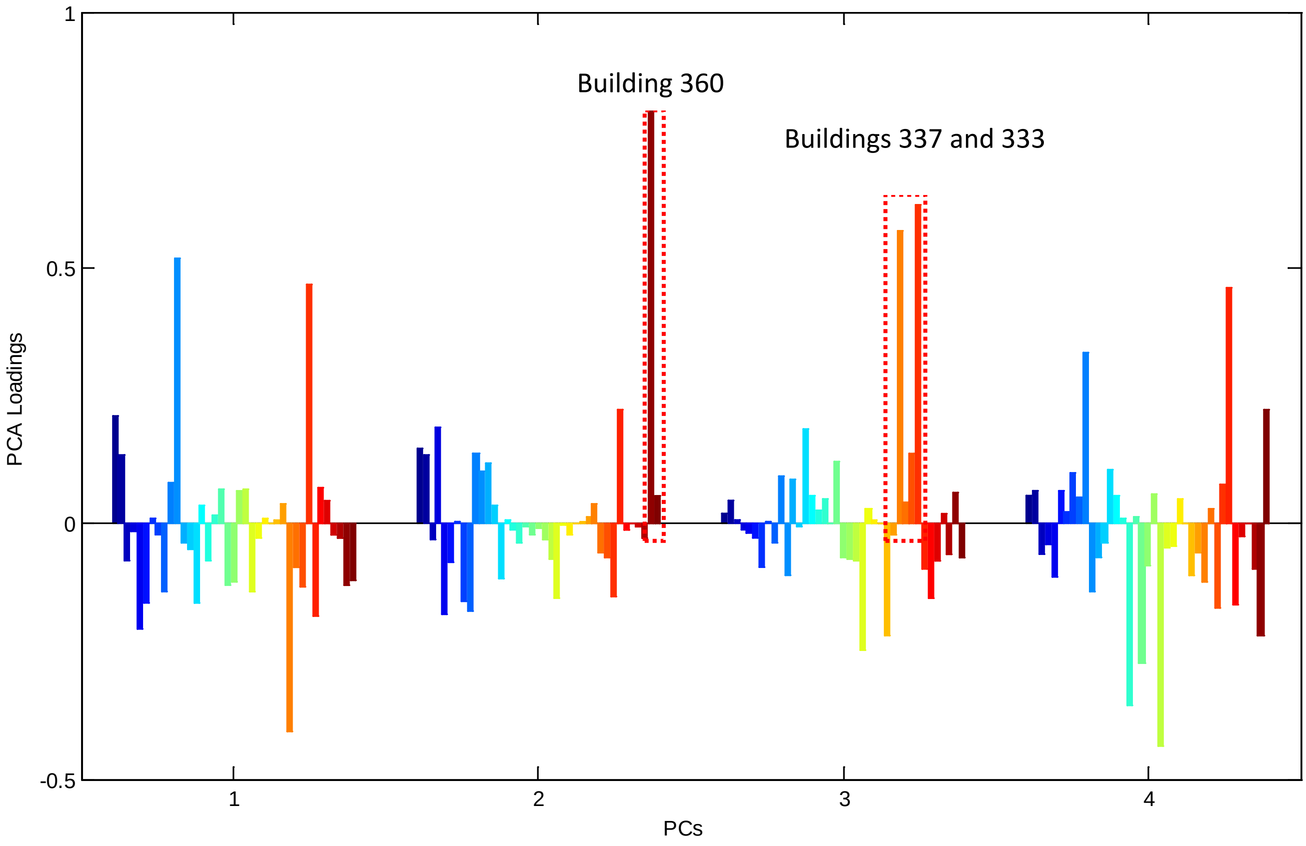


Figure 39. PLS weights for Electricity energy use of the four most important Principal components (for year 2011)

By using procedure based on PLS weights, it was found that the most important „share" in main principal components have building 360 Realfagbygget (Natural Science Building),), 337 Byggteknisk (Building Technology) and 333 BERG Avd.

Q-statistics for electricity energy use data error for year 2011 is shown in Figure 40.

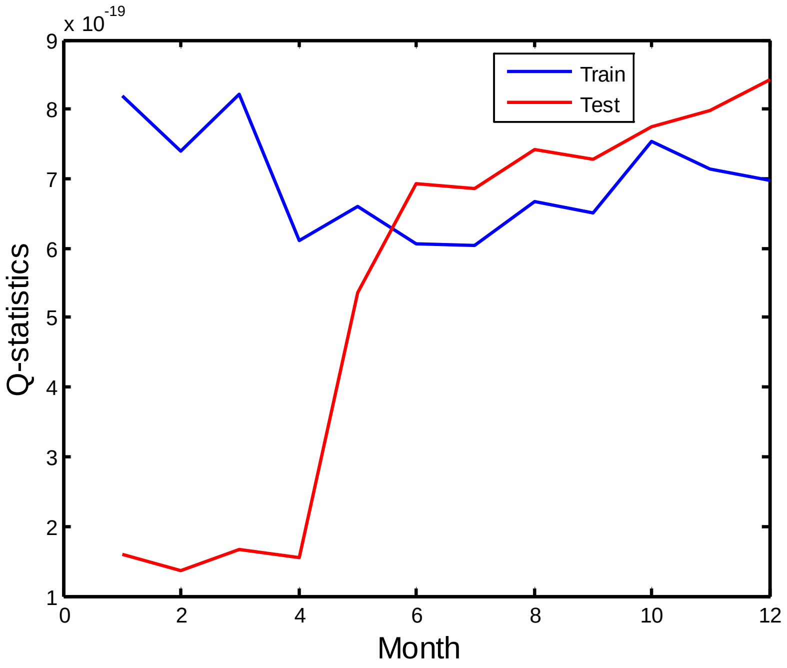


Figure 40. Q-statistics for electricity energy use data error for year 2011

Q-statistcs showed that significant errors from January to April in year 2011, while there are no significant differences from June 2011 (Figure 40). Analysis identified that the building (submeter) with biggest influence on error is building 360 Realfagbygget (Natural Science Building).

Same analysis was done for electricity energy use for year 2010. Again, data for year 2012 are used as train (taken as true).

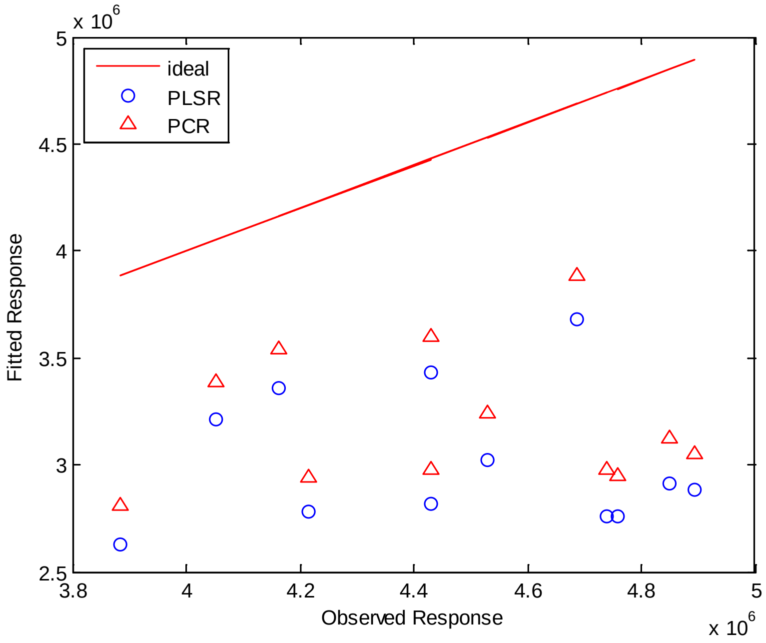


Figure 41. Fitted vs. observed response for the PLSR and PCR fits for electricity energy use data errors for year 2010

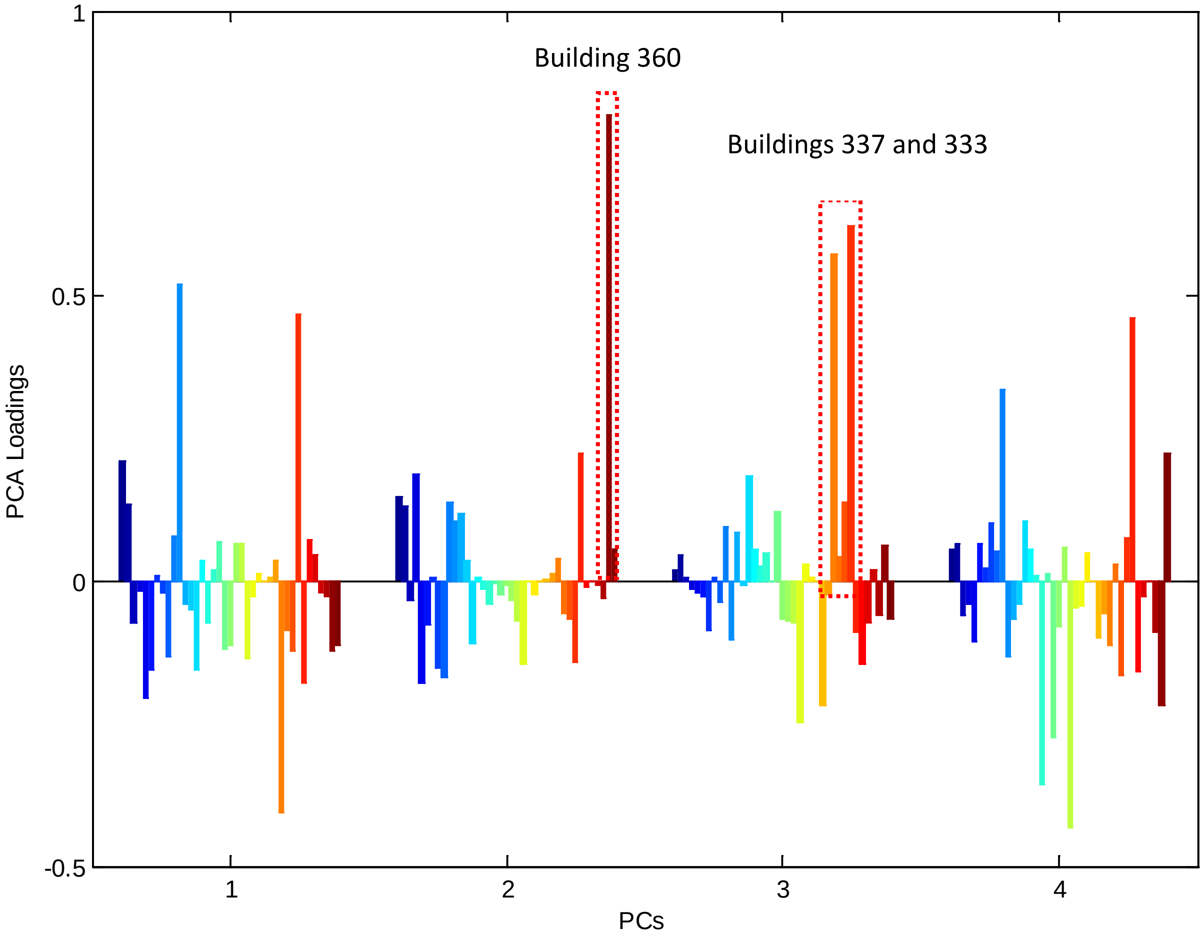


Figure 42. PLS weights for Electricity energy use of the four most important Principal components (for year 2010)

Based on PLS weights, it was found that the most important „share” in main principal components have buildings 360 Realfagbygget (Natural Science Building),), 337 Byggteknisk (Building Technology) and 333 BERG Avd (Figure 42). PLS weights for year 2011 (Figure 39) are similar with those for year 2010 (Figure 42).

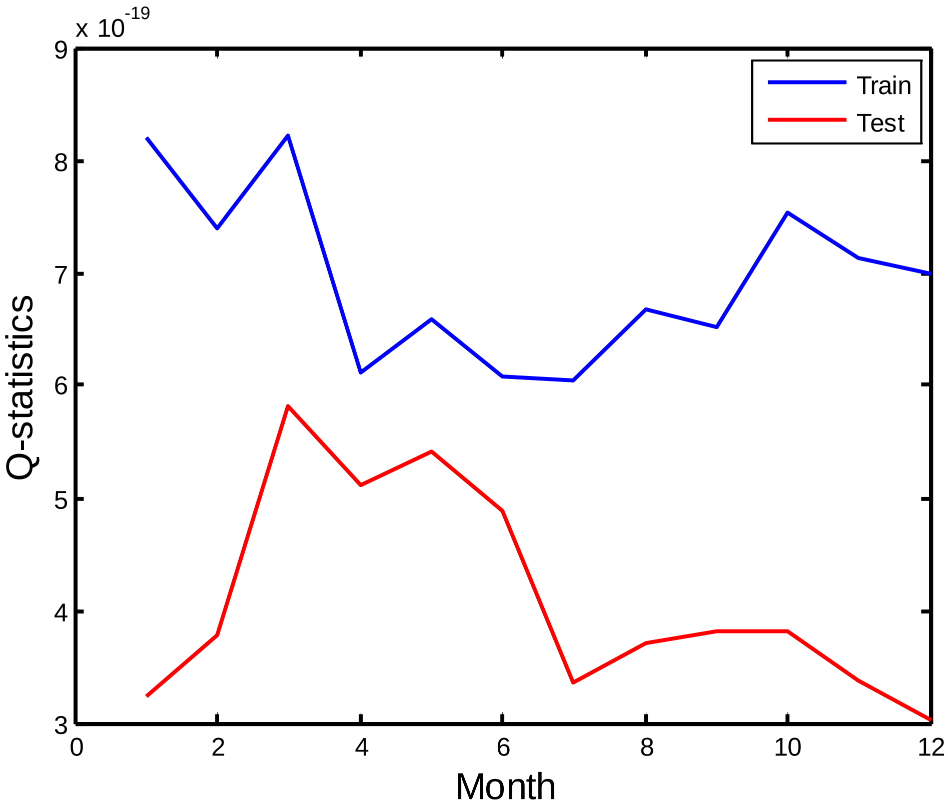


Figure 43. Q-statistics for electricity energy use data error for year 2010

Q-statistics (Figure 43) shows that there are significant errors for almost all months (totally different curves for train year 2012 and test year 2010). Based on Figure 34 and Figure 43, faulty data are appeared until June 2011, and after that, data shows increase in quality

9 Energy use model in Matlab

Based on previously created building database (major part of database is presented in Appendix B), set of data containing building information represent input variables (predictors) for energy use model. Output (response) is energy use (electricity or heating). Both set of variables are known (building database) or measured (energy use). Task is to define mathematical relationship between them.

$$\text{buildings}\left\{\left[\overbrace{\begin{bmatrix} X_{11} & \cdots & X_{1n} \\ \cdots & \cdots & \cdots \\ X_{m1} & \cdots & X_{mn} \end{bmatrix}}^{\text{building data}}\right]\right. \Rightarrow \begin{bmatrix} PC_{11} & \cdots & PC_{1p} \\ \cdots & \cdots & \cdots \\ PC_{m1} & \cdots & PC_{mp} \end{bmatrix} \qquad \overset{\text{energy use}}{\text{buildings}\left\{\left[\begin{bmatrix} Y_{1} \\ \cdots \\ Y_{m} \end{bmatrix}\right]\right. = f\left\{\left[\begin{bmatrix} PC_{11} & \cdots & PC_{1p} \\ \cdots & \cdots & \cdots \\ PC_{m1} & \cdots & PC_{mp} \end{bmatrix}\right]\right\}}$$

First, all data are standardized. This centers and scales the data.

Partial Least Squares Regression (PLSR) and Principal Components Regression (PCR) construct new predictor variables, known as components, as linear combinations of the original predictor variable (4.5.1).

Matlab functions are used to fit a PLSR model with 24 PLS components and one response.

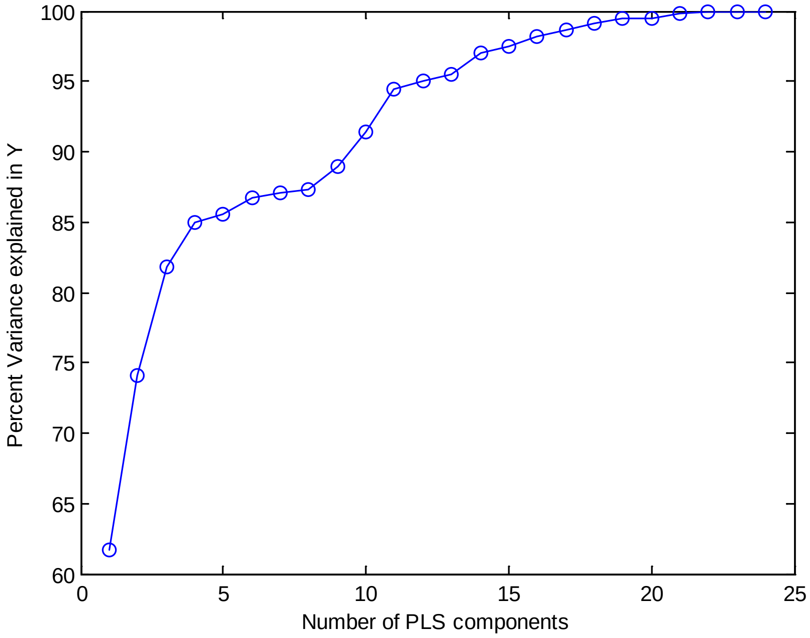


Figure 44. Percent of variance explained with PLSR model

Figure 44 suggests that PLSR with 18 components explains most of the variance in the observed Y (above 15 PLS components, variance of model approaches 100%). After that the fitted response values for the 18-component model is computed.

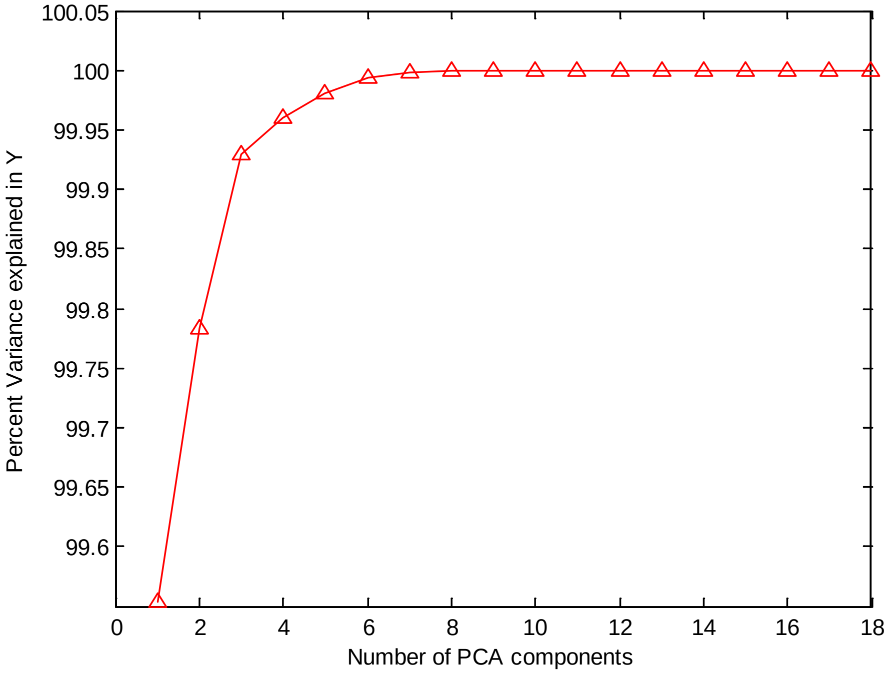


Figure 45. Percent of variance explained with PCR model

Figure 45 shows that PCR with 7 components explain almost all variance in the observed y (for 7 components variance of model approaches 100%). One of the main advantages of PCA is that set of 55 predictor components is reduced to 7 Principal components, without losing information about model.

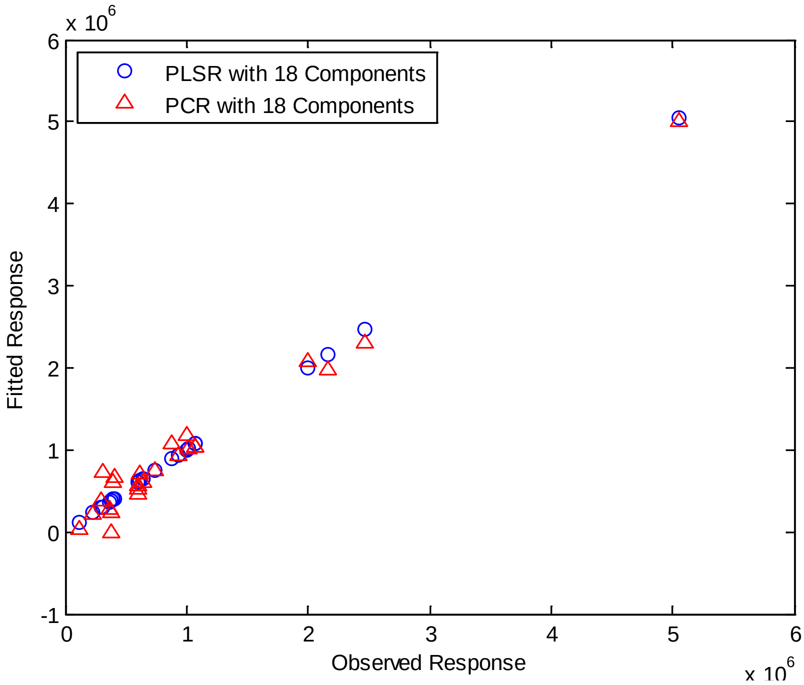


Figure 46. Fitted vs. observed response for the PLSR and PCR fits for heating energy use model

In Figure 46 fitted vs. observed response for the PLSR and PCR is shown. Both models fit heating energy use fairly accurately.

One way to compare predictive power of PCR an PLSR models is to show how much of variance are explained with each model (Figure 47). It can help also in hoosing number of components

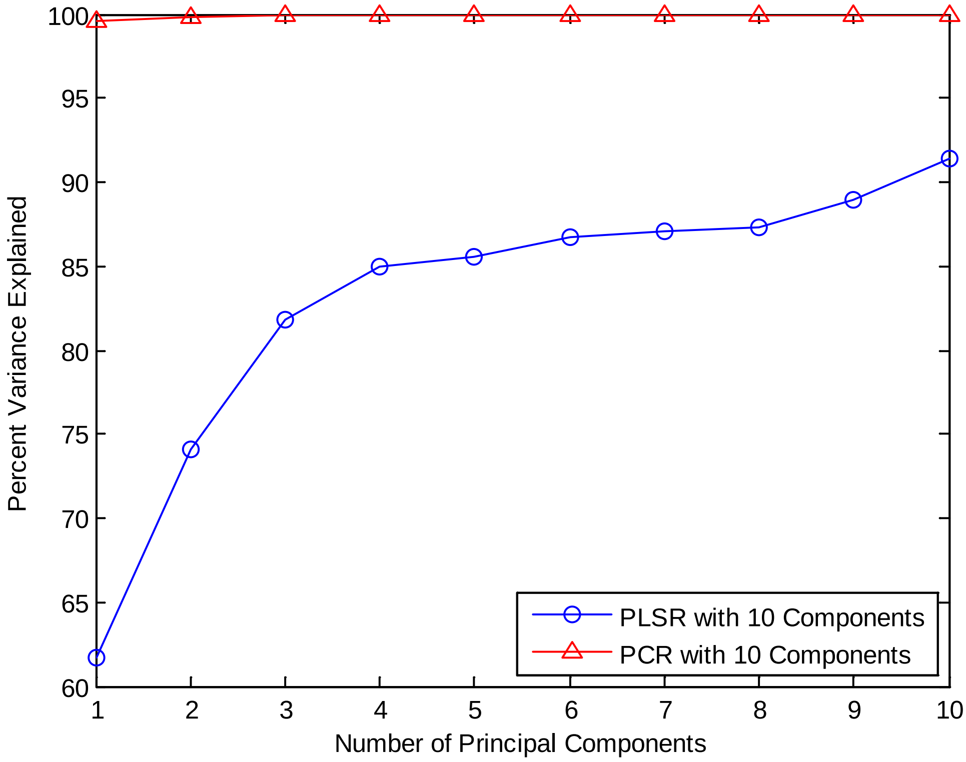


Figure 47. Percent Variance explained for PCR and PLSR model for heating energy use with 10 components

Figure 47 shows that modeling with PCR with one Principal Component explains more 99.5% of model, while PLSR explains only 62%. When using more components Percent Variances explained with PLSR comes closer to PCR, but even with 10 components PLSR does not explain more than 90% of mode (comparing to 100% with PCR).

The fact that the PCR curve is uniformly higher suggests why PCR with same number of components does such a poor job, relative to PLSR, in fitting Y. PCR constructs components to best explain X, and as a result, those first two components ignore the information in the data that is important in fitting the observed Y. As more components are added in PCR, it will necessarily do a better job of fitting the original data y, simply because at some point most of the important predictive information in X will be present in the principal components.

Choosing the Number of Components with Cross-Validation

Cross-validation is statistical method for choosing the number of components in either PLSR or PCR. It avoids over-fitting data by not reusing the same data to both fit a model and to estimate prediction error.

Mean squared prediction error (MSEP) was estimated for PLSR and PCR method. This is used for defining prediction accuracy for modeling – it shows quality of different models.

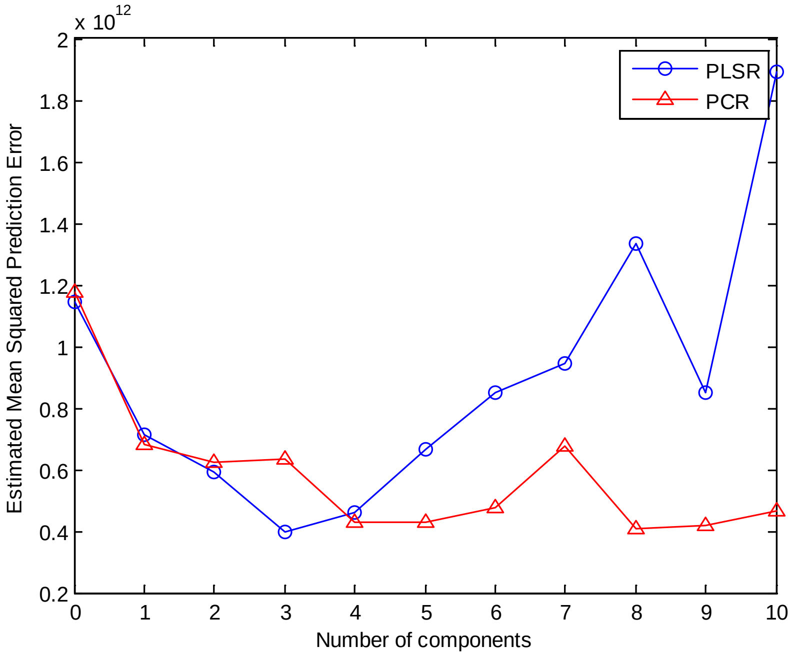


Figure 48. Model quality based on Estimated Mean Square Prediction Error (MSPE)

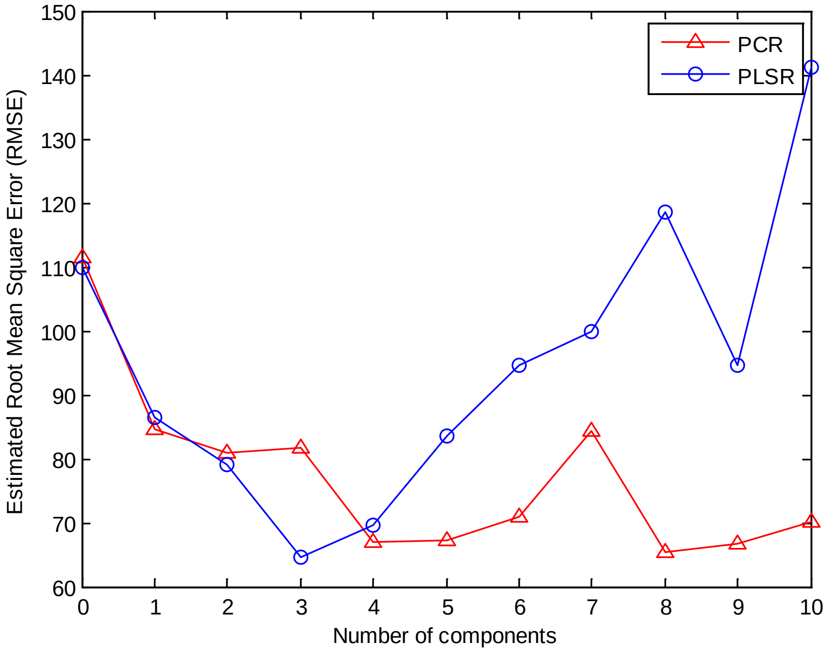


Figure 49. Model quality based on Estimated Root Mean Square Error (RMSE)

PCR model shows smaller errors (both MSPE and RMSE), with increasing number of components. As show in Figure 48and Figure 49 smallest errors (for both models) are for model with four components.

The PLS weights are the linear combinations of the original variables that define the PLS components, i.e., they describe how strongly each component in the PLSR depends on the original variables, and in what direction.

In the Figure 50 the importance of an original variable is presented for the four most important PCs by showing the PLS weights.

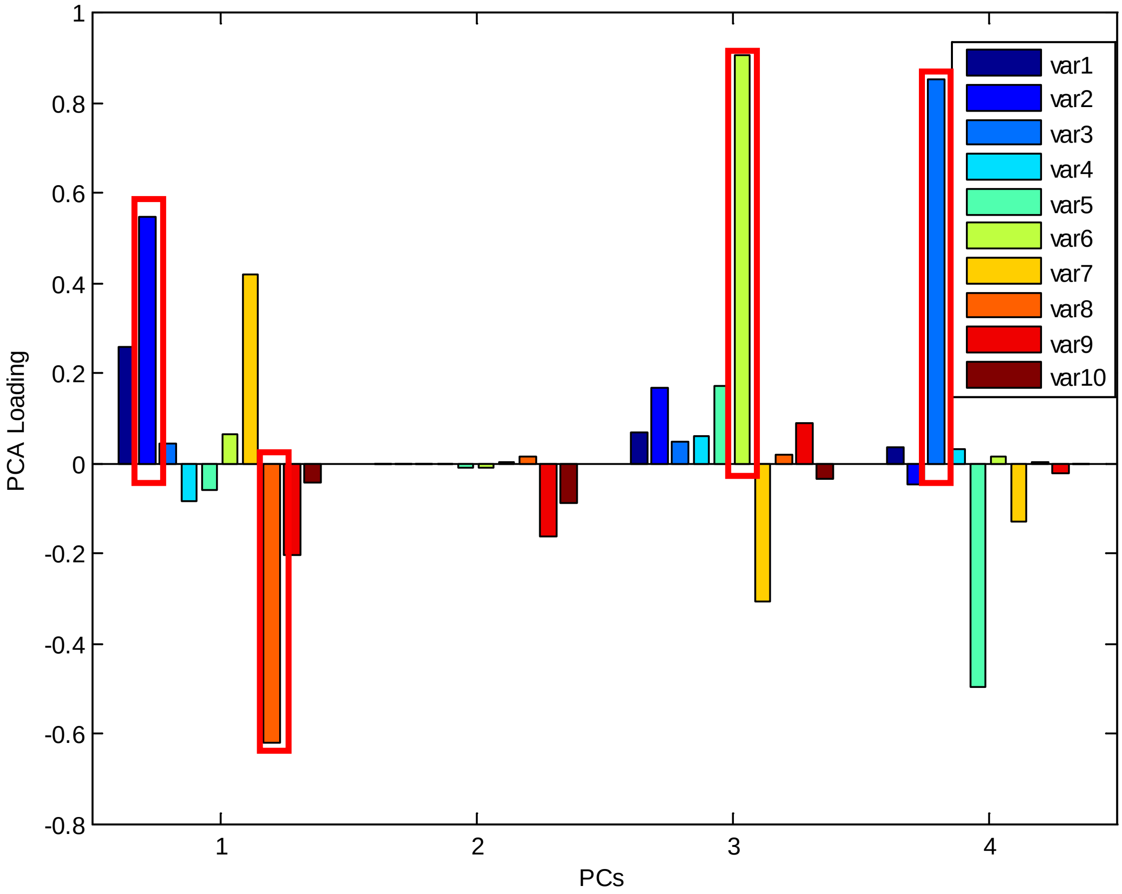


Figure 50. Variable loadings on the PCs

By using procedure for model scaling and finding driving variables based on PLS weights, it was found that the most important variables of the heating energy use are outside walls area (var3), windows, doors and glass area (var6), and heating volume (var8).

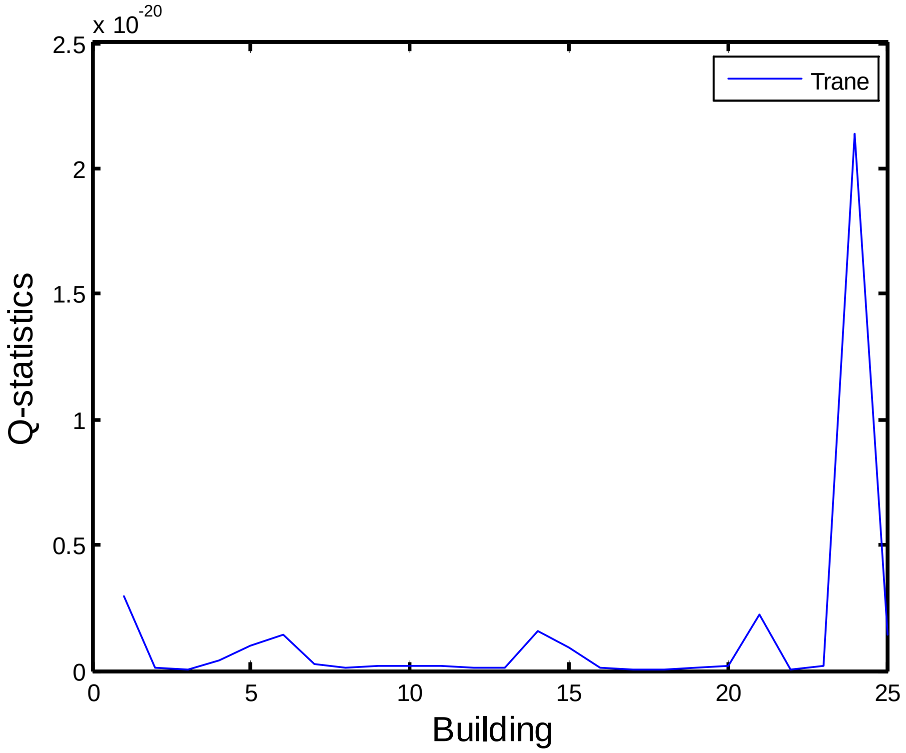


Figure 51. Q-statistics for Energy use model

Q-statistics (Figure 51) shows that highest error is calculated for building 360 Realfabygget (Natural science building). Measured data for that building should be further investigated.

10 Conclusion

Building database, using different sources of information, was created. After collecting all available data from meters and submeters at NTNU University campus Gloshaugen, heating and electricity energy use was analyzed.

Data error analysis using Principal Component Analysis (PCA) for heating and electricity energy use showed that there are some errors in measurements. For heating energy use year 2012 was taken as „true“ and used for training data from other years. Analysis of available main meters and submeters for heating energy use showed good correlation, with some faulty data. The biggest errors are found for January and December 2011; in both months biggest influence on error has building 301 Hovedbygningen (Main building).

Q-statistics showed that electricity energy use data have more significant errors. Totally different curves appear for train year 2012 and test year 2010. Faulty data are appeared until June 2011, and after that, data shows increase in quality.

Energy use model was made for heating energy use, considering that data for electricity energy use should be previously corrected. PCR and PLSR models were created. PCR explains more of model variance, while using the same number of components as PLSR model. Modeling with PCR with one Principal Component explains more 99.5% of model, while PLSR explains only 62%. With only four Principal Components PCR model explains close to 100% of model.

By using procedure for model scaling and finding driving variables based on PLS weights, it was found that the most important variables of the heating energy use are outside walls area, windows, doors and glass area, and heating volume.

Q-statistics shows that highest error is calculated for building 360 Realfabygget (Natural science building).

11 Future work

As it was shown in chapter related to Data error analysis, there are issues in collected data (especially from some building`s submeters). It is necessary to develop some mathematical model, which can more accurately point out errors in measurements, and if it is possible, help in correcting faulty data.

Other task is to find data for missing buildings, so the database can be completed, or expanded with additional building information. Missing data should be found, calculated or adequately assumed. The more data is available, the model will be more accurate and able to adequately predict energy use.

Also, there are some buildings that do not have submeters, so it is important to promote additional submeters installation, by showing benefits of detail metering. Propose installing submeters for most significant system, which can help in defining breakdown of energy use. Increasing the number of submeters provides better image of real energy consumption and shows possible „weak points" in heating system. It can improve the ability to accurately track energy use. Additionally installed submeters can be used to track loads of individual buildings, providing valuable information about the energy costs associated with specific functions, such as the operation of laboratories. It can help in calculating energy use for different consumers: air-conditioning, heating, domestic hot water, lighting, etc.

Detailed analysis for individual buildings that have heat pumps should be separately performed. Data for heat pumps submeters (heat produced and electricity consumed) are available mostly from July 2011. Those data have significant differences, probably a lot of „faulty" data. After correcting this, further detailed analysis can be done.

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Appendix A Building area and year of construction found in different sources

	Data from Maintenance staff		Data from Energy Efficiency Certificate			Data from System list (anleggsoversikt)
Building	area	Year built	total area	heated area	Year built	area
	[m^2]		[m^2]	[m^2]		[m^2]
301 HOVEDBYGNINGEN	17,285.2	1910	17,360.0	-	1910	17,400.0
302 VARMETEKNISK NORD	15,191.3	1962	15,026.0	15,026.0	1962	14,720.0
303 STROMNINGSTEK.	3,030.4	1965	3,030.0	3,030.0	1962	3,030.0
304 METALLURGI	2,215.3	1951	2,215.0	2,215.0	1951	2,169.0
305 OPREDNINGEN	3,954.8	1960	7,598.0	7,598.0	1960	3,806.0
307 VERKSTED TEKNISK	12,310.5	1966	11,400.0	11,400.0	-	11,778.0
308 MATERIAL TEKNISK	15,363.4	1958	12,600.0	12,600.0	1958	12,633.0
311 KJEMI 1	4,969.3	1954	6,067.0	6,067.0	-	3,801.0
312 KJEMI 2	5,236.7	1955	3,988.0	3,988.0	-	5,591.0
313 KJEMI 3	6,520.3	1967	5,050.0	5,050.0	2000	6,657.0
314 KJEMI 4	5,569.6	1965	4,510.0	4,510.0	-	5,340.0
315 KJEMI 5	5,627.8	1957	4,837.0	4,837.0	-	5,627.0
316 KJEMI 6 Kjemihallen	5,642.8	1959	4,440.0	4,440.0	-	5,485.0
317 IT BYGG	6,185.7	1973	5,484.0	5,484.0	1965	6,090.0
318 IT BYGG SYD	4,313.3	1965	3,684.0	3,684.0	1973	4,314.0
319 GAMLE FYSIKK	4,942.1	1924	4,116.0	4,116.0	1924	4,914.0
320 EFI	5,028.3	1960	-	-	-	5,027.0
321 SENTRALBYGG 1	17,936.4	1961	16,265.0	16,265.0	-	16,264.0
322 SENTRALBYGG 2	12,860.7	1968	12,497.0	12497.0	-	12,497.0
323 GAMLE KJEMI	3,753.8	1910	3,375.0	3,375.0		3,807.0
324 VANNKRAFTLAB.	2,525.1	1916	2,353.0	2,353.0	1916	2,300.0
325 GAMLE ELEKTRO	9,009.0	1910	DEL 1: 4,315.0	-	DEL 1: 1985	4,383.0
			DEL 2: 4,695.0	-	DEL 2: 1910	
326 ELEKTRO A	6,143.7	1961	6,006.0	6,006.0	1961	6,011.0
327 ELEKTRO B	3,599.2	1959	3,600.0	3,600.0	1959	3,361.0
328 ELEKTRO C	2,899.8	1960	2,889.0	2,889.0	1960	2,916.0
329 ELEKTRO D+B2	6,283.1	1971	6,228.0	6,228.0	1971	6,221.0
332 GRONNBYGGET	2,746.9	1958	2,311.0	2,311.0	-	2,472.0
333 BERG AVD	7,598.2	1981	3,955.0	3,955.0	1981	7,638.0

	Data from Maintenance staff		Data from Energy Efficiency Certificate			Data from System list (anleggsoversikt)
Building	area	Year built	total area	heated area	Year built	area
	[m^2]		[m^2]	[m^2]		[m^2]
335 IDRETTSBYGGET	4,906.2	1966	4,046.0	4,046.0	2005	3,420.0
337 BYGGTEKNISK	18,595.8	1975	18,175.0	18,175.0	2000	14,764.0
341 ELA (ELEKTRO E+F)	10,459.6	1986	10,457.0	10,457.0	1986	10,290.0
354 KJELHUSET	5,053.2	1951	-	-	-	5,057.0
356 PRODUKTDESIGN	2,652.3	1996	2,476.0	2,476.0	1996	2,652.0
358 HOGSKOLERINGEN	4,760.4	2002	4,312.0	4,312.0	2000	-
360 REALFAGBYGGET	60,805.7	2000	52,773.0	52,773.0	1997	58,000.0
365 PFI	4,781.2	1998	-	-	-	4,781.0

Appendix B Building database for University campus NTNU Gloshaugen (source:Energy Certificate)

Building	outside walls area	roof area	floor area	windows, doors and glass area	heated area	total area	heated air volume	U-value for exterior walls	U-value for roof	U-value for floor	U-value for windows, walls, glass	area of windows, walls, glass	Normalized thermal bridge value
	[m^{2}]	[m^{2}]	[m^{2}]	[m^{2}]	[m^{2}]	[m^{2}]	[m^{3}]	[W/(m^{2}K)]	[W/(m^{2}K)]	[W/(m^{2}K)]	[W/(m^{2}K)]	[%]	[W/(m^{2}K)]
302VARMETEKNISK NORD	5,504.0	4,315.0	4,824.0	2,293.0	15,026.0	15,026.0	73,600.0	0.35	0.35	0.12	2.04	15.30	0.09
303 STROMNINGSTEK.	1,632.0	1,098.0	1,098.0	354.0	3,030.0	3,030.0	12,520.0	0.87	0.58	0.23	2.05	11.70	0.09
304 METALLURGI	1,572.0	1,315.0	1,315.0	294.0	2,215.0	2,215.0	6,867.0	0.56	0.46	0.30	2.70	13.30	0.12
305 OPREDNINGEN	1,812.0	1,113.0	1,257.0	493.0	7,598.0	7,598.0	23,554.0	0.56	0.23	0.18	2.70	6.50	0.12
307 VERKSTED TEKNISK	2,592.0	3,064.0	3,214.0	1,830.0	11,400.0	11,400.0	39,000.0	0.43	0.81	0.28	2.01	16.10	0.09
308 MATERIAL TEKNISK	4,038.0	5,480.0	5,640.0	1,032.0	12,600.0	12,600.0	48,570.0	0.82	0.81	0.15	1.28	8.20	0.12
311 KJEMI 1	2,407.0	1,566.0	1,566.0	390.0	6,067.0	6,067.0	20,455.0	0.34	0.46	0.19	2.57	6.40	0.09
312 KJEMI 2	2,058.0	797.0	800.0	526.0	3,988.0	3,988.0	12,363.0	0.33	0.74	0.38	1.64	13.20	0.09
313 KJEMI 3	1,686.0	1,080.0	930.0	607.0	5,050.0	5,050.0	13,130.0	0.49	0.35	0.19	4.95	12.00	0.12
314 KJEMI 4	2,386.0	1,064.0	1,052.0	590.0	4,510.0	4,510.0	15,560.0	0.28	0.74	0.18	1.66	13.10	0.12
315 KJEMI 5	1,935.0	1,175.0	1,175.0	651.0	4,837.0	4,837.0	15,237.0	0.38	0.32	0.12	1.72	13.50	0.09
316 KJEMI 6 Kjemihallen	1,819.0	1,338.0	231.0	473.0	4,440.0	4,440.0	15,400.0	0.56	0.27	0.18	1.89	10.70	0.09
317 IT BYGG	1,963.0	5,484.0	1,021.0	942.0	5,484.0	5,484.0	15,630.0	0.58	0.46	0.17	2.10	17.20	0.12
318 IT BYGG SYD	1,210.0	1,700.0	1,600.0	390.0	3,684.0	3,684.0	10,500.0	0.56	0.46	0.14	1.85	10.60	0.12
319 GAMLE FYSIKK	2,186.0	1,068.0	1,128.0	588.0	4,116.0	4,116.0	11,320.0	0.97	0.70	0.22	2.99	14.30	0.12
321 SENTRALBYG 1	5,504.0	3,820.0	3,500.0	2,626.0	16,265.0	16,265.0	45,500.0	0.75	0.30	0.18	2.23	16.10	0.08
322 SENTRALBYG 2	4,420.0	2,270.0	2,000.0	1,959.0	12,497.0	12,497,0	35,000.0	0.77	0.37	0.19	2.48	15.70	0.08
323 GAMLE KJEMI	2,063.0	319.0	1,019.0	557.0	3,375.0	3,375.0	11,780.0	0.93	0.27	0.24	2.85	16.50	0.05

Building	outside walls area	roof area	floor area	windows, doors and glass area	heated area	total area	heated air volume	U-value for exterior walls	U-value for roof	U-value for floor	U-value for windows, walls, glass	area of windows, walls, glass	Normalized thermal bridge value
	[m^2]	[m^2]	[m^2]	[m^2]	[m^2]	[m^2]	[m^3]	[W/(m^{2}K)]	[W/(m^{2}K)]	[W/(m^{2}K)]	[W/(m^{2}K)]	[%]	[W/(m^{2}K)]
324 VANNKRAFTLAB.	1,684.0	910.0	483.0	289.0	2,353.0	2,353.0	8,218.0	0.70	1.29	0.13	3.32	12.30	0.12
325 GAMLE ELEKTRO Del 1	392.0	2,130.0	2,131.0	1,264.0	4,315.0	4,315.0	31,568.0	0.40	0.23	0.06	1.96	29.3	0.12
326 ELEKTRO A	1,508.0	1,092.0	1,114.0	1,348.0	6,006.0	6,006.0	18,772.0	0.52	0.46	0.15	2.01	22.4	0.12
327 ELEKTRO B	1,368.0	660.0	663.0	366.0	3,600.0	3,600.0	11,000.0	0.50	0.46	0.16	2.13	10.2	0.12
328 ELEKTRO C	1,301.0	567.0	583.0	311.0	2,889.0	2,889.0	9,534.0	0.52	0.46	0.15	2.11	10.8	0.12
329 ELEKTRO D+B2	2,479.0	828.0	1,434.0	857.0	6,228.0	6,228.0	20,552.0	0.55	0.46	0.12	2.12	13.8	0.12
332 GRONNBYGGET	1,010.0	0.0	575.0	279.0	2,311.0	2,311.0	6,932.0	0.99	0.00	0.25	2.76	12.10	0.09
333 BERG AVD	2,377.0	1,274.0	1,274.0	607.0	3,955.0	3,955.0	12,260.0	0.45	0.23	0.23	2.10	15.30	0.12
335 IDRETTSBYGG	1,784.0	1,540.0	1,548.0	240.0	4,046.0	4,046.0	16,006.0	0.57	0.34	0.12	2.10	5.90	0.10
337 BYGGTEKNISK	6,216.0	5,884.0	5,884.0	1,955.0	18,175.0	18,175.0	58,156.0	0.23	0.19	0.39	1.86	10.80	0.07
341 ELA (ELEKTRO E+F)	1,332.0	1,575.0	3,166.0	2,212.0	10,457.0	10,457.0	48,440.0	0.35	0.23	0.06	1.99	21.20	0.12
356 PRODUKTDESIGN	999.0	873.0	887.0	350.0	2,476.0	2,476.0	8,047.0	0.22	0.20	0.14	2.01	14.10	0.09
358 HOGSKOLERINGEN	1,807.0	771.0	771.0	768.0	4,312.0	4,312.0	16,199.0	0.21	0.15	0.14	1.84	17.80	0.09
360 REALFAGBYGGET	14,448.0	6,651.0	9,380.0	6,478.0	52,773.0	52,773.0	187,429.0	0.21	0.15	0.07	1.67	12.30	0.09

Building	Infiltr.	Temp. eff. of heat recovery	Specific fan power (SFP) related to air flow in the operating time	Average specific ventilation airflow in the operating time	Annual average system efficiency for heating system	Installed capacity for space heating and ventilation heat (heating coil)	The set-point temperature for heating operation time	Annual average cooling factor for the cooling system	Set point temperature for cooling	Installed capacity for space cooling and ventilation cooling
	[1/h]	[%]	[kW/(m^3/s)]	[m^3/(m^{2}h)]	[%]	[W/m^2]	[°C]	[%]	[°C]	[W/m^2]
302 VARMETEKNISK N.	2.70	62.00	2.42	10.50	85.00	100.00	21.00	250.00	22.00	31.00
303 STROMNINGSTEK.	2.00	9.00	4.53	8.00	84.00	80.00	21.00	250.00	22.00	30.00
304 METALLURGI	3.00	11.00	2.62	8.00	84.00	181.00	21.00	250.00	22.00	0.00
305 OPREDNINGEN	3.00	31.00	2.36	8.00	84.00	53.00	21.00	250.00	22.00	0.00
307 VERKSTED TEKNISK	2.00	68.00	2.90	12.00	88.00	90.00	20.00	240.00	22.00	6.00
308 MATERIAL TEKNISK	1.50	40.00	2.00	8.00	88.00	150.00	21.00	250.00	22.00	0.00
311 KJEMI 1	1.90	68.00	3.03	8.80	88.00	176.00	20.00	220.00	22.00	42.00
312 KJEMI 2	1.50	51.00	3.34	13.70	88.00	250.00	20.00	220.00	22.00	68.00
313 KJEMI 3	0.91	40.00	4.00	8.00	88.00	200.00	21.00	250.00	22.00	0.00
314 KJEMI 4	1.50	51.00	3.77	17.70	84.00	220.00	20.00	240.00	22.00	122.00
315 KJEMI 5	1.50	30.00	4.00	13.00	89.00	130.00	20.00	220.00	22.00	10.00
316 KJEMI 6 Kjemihallen	1.50	30.00	4.00	13.00	89.00	140.00	20.00	240.00	22.00	90.00
317 IT BYGG	4.00	45.00	1.53	8.00	84.00	110.00	21.00	250.00	22.00	80.00
318 IT BYGG SYD	4.00	65.00	3.15	11.10	84.00	80.00	21.00	250.00	22.00	0.00
319 GAMLE FYSIKK	4.00	27.67	2.97	8.00	84.00	300.00	21.00	250.00	22.00	0.00
321 SENTRALBYG 1	6.00	79.00	2.00	8.00	88.00	120.00	20.00	250.00	22.00	0.00
322 SENTRALBYG 2	6.00	79.00	2.00	8.00	88.00	120.00	20.00	250.00	22.00	0.00

Building	Infiltr.	Temp. eff. of heat recovery	Specific fan power (SFP) related to air flow in the operating time	Average specific ventilation airflow in the operating time	Annual average system efficiency for heating system	Installed capacity for space heating and ventilation heat (heating coil)	The set-point temperature for heating operation time	Annual average cooling factor for the cooling system	Set point temperature for cooling	Installed capacity for space cooling and ventilation cooling
	[1/h]	[%]	[kW/(m^3/s)]	[m^3/(m^{2}h)]	[%]	[W/m^2]	[°C]	[%]	[°C]	[W/m^2]
323 GAMLE KJEMI	1.50	50.00	4.00	13.00	89.00	120.00	20.00	220.00	22.00	0.00
324 VANNKRAFTLAB.	3.90	35.00	2.38	8.00	84.00	158.00	21.00	250.00	22.00	0.00
325 GAMLE ELEKTRO Del 1	2.00	70.00	2.00	8.00	84.00	130.00	21.00	250.00	22.00	0.00
326 ELEKTRO A	3.00	50.00	2.00	8.50	84.00	103.00	21.00	250.00	22.00	0.00
327 ELEKTRO B	3.00	50.00	2.00	8.00	84.00	100.00	21.00	250.00	22.00	0.00
328 ELEKTRO C	3.00	50.00	2.00	8.00	84.00	130.00	21.00	250.00	22.00	0.00
329 ELEKTRO D+B2	2.00	50.00	2.00	5.00	84.00	100.00	21.00	250.00	22.00	0.00
332 GRONNBYGGET	1.50	77.00	2.15	9.90		108.00	20.00	240.00	22.00	49.00
333 BERG AVD	3.00	51.00	3.32	17.70	84.00	303.00	21.00	250.00	22.00	1.00
335 IDRETTSBYGGET	1.50	61.00	2.94	13.20	84.00	180.00	19.00	250.00	22.00	0.00
337 BYGGTEKNISK	1.62	53.00	2.72	9.40	84.00	115.00	21.00	250.00	22.00	106.00
341 ELA (ELEKTRO E+F)	3.00	70.00	2.00	8.00	84.00	130.00	21.00	250.00	22.00	14.00
356 PRODUKTDESIGN	2.50	70.00	2.84	10.70	84.00	200.00	21.00	250.00	22.00	0.00
358 HOGSKOLERINGEN	2.00	72.00	2.00	9.80	84.00	120.00	21.00	250.00	22.00	30.00
360 REALFAGBYGG	1.50	65.00	3.50	13.00	88.00	85.00	21.00	220.00	22.00	40.00

Appendix C Collected data for annual heating consumption for all meters and submeters in University campus NTNU Glosahugen

ANNUAL HEATING CONSUMPTION IN NTNU GLOSHAUGEN				
Building	Area [m^2]	Meter/Submeter	year	Eh [kWh]
301 HOVEDBYGNINGEN	17,285.2	WM01 FJERNV 301	2012	2,526,708
			2011	2,347,731
			2010	3,194,500
			2009	3,160,953
			2008	2,695,199
			2007	3,040,020
302 VARMETEKNISK	15,191.3	WM02 FJERNV 302	2012	929,209
			2011	385,714
			2010	1,048,847
			2009	959,938
			2008	1,121,850
			2007	1,522,071
		WM50 Heat pump KJ01	2012	341,712
			1/2 2011	82,138
		WM51 Heat pump KJ02	2012	299,182
			1/2 2011	227,006
303 STRØMNINGSTEK.	3,030.4	WM01 FJERNV 303	2012	400,250
			2011	298,108
			2010	401,330
			2009	283,408
			2008	342,970
			2007	428,074
304 METALLURGI	2,215.3	WM011 (FORBRUK VE11)	2012	20,343
		WM01 FJERNVARME 304	2012	383,970
			2011	370,757
			2010	620,470
			2009	530,197
			2008	480,400
			2007	447,038
305 OPPREDNINGEN	3,954.8	WM01 FJERNVARME 305	2012	606,689
			2011	639,200
			2010	726,969
			2009	643,291
			2008	521,720
			2007	600,578

Building	Area [m^2]	Meter/Submeter	year	Eh [kWh]
306 GEOLOGI	3,167.8			NO DATA
307 VERKSTEDTEKNISK	12,310.5	WM01 FJERNVARME 307	2012	883,446
			2011	1,083,301
			2010	1,271,440
			2009	943,756
			2008	635,600
			2007	1,049,630
		WM50 VGVH	2012	162,968
			2011	166,835
			2010	245,932
308 MATERIALTEKNISK	12,616.4	WM01 FJERNVARME 308	2012	1,068,613
			2011	1,216,401
			2010	1,079,840
309 DRIFTSSENTR.	2,017.0			NO DATA
311 KJEMI 1	4,969.3	WM01 FJERNV. 311	2012	3,148,733
			2011	3,413,600
			2010	4,527,775
			2009	3,663,100
			2008	3,356,000
			2007	3,524,422
		WM03 VARMEKURS. RAD K1	2012	144,985
			2011	172,750
			2010	148,060
			1/2 2009	109,100
311 KJEMI 1		WM04 VARME VENT.	2012	259,321
			2011	304,520
			2010	318,380
			1/2 2009	236,320
		WM50 TP PROD. VA03	2012	565,365
			2011	104,083
312 KJEMI 2	5,236.7	WM01 VARME K2	2012	277,312
			2011	185,904
			2010	154,637
			1/2 2009	124,620
		WM02 VENT. K2	2012	722,510
			2011	870,212
			2010	965,433
			1/2 2009	367,775

Building	Area [m^2]	Meter/Submeter	year	Eh [kWh]
313	6,520.3	WM01	2012	140,384
KJEMI 3		VARME K3 ØST	2011	156,665
			2010	167,313
			1/2 2009	81,280
		WM02	2012	214,886
		VARME K3 VEST	2011	245,133
			2010	293,620
			1/2 2009	125,830
		WM03	2012	2,108,732
		VARME K3 VENT.	2011	1,854,008
			2010	1,930,600
			1/2 2009	893,040
314	5,569.6	WM01	2012	752,414
KJEMI 4		RAD ØST	1/2 2011	246,100
		WM02	2012	985,426
		RAD VEST	1/2 2011	304,700
		WM03	2012	428,257
		VENT KURS	1/2 2011	114,300
315	5,627.8	WM01	2012	2,077,975
KJEMI 5		FJERNVARME 315	2011	1,876,966
			2010	2,481,334
			2009	2,040,297
			2008	2,406,200
			2007	3,456,373
316 KJEMIHALL	5,642.8	WM010 TP KJ06	2012	92,490
317	6,185.7	WM01	2012	607,395
IT BYGGET		VARM BYGG 317	1/2 2011	210,700
318	4,313.3	WM01	2012	1,007,944
IT BYGGET SYDFLØY		FJERNVARME 318	2011	930,051
			2010	1,103,096
	TOTAL		2009	1,618,074
	10,499.0		2008	874,760
			2007	1,027,116
		WM04	2012	360,256
		VARME BYGG 318	1/2 2011	112,900
319	4,942.1	WM01	2012	741,332
GAMLE FYSIKK		FJERNVARME 319	2011	717,500
			2010	835,923
			2009	762,608
			2008	721,791
			2007	823,070

Building	Area [m^2]	Meter/Submeter	year	Eh [kWh]
320	5,028.3	WM01	2012	366,590
EFI		FJERNVARME 320	2011	385,065
SINTEF ENERGI			2010	486,028
			2009	357,576
			2008	406,137
			2007	472,480
321	17,936.4	WM01	2012	2,000,769
SENTRALBYGG 1		FJERNVARME 321	2011	1,675,273
			2010	2,056,841
			2009	1,773,554
			2008	1,919,980
			2007	2,140,005
322	12,860.7	WM01	2012	639,956
SENTRALBYGG 2		FJERNVARME 322	2011	453,506
			2010	853,700
			2009	828,014
			2008	854,700
			2007	1,055,597
		WM010 TP KJ02/KJ05	2012	401,677
		WM50 TP	2012	257,146
		KJ02	1/2 2011	144,685
		WM51 TP	2012	150,977
		KJ05	1/2 2011	67,631
323	3,753.8	WM01	2012	381,773
GAMLE KJEMI		FJERNVARME 323	2011	550,440
			2010	543,456
			2009	423,677
			2008	427,630
			2007	465,605
324	2,525.1	WM01	2012	309,361
VANNKRAFTLAB.		FJERNVARME 324	2011	305,305
			2010	371,103
			2009	308,996
			2008	257,059
			2007	329,460
325	9,009.0	WM01	2012	25,703,615
GAMLE ELEKTRO		FJERNVARME	2011	27,531,082
		HOVED	2010	40,079,197
		GLØS.	2009	32,768,055
			2008	22,901,355

Building	Area [m^2]	Meter/Submeter	year	Eh [kWh]
326	6,143.7	WM01	2012	57,563
ELEKTRO A		ØSTFLØY	1/2 2011	29,917
		WM02	2012	206,563
		VESTFLØY	1/2 2011	188,367
327	3,599.2	WM010 TP KJ10	2012	523,051
ELEKTRO B		WM01	2012	1,496,968
		FJERNVARME 327	2011	1,597,505
328 ELEKTRO C	2,899.8		2010	2,214,702
			2009	1,852,207
			2008	1,778,560
			2007	3,129,024
329 ELEKTRO D	6,238.1	WM01	2012	467,104
		VARME 329	1/2 2011	164,500
330	596.2	WM01	2012	117,095
TEORETISK FYSIKK		VARME 330	2011	34,600
332	2,746.9	WM01	2012	122,223
GRØNBYGGET		VARME 3332	1/2 2011	46,344
		WM010 TP	2012	251,065
333	7,598.2	WM01	2012	1,017,417
BERG AVD		FJERNVARME 333	2011	996,857
			2010	1,344,663
			2009	958,689
			2008	897,480
			2007	1,085,764
335	4,906.2	WM01	2012	600,763
IDRETTSBYGGET		FJERNVARME 335	2011	654,286
			2010	712,625
			2009	561,030
			2008	798,660
			2007	974,906

Building	Area [m^2]	Meter/Submeter	year	Eh [kWh]
337	18,595.8	WM01	2012	619,552
BYGGTEKNISK		FJERNVARME 337	2011	559,146
			2010	1,849,209
			2009	1,427,468
			2008	1,259,700
			2007	1,312,915
		WM010 TP KJ10	2012	938,074
		WM05	2012	1,120,194
		FRA KM TIL	2011	1,195,289
		VE01-02	2010	1,547,470
			2009	1,067,253
			2008	926,580
			2007	1,500,260
		WM06	2012	981,097
		FRA KM TIL	2011	868,577
		VE03-05	2010	1,136,473
			2009	725,473
			2008	706,120
			2007	1,062,994
		WM07	2012	900,301
		VVX KONDENSAT	2011	500,611
			2010	11,103
			2009	988,393
			2008	1,083,190
		WM09		
		VARME NBI	2012	225,791
341	10,459.6	WM01	2012	1,118,307
ELA (ELEKTRO E+F)		FJERNARME 341	2011	1,121,330
			2010	1,629,318
			2009	1,062,144
			2008	992,020
			2007	2,327,744
354	5,053.2	WM01	2012	490,354
KJELHUSET			2011	469,159
		FJERNARME 354	2010	602,627
			2009	621,428
			2008	528,620
			2007	573,939

Building	Area [m^2]	Meter/Submeter	year	Eh [kWh]
356 PRODUKTDESIGN	2,652.3	WM01 FJERNARME 356	2012	229,126
			2011	257,783
			2010	254,499
			2009	258,129
			2008	310,110
			2007	337,751
358 HØGSKOLERINGEN	4,760.4	WM01 GFJ.VARME HOVED	2012	301,556
			1/2 2011	148,175
360 REALFAGBYGGET	60,805.7	WM01 HOVED	2012	5,033,384
			1/2 2011	1,543,480
		WM01 KJ01	2012	5,427
			2011	8,487
		WM01 KJ04	2012	13,118
			2011	2,210
		WM01 KJ05	2012	1,384,826
			2011	997,618
		WM03 KJ05	2012	1,500,180
			2011	607,150
		WM04	2012	6,217,914
			2011	2,415,744
		WM01	2012	5,047,933
			2011	4,024,916
			2010	7,109,960
			1/2 2009	2,441,962
365 PFI	4,781.2	WM01 FJERNVARME 365	2012	375,899
			2011	366,286
			2010	765,347
			2009	656,608
			2008	660,348
			2007	616,428
		WM50 KJ01	2012	409,800
			2011	122,627
MAIN METER	317,051.1		2012	27,853,600
			2011	27,482,446
			2010	39,934,449
			2009	32,593,300
			2008	32,457,600

Appendix D Collected data for annual electricity consumption for all meters and submeters in University campus NTNU Glosahugen

ANNUAL ELECTRICITY CONSUMPTION AND CO2 EMISSION IN NTNU GLOSHAUGEN					
Building	Meter/Submeter	year	Eel [kWh]	CO2 [Tonnes]	Carbon [Tonnes]
301	RE01 230 V	2012	1,374,586	744.48	203.04
		2011	1,175,706	636.76	173.66
		2010	1,217,981	659.66	179.91
302	RE01 230 V	2012	1,539,099	833.58	227.34
		2011	936,725	507.33	138.36
		2010	258,875	140.21	38.24
		2009	560,655	303.65	82.81
		2008	159,120	86.18	23.50
		2007	147,389	79.80	21.76
	RE03 400 V	2012	452,555	245.10	66.85
		2011	257,721	139.58	38.07
		2010	51,773	28.04	7.65
		2009	112,137	60.73	16.56
		2008	31,824	17.24	4.70
		2007	29,451	15.95	4.35
303	RE01 400V	2012	263,994	142.98	38.99
		2011	214,683	116.27	31.71
		2010	199,752	108.19	29.51
304	RE01 230V	2012	240,263	130.13	35.49
		2011	236,941	128.33	35.00
		2010	245,639	133.04	36.28
	RE01 400V	2012	248,596	134.64	36.72
		2011	132,688	71.86	19.60
		2010	83,430	45.19	12.32
305	RE01 230V	2012	330,408	178.95	48.80
		2011	275,435	149.18	40.68
		2010	257,749	139.60	38.07
306	RE01 230V	2012	601,494	325.77	88.85
		2011	469,832	254.46	69.40
		2010	515,480	279.18	76.14

Building	Meter/Submeter	year	Eel [kWh]	CO2 [Tonnes]	Carbon [Tonnes]
307	RE01 230V	2012	1,074,225	581.80	158.67
		2011	1,259,829	682.32	186.09
		2010	1,283,856	695.34	189.64
		2009	1,313,300	711.28	193.99
		2008	1,182,413	640.39	174.65
		2007	1,311,719	710.23	193.70
	RE02 400V	2012	233,476	126.45	34.49
		1/2 2011	161,782	87.62	23.90
	RE03 400V	2012	10,356	5.61	1.53
		1/2 2011	6,310	3.42	0.93
	RE04 400V	2012	4,326	2.34	0.64
		1/22011	2,114	1.14	0.31
308	RE01 400V	2012	620,975	336.32	91.72
		2011	394,720	213.78	58.30
		2010	1,147,615	621.55	169.51
	RE02 230V	2012	1,269,292	687.45	187.49
		2011	1,081,948	585.98	159.81
		2010	290,567	157.37	42.92
	RE03 230V	2012	99,146	53.70	14.64
		1/2 2011	75,207	40.73	11.11
	RE04 230V	2012	303,742	164.51	44.87
		1/2 2011	169,753	91.94	25.07
	RE05 230V	2012	139,255	75.42	20.57
		1/2 2011	74,507	40.35	11.01
	RE06 400V	2012	12,319	6.67	1.82
		2011	5,216	2.82	0.77
		2010	4,063	2.20	0.60
	RE07 400V	2010	293,005	158.69	43.28
309	RE01 230V	2012	404,036	218.83	59.68
		2011	298,522	161.68	44.09
		2010	346,246	187.53	51.14

Building	Meter/Submeter	year	Eel [kWh]	CO2 [Tonnes]	Carbon [Tonnes]
311	M1 400V	2012	953,768	516.56	140.88
		1/2 2011	366,159	198.31	54.09
	M2 400V	2012	1,366,111	739.89	201.79
		1/2 2011	825,342	447.01	121.91
	M3 230V	2012	112,289	60.82	16.59
		1/2 2011	104,049	56.35	15.37
	M4 230V	2012	213,767	115.78	31.58
		1/2 2011	95,990	51.99	14.18
	M5 400V	2012	397,083	215.06	58.65
		1/2 2011	270,269	146.38	39.92
	M6 230V	2012	93,091	50.42	13.75
		1/2 2011	33,490	18.14	4.95
313	RE03 230V	2012	1,164,742	630.82	172.04
		2011	1,286,603	696.82	190.04
		2010	1,437,860	778.74	212.38
314	RE01 400V	2012	762,274	412.85	112.59
		2011	1,881,038	1,018.77	277.85
		2010	2,472,846	1,339.29	365.26
	RE02 230V	2012	8,885	4.81	1.31
		2011	6,583	3.57	0.97
315	RE01 230V	2012	846,480	458.45	125.03
		2011	764,199	413.89	112.88
		2010	797,462	431.91	117.79
316	RE01 230V	2012	336,605	182.31	49.72
		2011	223,203	120.89	32.97
		2010	958,209	518.97	141.54
	RE02 230V	2012	249,211	134.97	36.81
		2011	12	0.01	0.00
317	RE01 230V	2012	876,547	474.74	129.47
		2011	848,027	459.29	125.26
		2010	823,381	445.94	121.62
318	RE01 230V	2012	443,632	240.27	65.53
		1/2 2011	143,571	77.76	21.21
319	RE01 230V	2012	279,996	151.65	41.36
		2011	374,514	202.84	55.32
		2010	667,070	361.29	98.53
	RE02 400V	2012	168,178	91.09	24.84
		1/2 2011	75,854	41.08	11.20

Building	Meter/Submeter	year	Eel [kWh]	CO2 [Tonnes]	Carbon [Tonnes]
320	RE01 230V	2012	1,005,024	544.32	148.45
		2011	970,576	525.66	143.36
		2010	1,003,788	543.65	148.27
321	RE01 230V	2012	1,790,217	969.58	264.43
		2011	1,514,848	820.44	223.76
		2010	1,424,125	771.31	210.36
	RE02 230V	2012	283,508	153.55	41.88
		2011	267,216	144.72	39.47
		2010	272,512	147.59	40.25
322	RE01 230V	2012	2,148,848	1,163.82	317.40
		2011	1,811,520	981.12	267.58
		2010	1,708,815	925.49	252.41
323	RE01 230V	2012	323,658	175.29	47.81
		2011	302,170	163.66	44.63
		2010	323,220	175.06	47.74
324	RE01 400V	2012	25,467	13.79	3.76
		2011	57,416	31.10	8.48
		2010	43,963	23.81	6.49
	RE02 230V	2012	2,206	1.19	0.33
		2011	36,202	19.61	5.35
		2010	191,814	103.89	28.33
325	RE01 230V	2012	758,128	410.60	111.98
		2011	742,337	402.05	109.65
		2010	757,287	410.15	111.86
326	RE01 230V	2012	540,520	292.75	79.84
		2011	484,151	262.22	71.51
		2010	467,448	253.17	69.05
	RE02 400V	2012	102,379	55.45	15.12
		1/2 2011	54,780	29.67	8.09
327	RE01 400V	2012	508,102	275.19	75.05
		2011	787,435	426.47	116.31
		2010	1,358,162	735.58	200.61
	RE010 TP	2012	109,537	59.33	16.18
	RE02 230V	2012	1,338,238	724.79	197.67
		2011	703,533	381.03	103.92
333	RE01 400V	2012	703,482	381.01	103.91
		2011	1,026,106	555.74	151.57
		2010	1,265,590	685.44	186.94
	RE02 400V	2012	598,490	324.14	88.40
		1/2 2011	380,961	206.33	56.27

Building	Meter/Submeter	year	Eel [kWh]	CO2 [Tonnes]	Carbon [Tonnes]
335	RE01 230V	2012	513,340	278.03	75.83
		2011	335,844	181.89	49.61
		2010	183,275	99.26	27.07
337	RE01 400V	2012	534,880	289.69	79.01
		1/2 2011	174,822	94.68	25.82
		1/2 2010	2,247,718	1,217.36	332.01
	RE010 TP	2012	196,339	106.34	29.00
	RE02 230V	2012	862,209	466.97	127.36
		2011	866,914	469.52	128.05
		2010	802,070	434.40	118.47
	RE03 230V	2012	81,506	44.14	12.04
		1/2 2011	39,150	21.20	5.78
		1/2 2010	98,180	53.17	14.50
	RE04 400V	2012	3,743,945	2,027.72	553.01
		2011	2,773,298	1,502.02	409.64
		2010	42,161	22.83	6.23
341	RE05 400V	2012	2,423,064	1,312.33	357.91
		2011	2,099,957	1,137.34	310.18
	RE01 400V	2012	2,622,985	1,420.61	387.44
		2011	2,351,882	1,273.78	347.39
		2010	2,363,324	1,279.98	349.08
	RE02 400V	2012	305,827	165.64	45.17
		2011	156,501	84.76	23.12
		2010	30,988	16.78	4.58
	RE03 400V	2012?	89	0.05	0.01
		2011?	173	0.09	0.03
		2010	178,266	96.55	26.33
	RE05 400V	2012	166,068	89.94	24.53
		1/2 2011	137,590	74.52	20.32
354	RE02 400V	2012	672,613	364.29	99.35
		2011	659,737	357.31	97.45
		2010	619,357	335.44	91.48
356	RE02 400V	2012	290,154	157.15	42.86
		2011	263,169	142.53	38.87
		2010	247,676	134.14	36.58
357	RE02 230V	2012	148,452	80.40	21.93
		1/2 2011	76,920	41.66	11.36
358	RE01 400V	2012	373,243	202.15	55.13
		1/2 2011	222,832	120.69	32.91

Building	Meter/Submeter	year	Eel [kWh]	CO2 [Tonnes]	Carbon [Tonnes]
360	RE01 400V	2012	1,524,616	825.73	225.20
		1/2 2011	693,712	375.71	102.47
		2010	10,331,835	5,595.72	1,526.11
	RE02 400V	2012	1,451,640	786.21	214.42
		2011	1,229,071	665.67	181.55
		2010	1,083,241	586.68	160.00
	RE03 400V	2012	1,916,459	1,037.95	283.08
		1/2 2011	1,379,021	746.88	203.69
	RE04 400V	2012	1,364,918	739.24	201.61
		1/2 2011	888,711	481.33	131.27
	RE05 400V	2012	1,399,870	758.17	206.77
		1/2 2011	1,044,062	565.46	154.22
	RE06 400V	2012	2,863,090	1,550.65	422.90
		1/2 2011	2,435,217	1,318.91	359.70
	RE07 400V	2012	1,112,961	602.78	164.39
		1/2 2011	732,635	396.80	108.22
	WM02 KJ04	2012	11,247	6.09	1.66
		1/2 2011	7,578	4.10	1.12
	WM02 KJ05	2012	6,828	3.70	1.01
		1/2 2011	4,874	2.64	0.72
	WM201	2012	337,709	182.90	49.88
		1/2 2011	210,556	114.04	31.10
365	RE01 400V	2012	976,510	0.00	0.00
		1/2 2011	671,905	0.00	0.00
MAIN METER		2012	62,405,546	33,798.84	9,217.87
		2011	61,286,821	33,192.94	9,052.62
		2010	60,839,328	32,950.58	8,986.52
		2009	57,495,284	31,139.45	8,492.58
		2008	55,621,396	30,124.55	8,215.79