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Activity-based modeling of domestic energy demand with high time resolution

A case study on Gothenburg

Master thesis within the Master's Program Industrial Ecology

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ABSTRACT

In domestic buildings, a great potential to reduce energy consumption exists. To achieve this reduction, a more detailed understanding of the energy demand is required. Currently, there is sufficient information on an aggregated level. Nevertheless, further knowledge about the timing of the energy use is needed. Previous attempts to gain that knowledge are mostly based on conclusions from measurements. However, in this study a bottom up, activity-based modeling approach is chosen. Hence, knowledge can be increased on a more detailed level and the generation of synthetic load curves can be facilitated. The derived model focuses on residential buildings and is applied in a case study on Gothenburg, Sweden.

Existing bottom-up models are mostly focused on specific dwellings and require a large amount of detailed input data. In contrast, the goal of the present report is a simple model with as few input parameters as possible. Thus, it can be quickly applied and transferred to other cities in Europe to get a first estimation on the composition of the energy demand. The practicality of such a model and its limitations are assessed by the present study. Furthermore, areas with low data availability and uncertain data should be identified.

To gain more understanding of the timing of energy use, four end-uses are modeled. Those are electrical appliances, lighting, hot water and heated rooms. The major focus lies on the consumer side. A large part of the work is the collection of reliable input data. Important input data sets are the time-use surveys and data about the weather (temperature, solar irradiation and natural illuminance). The modeling of the hot water and the electrical appliances is heavily based on the time-use surveys. For the lighting those are combined with the natural illuminance. To model the space heating demand, the energy balance over the building envelope is calculated and combined with information on the external temperature, the solar irradiation and the building stock.

The developed model can be used to predict the general shape of the demand curve in a residential area. However, the levels of the peak are rather uncertain. Nevertheless, in combination with measurements of the aggregated demand the model can be a useful tool to assess the current situation in an existing city. The input data needed to model the demand curve’s shape is extractable from established, official sources and data bases. That data includes weather data and time use data. Since that is available for other European countries, the model could be transferred to different cities. From the present study, it can be concluded that the time-use surveys are a promising tool for energy load curve modeling. Moreover, it could be detected how and where those surveys can be adjusted for that purpose.

Keywords: Urban Energy Systems, load curves, timing of energy use, modeling of energy use, high resolution, residential areas, activity-based energy demand modeling, time use surveys

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Abbreviations

A	Area
BETSI	Byggnaders Energi, Tekniska Status och Inomhusmiljö (Buildings' energy, technical state and indoor climate)
E	East
E	Energy
e	External
e.g.	exempli gratia (for example)
El.	Electrical
et al.	et alii (and others)
h	Heat
h	Hour
HETUS	Harmonised European Time Use Survey
hw	Hot water
i	Internal
in	inflowing

J	Joule
K	Kelvin
k	kilo
l	liter
M	Mega
m	meter
m^2	Square meter
N	North
n.d.	No data/ no date
out	Outflowing
P	Power
s	second
S	South
S	Surface
SCB	Statistiska centralbyrån
SMHI	Swedish Meteorological and Hydrological Institute
SVEBY	Standardisera och verifier energiprestanda för byggnader (Standardized and verified energy performances for buildings)

TU	Time use
T	Temperature
t	Time
TUS	Time use survey
U	U-value/ heat transmittance value
UK	United Kingdom
V	Volume
W	Watt
W	West

Notations

C_i	Thermal capacitance of internal air
c_p	Heat capacity
$f_{horizontal}$	Factors to compensate windows not being horizontal
f_{Shadow}	Shadow factor for windows
G	Transmittance coefficient for windows
I_{global}	Global irradiation orthogonal to the ground
p_i	Probability of activity i

$\dot{q}$	Heat flow
$\dot{q}_{is}$	Internal heat gain
$\dot{q}_v$	Heat losses due to ventilation
T_{vent}	Temperature of supplied air for ventilation
V_c	Ventilation rate
ρ	Density
Δ	Difference

1 INTRODUCTION

There is a high potential to decrease the energy demand (especially the heating demand) in the building sector. To implement carbon-reducing strategies or to manage energy systems better detailed information about the building sector is needed. Sufficient information about the energy consumption on an aggregated level is available. However, there is a need for more detailed information about the timing of the energy demand.

There exist data on the production side. Nevertheless, information about the demand side is harder to obtain. Thus, in the present report, a modeling tool for the demand side of an urban energy system is developed. To understand the structure of energy demand it is important to understand the timing of it. Moreover, this understanding helps to make estimations on how the energy system is going to develop in the future.

With the model derived in this report, residential areas in the city of Gothenburg are modeled. Possible applications and limitations of the model are assessed. Moreover, areas of uncertain data and factors that have a major contribution to the energy demand are identified.

1.1 Goal and scope

In this report, the end uses electrical appliance, lighting, hot water and warm rooms are modeled. The major goal is to achieve a simple model with as few input parameters as possible that is transferable to other cities in Europe to give a first estimation on how the energy demand looks like.

Finally, hot spot areas are identified. Those are areas where a lack of data or uncertain data exists. Furthermore, it includes the analysis of the most influencing factors. The main research questions are:

- Which are the most influencing factors?
- Where is a lack of data or a highly uncertain data?
- Can the model be transferred to other cities?
- Is it possible to develop a simple model with as few input parameters as possible for a whole area?

1.2 System boundaries and assumptions

In the present report, different end uses for a residential area are modeled. Single-family and multi-family houses are included in the study. However, office houses as well as industry lie out of the scope of the report.

The end uses modeled are: electrical appliances, lighting, hot water and warm rooms. The effects of cooling are not included. Since end uses are modeled, losses in the grid or the fossil energy demand are not covered by the model. Data from the year 2000 is used for the case study. Although more recent data exists for the required input data, the year 2000 is the year for which the most data sets exist.

The method of the model is heavily based on time use surveys. Since those only consider participants older than 20 years in Sweden, occupants under 20 are excluded from the model.

2 BACKGROUND

In this chapter, the relevant parameters to predict the timing of energy end-use demand are presented. The types of end-use studied are electrical appliances, hot water, lighting and warm rooms. Electrical appliances and hot water can be modeled in a similar way. Thus, they are combined in one section.

Furthermore, frequently cited models on timing of energy use on high resolution in residential areas are described and discussed. The distinction between them and the later derived model is made. Despite the significant number of detected journal articles on this topic only models developed after 2000 are presented.

Parts of the following sections are heavily based on a recent literature review by Torriti (2014) and references therein. In Figure 2.1, the different input parameters and the number of citations found by the Torriti (2014) are depicted. For each input parameter, the bar represents how many of the scientific papers taken into consideration by the authors, address that parameter. However, it cannot be said that the number of citations is representative for the relevance of the parameter (Torriti, 2014).

The different input parameters are explained and allocated to a type of end-use in the following paragraphs. Nevertheless, the section technology (water and space heating type) lies out of the scope of the report. The parameters shown in Figure 2.1 can be grouped into different sections. Those sections and the types of end-use that can be allocated to the parameter are listed on the next page.

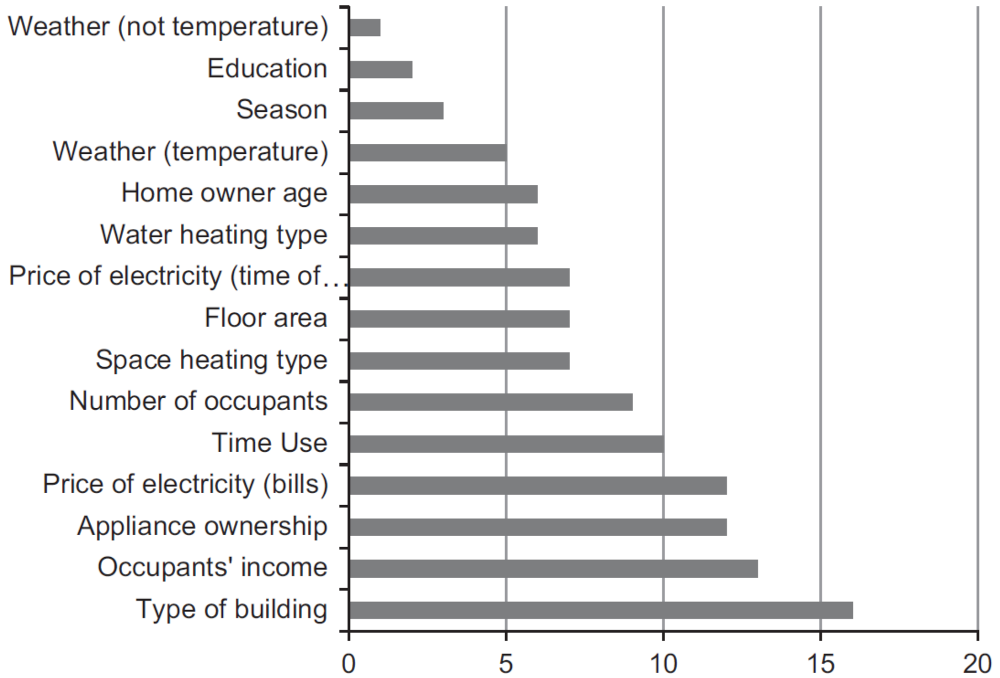


Figure 2.1: Typical input parameters for load modeling of energy and their numbers of citation in literature (Torriti, 2014).

• Climate		
	○ Weather (not temperature)	Space heating
	○ Weather (temperature)	Space heating
	○ Season	Space heating
	○ Daylight availability	Lighting
• Building		
	○ Floor area	Space heating
	○ Type of building	Space heating
• Household		
	○ Time use	El. appliances, hot water, lighting
	○ Appliance ownership	El. appliances
	○ Number of occupants	El. appliances, hot water, lighting
	○ Home owner age	All
	○ Education	All
• Economy		
	○ Occupants’ income	El. appliances, space heating
	○ Price of electricity (time of use)	All
	○ Price of electricity (bills)	All
	○ Type of bill	All
• Technology		
	○ Water heating type	Hot water
	○ Space heating type	Space heating

2.1 Electrical appliances and hot water

Hot water demand is often modeled similar to electricity for electrical devices (Widén, et al., 2009a), (Yao & Steemers, 2005). Thus, the two end-uses are presented in one section. From the literature, it is concluded that the factors that can be used to predict the electricity demand for electrical appliances and the heat demand for hot water are:

- Time use
- Appliance ownership
- Number of occupants

In many models, the time use is derived from time use surveys - TUSs (Bourgeois, et al., 2006), (Reinhart, 2005), (Richardson, et al., 2009). Those contain information about when and for how long people are doing things. According to several authors, it might be one of the most important factors for simulations of the timing of energy use (Torriti, 2014).

During those surveys, the participants list the activities they do during a day on a ten-minute resolution. Most of the activities can directly be matched with a device and a related energy demand, e.g. “watching TV and videos” and “dish washing”. However, there are a couple of activities for which the connection to the energy consumption is more difficult such as for “other personal care”. This leads to uncertainty.

As a TUS is an elaborate and costly procedure, it is seldom conducted. Thus, for some countries the available data is relatively old (Torriti, 2014). Today’s usage of electrical devices for entertainment, e.g. tablets and smartphones, might be higher than in the past. Furthermore, it is questionable if the data collected in the past is transferrable to the future.

Participants of TUSs are asked to fill in the diary for one weekday and one weekend day. However, user patterns could change during seasons due to different external temperatures and daylight availability. Hence, it is doubtful if one day can be representative for all the other days during the year. Moreover, the highest peaks mostly occur on exceptional days, e.g. national holidays, extreme cold or windy days (Torriti, 2014).

Possibly, it makes a difference if occupants filled in the diary for the weekday on Monday till Thursday or on a Friday. People may arrange their evenings differently if they have a day off on the following day. The same yields for the weekend. A Saturday can differ a lot from a Sunday as the majority of people works on Mondays.

The TUS is conducted for a whole country. Hence, the application of the data on a specific city might be less accurate, especially, if the nation's climate or economic characteristics differ a lot within the country. Additionally, only one person of the household fills in the diary. This makes it hard to model shared use of appliances in dwellings with several occupants. In some models this is solved by stochastically modeling every other occupant (Torriti, 2014).

A second relevant factor for the energy consumption in a household is the appliance ownership. This includes the type of appliances used during a certain activity and their energy consumption. The appliances possibly differ between households which is influenced by the occupant's age and educational level. Those factors are explained and discussed in 2.4 (Widén, et al., 2009a), (Richardson, et al., 2010), (Torriti, 2014).

Due to shared use of appliances and simultaneous activities, the number of occupants in a dwelling plays a role for the energy consumption. People watch TV together in the evening or do the dishes together. This should be sufficiently represented in the model. Otherwise, the modeled energy demand might be too high. As already mentioned previously, this aspect is often difficult to derive from the TUSs (Richardson, et al., 2009), (Richardson, et al., 2010).

TUSs are an important and helpful input parameter for load modeling of energy consumption although there is a conflict between the accuracy and the detail/amount of input data. Furthermore, the correctness of the diaries can be questioned since it is a demanding task for the participants. In combination with the number of occupants and the appliance ownership estimations on load curves for hot water and electrical devices can be made.

Four papers on modeling of energy demand for electrical appliances and hot water are presented below. The models combine time-use data with load profiles of appliances and data on appliance ownership.

Paatero & Lund (2006) developed an often-cited "model for generating household electricity load profiles". Their attempt led to a bottom up load model on electricity demand in single households. According to Paatero & Lund (2006) all existing data on electricity demand is aggregated electricity consumption on a multiple household level. However, no knowledge on individual households exists. The input data is taken from public reports and statistics. In a first step, household load curves are developed with the help of probability factors for activities. Those are matched with a set of appliances per household afterwards. The model is even applicable for demand side management as shown by the authors. The results from the model correlate well with real data and give a good estimation on the electricity consumption. However, the probability factors are either hard to find or give only reflect a very general day. Paatero & Lund (2006) multiply seasonal as well as hourly probability factors. Nevertheless, there is no difference between weekends and weekdays.

The model derived by Richardson, et al. (2010) uses the same method as Paatero & Lund (2006). They model “domestic electricity use [with] a high-resolution energy demand model” in the UK. The probability factors are taken from time use surveys and matched with the consumption of the appliances. Nevertheless, in contrast to other models, Richardson, et al. (2010) develop the simulation of simultaneous use of appliances further.

Widén, et al (2009a) constructed “load profiles for household electricity and hot water from time-use data”. The authors saw a huge potential in using time-use data to model energy demand in households. They claim that the time-use data is rather unutilized in the energy field. Thus, one major goal was to assess the contribution of that data to energy demand modeling. To do so, simple conversion schemes were used. Information about the time-us was extracted from time-use surveys. Each activity was connected to an end-use category and the energy consumption of it was defined. For the lighting demand, data on natural illuminance was added as well. The model has been validated against detailed, end-use specific electricity measurements in small sample of households but also on aggregated profiles of multiple households. The electricity demand shows a slightly better match than the hot water demand. Nevertheless, the model shows sufficient correlations for small samples as well as aggregated data. Hence, the usefulness of time-use data for energy-use modeling could be proven. Furthermore, the model included hot water use and electricity use which has the advantage that interrelations between the two are respected and can be detected. However, the authors mention that there is still further development needed to make a generalization of the model. Additionally, it is mentioned that the time-use data is relatively old (from 1996) and that a significant higher use of computers can be assumed. That would influence the electricity use.

Finally, it can be said that the model proofs the relevance of time-use data and delivers efficient results but is focused on one person or on households.

Yao & Steemers (2005) developed "a method of formulating energy load profile for domestic buildings in the UK". They modeled space heating, domestic hot water and electricity use of appliances. The aim of the work is to construct a simple model to predict energy demand in the UK. This model is meant to support strategies for the implementation of Renewable Energy systems in residential buildings. Yao & Steemers (2005) combine different methodologies that have been explained before. For the electricity demand for appliances and the hot water demand, they use a similar approach to Widén, et al. (2009a) since they align power/water consumption of appliances to time-use data. The calculations for space heating are based on energy balances of the building similar to the models described before. The model can be used on national and regional level as well as on individual houses.

The models described above are very similar considering their method and input parameters. It can be concluded that the time-use of occupants is a crucial input parameter for the electricity as well as for the hot water demand modeling.

2.2 Electricity for lighting

Based on the literature reviewed, it is concluded that the daylight availability and the time use are important factors that influence the electricity demand for lighting. It is not clear if daylight availability is included in Torriti's study. Possibly, it is part of the weather (not temperature) or the season parameter. According to own investigations of further literature, it could be recommended to introduce a specific section called "daylight availability" to emphasize its relevance (Reinhart, 2005), (Yao & Steemers, 2005), (Hunt, 1979).

According to Richardson, et al. (2009), the consumption of electricity for lighting in residential houses is mainly dependent on two aspects. Those are the amount of natural light coming in the building and the occupants' activities. The opinion on the significance of natural daylight availability is shared by Hunt (1979), Abu-Sharkh, et al. (2005) as well as Reinhart (2005) and Yao & Steemers (2005). It is obvious that the daylight availability is highly correlated to the coverage of the sky as well as the season.

The occupants' activities can be extracted from the TUS explained in section 2.1. Based on them, it can be derived at which time people are at home. Additionally, estimations on the need of light for those activities can be made.

Reinhart (2005) derived a model for "manual and automated control of electric lighting and blinds". The aim of the study is the analysis of the potential energy savings of automatic control of lighting in private and two-person offices. The input data of the model were the user occupancy (active/in-active) and the illuminance at the working place. Those are used for the automatic system. Moreover, probabilistic switching patterns are developed with an algorithm. Those are used to model manual usage by the occupants. Four different kinds of occupants based on existing occupants are simulated to compare the automatic system against the manual system. Due to the derivation of the probability function for the switching events, it can be examined how much energy can be saved with the automatic system. However, the model does not take into account all technical issues as privacy issues or seating orientation. It is only focused on lighting but blinds could be used to reduce solar gains through the window and influence the heating and cooling demand. Furthermore, it is limited to private and two-person offices and does not simulate a whole area (Reinhart, 2005).

The above described model has been further developed by the author and two co-authors (Bourgeois, et al., 2006). They used the algorithm developed in (Reinhart, 2005) but added a more advanced behavioral model. Additionally, the authors also looked at the effect on cooling and heating. Nevertheless, more detailed input data is needed and the model is very specific for existing work places and offices.

Richardson, et al (2009) developed "a high-resolution energy demand model" on domestic lighting. The purpose of the model was to estimate the domestic lighting demand to implement low-carbon strategies. Input parameters of the model were data on the light coming from outdoors and time use data from occupants. Furthermore, statistical data has been used to populate each dwelling with a realistic set of lighting units. The model is available online as an excel table and is used to validate the results on the lighting demand in the derived model in this report. The developed model is very efficient and data can be derived on a one-minute resolution. The sharing of lighting can be modeled as well. However, the model can just be used to model single dwellings and only one day per month can be extracted from the excel tool even though the demand may differ.

Summarizing, it can be said that there are two crucial input parameters for domestic lighting models. The first aspect is the perception of natural light inside the building. This is used and supported by (Reinhart, 2005), (Bourgeois, et al., 2006), (Richardson, et al., 2009). (Hunt, 1979) and (Yao & Steemers, 2005). The second aspect that is considered relevant for the lighting demand is the user pattern. This is supported by (Reinhart, 2005), (Bourgeois, et al., 2006), (Wright & Firth, 2007) and (Richardson, et al., 2009).

2.3 Space heating

According to Torriti (2014), the floor area and the type of building are important parameters that influence the load curves of space heating in domestic households. One important factor that influences the heating demand of buildings is the heat loss due to transmittance over the different components (roof, wall, windows, etc.). To calculate that heat flow Equation 2.1 can be used. The driving force is the temperature difference over the component. However, the heat flow is proportional to the product of the surface area and the thermal transmittance of the component.

Equation 2.1 based on (De Rosa, et al., 2014):

$$\dot{q}_{transmittance} = (T_e - T_i) * \sum_j U_{component,j} * S_{component,j}$$

$T_i - internal\ temperature$

$T_e - external\ temperature$

$U_{component,j} - Thermal\ transmittance\ of\ component\ j$

$S_{component,j} - Surface\ area\ of\ component$ j

The “type of building” describes specific building characteristics. Those are for example the age of the building and the size of the different components (windows, roof…) as well as the construction materials. With information about the construction material of the components and the glazing of the window the thermal transmittance can be derived. For European cities, it is assumed that the age of the building correlates with the thermal transmittance coefficient. This is due to the fact that architectural époques can be distinguished from each other and that usually a certain construction material is representative for a specific époque.

Furthermore, in different time periods different regulations are binding. According to Nair, et al. (2010), “in Sweden, a large number of existing houses were built during the 1960s and 1970s, before the Swedish building code that focused on energy efficiency was introduced in 1977. These houses typically have [higher thermal transmittance coefficients]”.

The external temperature and the solar irradiation are probably the most crucial input parameters to model the influence of the climate on domestic heating demand. Nevertheless, the wind velocity and direction can also be a relevant input parameter for the heating demand. As can be seen in Equation 2.1, the amount of heat outflow is dependent on the difference between the outdoor temperature and the desired indoor temperature (base temperature). Nevertheless, De Rosa et al. (2014) mention that the “normal direct radiation and diffused horizontal radiation [as well as] the wind intensity and direction” are important parameters as well. The radiation plays a role as the solar energy is considered to be an additional gain in the building. Some models include the wind velocity and direction to calculate the convection characteristics (De Rosa, et al., 2014).

There exist a correlation between the space heating demand and the type of building. This is based on physical circumstances. Due to that, it is easier to quantify than the influence of other input data. Combined with weather data on solar irradiance and the external temperature, the space heating demand can be modeled.

The need for heating can be modeled applying a thermal resistance method based on energy balances. This supplies an appropriate compromise between complexity, input data, accuracy and computational expense. Simplifying, it can be said that the thermal resistance model builds the sum of heat sources and heat consumers. The sources are for example internal gains and solar gains. An example of heat consumers is the heat losses over the building envelop. There exists software to model specific houses accurately. However, skilled users and detailed input data are needed for those. In the following paragraphs quicker modeling approaches using the energy balance method are explained (Yao & Steemers, 2005), (Kämpf & Robinson, 2007), (De Rosa, et al., 2014).

Catalina et al. (2008) developed and validated “regression models to predict monthly heating demand for residential buildings”. The aim was to supply architects and design engineers with a tool to find energy efficient solutions during the first stage. One major finding is that the shape of the building is an important parameter that influences the energy consumption. Thus, a further purpose is to optimize the building structure versus environmental and economic criteria. Even though the model is supposed to be quick, a list of input parameters is need. Those are the building shape, the heat transmittance coefficient of the building envelop, the window to floor area as well as the climate (sol-air temperature and desired indoor temperature). The model showed relatively accurate predictions and delivers good results for first estimations of the heating demand of single-family houses. Nevertheless, it is only valid for those houses and for temperate and warm climates. It is not suggested to use the model outside the valid range of input parameters used. Furthermore, an extension of the model on a whole city would require very detailed input parameter of each house in the area.

In contrast to Cataline, et al. (2008), De Rosa, et al (2014) used the degree days approach for their study on “Heating and cooling building energy demand evaluation; a simplified model and a modified degree day approach”. The aim of their study was to develop a simple model for heating and cooling loads. The authors used several energy balances equations for external and internal components of the building. One parameter of those equations is the number of degree days in a month. Those are the days per month on which cooling or heating is needed. The model has been implemented in Matlab/Simulink and has been applied for several European cities. In all cities it showed a sufficient correlation to real data. Additionally, the model showed a high correlation between the degree days and the heating/cooling demand. Thus, the model supports the degree day method. However, Catalina, et al (2008) criticize this method and finds it not accurate enough. De Rosa, et al. (2014) use very detailed data about the localization (wind velocity, direction) and the building (ground cover, shadowing factor). This data might not available on a larger scale. Moreover, the degree day method only uses average temperatures during a month. Hence, the model does not show difference within a day.

Kämpf & Robinson (2007) derived a model on heat flows in an urban district. They assume multi-layered walls. Every layer and every component in the building represents a node. Those are connected according to Kirchoff’s law for electrical circuits. The model is highly mathematic and simulates different thermal zones in the building. The model is fed with a lot of detailed input data and is conducted for every room.

The above explained models differ a lot in the amount of input data needed. Nevertheless, all authors agree on the relevance of the heat transmittance coefficient and the external temperature. Looking at the existing models of space heating the conflict between detail and complexity becomes clear. Kämpf & Robinson (2007) use a highly complex method but the results are relatively detailed. In contrast to that, De Rosa, et al. (2014) apply simpler calculations based on the degree day method. However, the accuracy of that method is questioned.

2.4 Societal and economic factors

Some societal and economic factors influence all four end uses. Those are the home owner’s age and education as well as the price of electricity and the type of bill.

The home owner’s age or the type of people living in the dwelling can be used to predict the type of appliances in the dwelling and the activities done. One example is the heating demand. A higher amount of space heating is suggested by CEN Standard EN15251 for households occupied by sensitive persons, as elderly, sick or handicapped people as well as very young children. Nair, et al. (2010) find that older people are less likely to adapt to new behavior which can lead to the assumption that they seldom pick up more energy efficient arrangements.

But it is not only the age that matters. Nair, et al. (2010) also state that according to a survey only 17 % of Swedish people switch off the light when leaving the room. However, they also referenced a study saying that 85 % of Swedes consider themselves well informed about climate change but only 56 % in whole Europe. Hence, the nationality and the attitude towards energy consumption might be useful predictors of behavior as well.

The presence of a technically skilled person encouraged investments in new technologies due to better understanding of the matter (Nair, et al., 2010). According to Zelezny, et al (2000), female occupants show more environmental-friendly behavior than men. Nevertheless, other studies see no correlation (Poortinga, et al., 2003), (Sardianou, 2007). Thus, the gender might be a factor to predict occupants’ behavior as well.

The last societal aspect discussed is the educational level of the occupants. It can be said that younger and higher-educated home owners are more content to invest in energy efficient appliances or technologies than older and less educated ones. However, less educated people show to accept behavioral non-investment measures, like switching off the light or down-regulating the heater during nights, quicker (Nair, et al., 2010).

An additional aspect about the influence of the educational level on the energy consumption is more nation-wide and long-term. Aixiang (2011) made a study in China which showed that more scientifically educated people in the society led to more advanced technologies and reduced energy consumption. However, a study in Northern Cyprus displayed that an increasing number of international students moving to the island correlated with a higher electricity and oil consumption (Katircioglu, 2014). It could be possible that an increased educational level in a society has a long-term influence on the energy consumption. Nevertheless, the direction of that change cannot be predicted with the information above.

As presented in Figure 2.1, it can be considered that the occupants' income and the price of electricity influence the household's energy consumption as economic factors. Especially, the occupant's income and the electricity price in bills are often cited (Torriti, 2014). However, the type of bill can also be regarded as an influencing factor.

It could be guessed that owners/ landlords with a lower income save more energy than those with higher incomes. Thus, the price elasticity of their demand would be lower. Furthermore, one could think that houses owned by higher earners show better performances according to the energy efficiency. Those might be equipped with more expensive technology. However, the predominant opinion is that the income only slightly influences the price elasticity of the energy demand and that this influence can be neglected (Nair, et al., 2010). Also the correlation of investment in energy efficient technology and high income is questionable. Several authors make contradicting statements about how the home owner's income influences their investments in energy efficiency technologies. Some argue that there is a correlation between them (Bartiaux, et al., 2006), (Black, et al., 1985), (Constanzo, et al., 1986), (Dillman, et al., 1983), (Herring, et al., 2007) and some argue against that (Barr, et al., 2005), (Ruderman, et al., 1987).

The price elasticity of the energy demand reflects how consumers react to changing energy prices. Numbers in a wide range can be found in the literature. According to Alberini, et al. (2011), there is a strong response to energy prices on a short and a long term perspective in the U.S. However, other studies cited by these authors show a lower dependency between the energy demand and prices in European countries. Most authors and studies argue for a low correlation. Some even state that the demand is price-inelastic (EPRI - Electric Power Research Institute, 2008). Nevertheless, concrete numbers can hardly be found and differ very much from each other. It can be questioned if price-elasticity is a relevant influence factor for models of residential load curves as the transferability of past data to the future might not be given (Boonekamp, 2007).

Another factor that plays a role when looking at the energy prices is the difference between the prices in the bill and the prices at the time of use. Nair, et al. (2010) argue that people react more to the prices in the bill and that current behavior is more influenced by the prices in the previous billing period. People rather adjust their behavior if they got a very high bill once as they directly react to higher prices on the market.

Two different kinds of bills are elaborated. Either the landlord or the tenant fully bares the costs of higher energy consumption. This can cause misaligning interest in the energy-efficiency of the property, the so called landlord/tenant dilemma (Ástmarsson, et al., 2013). Typically, the tenant fully bears the energy costs of the building. Thus, there are no incentives for the landlord to invest into sustainable retrofitting and renovation or low energy-consuming devices and technologies (Ástmarsson, et al., 2013).

The landlord/tenant dilemma exists when considering electricity consumption. In Sweden, the landlord provides the occupants with certain white goods. However, the electricity consumed by those devices is paid by the tenant. Hence, costs of increasing electricity consumption are paid by the tenant and the landlord has no incentive to invest into appliances with higher efficiencies. Nevertheless, for owned houses, this conflict does not exist.

For the heat consumption, the situation is slightly different. In the Sweden, the heating costs are included as a fixed cost in the rent. Hence, it can be said that costs of increased heat consumption are mostly borne by the landlord (Lind, 2012). Due to that, the landlord has a higher interest in investing in more efficient technologies for heating and retrofitting to reduce thermal losses. Additionally, it can be assumed that the landlord thinks in a rather long-term, economic way since it is likely that (s)he is owning the property for a longer time period. Thus, long-term investments that pay off after a couple of years can be considered to become more interesting. The dilemma can be said to shift from the landlord/tenant dilemma to the conflict between energy prices and energy efficiency investment costs.

Nair, et al (2010) studied the factors influencing investments in energy efficiency in Sweden. The authors conducted a questionnaire with Swedish homeowners of detached houses. It showed that most homeowners primarily undertook no-cost measures, e.g. switching off the light or other behavioral changes, than investment measures if they considered the energy prices as high. This means that people rather change their user patterns than investing in retrofitting. However, this is only valid for owner-occupied flats and houses. In general, the study showed that the drivers for investments in energy efficient technologies are mostly driven by non-economic factors as education, age, gender, age of the house and personal preferences.

In contrast to the situation explained above, owners of rented apartments might have incentives to invest in energy efficient retrofitting. As previously explained, in Sweden, those bear the costs for increasing heating consumption. However, Lind (2012) argues that this only yields for a perfect market system. In Sweden, the rents are negotiated but not all characteristics, e.g. the indoor climate, are reflected in the rent. Due to that, investments in energy efficiency can actually force the owner to reduce the rent as they reduce her/his costs. According to (Lind, 2012), there are no real economic incentives for energy efficiency in Sweden.

Finally, it can be said that the influence of societal and economic factors on the energy consumption and the investments in energy efficiency is highly uncertain. Moreover, those factors might allow qualitative conclusions but the effects are hard to quantify.

2.5 Summary

Summarizing, it can be said that the most important input parameters are the time-use, the power consumption of appliance and the natural illuminance as well as the power consumption of appliances and the external temperature. The method used in the model derived in the present report is mostly based on the previously described studies.

The above mentioned input parameters can all be quantified to some extent. However, the societal and economic factors are hard to estimate. They mostly only give a first and qualitative idea. Moreover, authors disagree on how some of them are correlated to the energy demand.

The models listed are mostly focused on a certain type of dwelling (e.g. single-family houses, two-person offices…). Furthermore, they mainly simulate one energy service (e.g. only lighting, space heating…). Hence, the interrelation of the different energy services in not taken into account. Some of the models can theoretically be implemented in a bigger scale. However, a huge amount of impact data would be needed for that. In the later developed model an attempt is made to create an easy, less input data demanding model for a whole city. Additionally, that model should include all energy services.

Table 2.1: Overview of earlier studies including the applied methods and the input parameters used Part I.

Study	Method	Input parameter
Lighting		
(Reinhart, 2005)	Algorithm to derive the probability that the lighting is switched on. Based on user occupancy, natural illuminance and probability of switching.	Time-use, Natural illuminance
(Bourgeois, et al., 2006)	Extension of (Reinhart, 2005) with a more advanced behavioral model and inclusion of heating and cooling	Time-use, Natural illuminance, Building characteristics
(Richardson, et al., 2009)	Probability function of usage of lighting based on time-use and illuminance combined with type and number of light bulbs.	Time-use, Natural illuminance, Statistical data on lighting units in buildings
Heating	Thermal resistance models based on energy balances.	
(Catalina, et al., 2008)	Energy balance over the building envelop based on the sol-air temperature over time.	Shape of the building, Heat transmittance coefficients, Window to floor area, Sol-air temperature
(De Rosa, et al., 2014)	Energy balance over the building envelop based on the degree day method.	A long list of very detailed and specific data
(Kämpf & Robinson, 2007)	Highly mathematical model based on Kirchoff’s law for electrical curcuits.	A long list of very detailed and specific data
Electricity and hot water		

Table 2.2: Overview of earlier studies including the applied methods and the input parameters used Part II

Study	Method	Input parameter
(Paatero & Lund, 2006)	Derivation of probability factors of activities and matching them with set of appliances	Probability factors of activities, Power consumption of appliances
(Richardson, et al., 2010)	Based on (Paatero & Lund, 2006) but inclusion of simulation of similar use of appliances	Time us data, Power consumption of appliances
(Widén, et al., 2009a)	Hot water and electricity demand based on time-use, power consumption of appliances and natural illuminance.	Time us data, Power consumption of appliances, Natural illuminance
(Yao & Steemers, 2005)	Modeling of space heating, hot water heating as well as electricity for appliances and lighting based on several methods from models described above	Time us data, Power consumption of appliances, Natural illuminance, Building characteristics

3 METHOD

In the following chapter the applied method is explained. The focus lies on how input data is transformed to be adaptable for Gothenburg. Moreover, relevant equations are presented.

3.1 Electricity and water heating

In this section, the derivation of load curves for the energy demand of electrical appliances, lighting and hot water is explained. In the background (see section 2), promising, earlier approaches for the energy demand modeling are discussed. Based on those articles, it is decided to combine power consumption of activities, time-use data and daylight availability for the present model. However, the available data has to be adapted to extend it to an entire city.

3.1.1 Estimation of energy consumption per activity

The power consumption for electrical devices is accessible from literature. It is measured in watt per activity. The energy consumption for water heating is estimated with the help of the Equation 3.1 below. That equation shows the calculation of the amount of energy needed to heat a certain volume of water from the temperature in the pipes to the desired temperature. Afterwards, the amount of energy is divided by an assumed duration of the activity to convert it to an energy flow.

Equation 3.1 based on (Yao & Steemers, 2005):

$$E_{hw} = \frac{C_p * \rho * V * (T_{out} - T_{in})}{t}$$

$E_{hw} - Energy\ flow\ for\ water\ h$

$C_p - Heat\ capacity\ of\ water$

$\left(4187\ \frac{J}{kg*K}\right)$ (engineering toolbox, n.d. c)

$\rho - Density\ of\ water$

$\left(1\ \frac{kg}{l}\right)$ (engineering toolbox, n.d. c)

$V - Desired\ volume\ of\ hot\ water\ in\ liter$

$T_{in} - Water\ temperature\ before\ heating$

(Yao & Steemers, 2005)

$T_{out} - Temperature\ of\ hot\ water\ used$

$t - \ Assumed\ duration\ of\ the\ activity$

For the lighting electricity demand, a fixed value for the power consumption is assumed. However, there is no difference made between different activities or different rooms. It could be argued that in some rooms several light bulbs are installed and that people prefer dimmed lighting for certain activities (e.g. watching TV). Nevertheless, these aspects are not covered by the model.

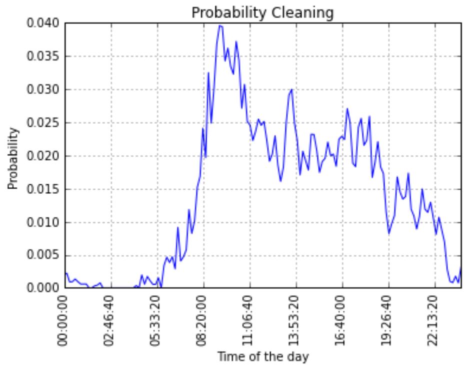
3.1.2 Transformation of time use data for load curves

The time use data extracted for the model is transformed to be applicable for the case study. The aim is to derive load curves per household. Those are supposed to be extendable for the whole city by multiplying with the number of households. Moreover, one load curve for the whole city for each type of day (working day, day off…) is required. Those load curves should be allocated to the days occurring during the year that is modeled (The load curve of a typical Saturday is matched to all Saturdays during the year). The final outcome is the load curve during a whole year.

In the following, the different steps to transform extracted time-use data are explained. Those steps are illustrated and can be followed in Figure 3.3 at the end of this section. For the each energy service (lighting, hot water, electrical appliances), specific data sets have to be derived:

- Lighting: Probability that an occupant is active at home (not sleeping)
- Hot water: Probability that an occupant does an activity including the use of hot water
- Electrical appliances: Probability that an occupant uses an electrical device

In a **first step**, time use data is extracted from the data base of the Harmonized European Time Use Survey. This source is further discussed in section 4.1.1. From the list of surveyed activities those that are done at home are extracted. Additionally, those activities are classified in groups for hot water use and electricity use. The approach is to multiply the probability-curve of an activity with its power consumption to derive the energy demand. This could look like in Figure 3.1 for the activity cleaning. However, there are some challenges due to the confidentiality and the limited access to the data base.



$$* \; P_{Cleaning} = E_{Cleaning}$$

Figure 3.1: Probability of cleaning over time multiplied by its power consumption to derive the energy demand.

Participants of time-use surveys – TUSs were asked to state if they were doing and activity in company with another family member. This is not extractable from the data base. However, it is important information to model shared use of appliances (see section 2.1). Two different cross-sections of the time-use data are extractable from the data base: 1) the probability of different activities over time and the size of the household the participant lives in, and 2) the probability of different activities over time and the type of day the diary was filled in. The data sets extractable can be seen in Figure 3.2. The challenge is how to combine the two cross-sections and include shared use of appliance.

Time	Type of household	Probability of activity
	1 person, 2 persons…	

⇔

Time	Type of day	Probability of activity
	weekday, weekend	

Figure 3.2: Cross-sections of data that is extractable from the time-use data base.

Since TUSs describe the activities of individuals, the above extracted data sets represent the probability over time that one person in the household does a specific activity. However, the energy consumption of multiple person households is higher as there are more active occupants. Simply multiplying the curves by the number of occupants may sometimes lead to double counting, since some activities are done simultaneously.

The author of the present report assumed that activities like watching TV are done in company with other family members or that people do some activities in the same room and share a lighting source. For the simplification of the model, the author assumed that those activities are always done in company. However, people still do these activities alone in reality. An estimation about how much time occupants spend alone and how much in company could be made. Nevertheless, this is not covered by the model.

In a **second step**, the activities that are identified to be done by several people together are listed. For all other activities the probability curve is multiplied by the number of household members. Since the probabilities of some activities were multiplied by the number of occupants, the outcome of this step are curves representing entire households according to their size.

The above derived curves for entire households represent an average over all participants of the TUS living in a household of a certain size. The kind of diary day is not included in those. Thus, the same procedure as explained above is done for the different kinds of days. The outcome is the shape of the curves of different days if they happened in a one person, two persons, three persons, etc. household.

The **third step** is the derivation of the power consumption per activity that has been explained above in section 3.1.1. These values are multiplied with the probabilities derived in step one and two. The result of this step is the average electricity and heat consumption per size of household for electrical devices, lighting and hot water heating.

The **fourth step** is only necessary for the electrical appliances. The power consumption of devices running for 24-hours has to be added. Those are assumed to be constant over time. They include for example the fridge, the freezer and stand-by devices.

Finally, the **fifth step** is the multiplication of the energy consumption per size of household by the number of those households in the city. The sum of these curves represents the energy consumption on an average day in the city. However, the aim is to make a difference between different days.

The **sixth step** is the adaption of the curves of different households to the different days. The outcomes of the previous steps are two kinds of load curves. The first type is representative curves for all households in the city that are of a certain type (number of those curves = number of different kinds of households). The second type is load curve representing the kind of day. To bring those two together the curves for the households are integrated to get the total energy consumption in that household. The curves for the different days are normalized to get the shape of those curves. This is done as shown in Equation 3.2.

Equation 3.2

$$P_{day\ n}(t_i) = \frac{E_{day\ n}(t_i)}{\int E_{day\ n}(t_i)dt}$$

$P_{day\ n}(t_i) - Share\ of\ energy\ consumption\ at\ time\ i\ including\ simultaneous\ usage$

$E_{day\ n}(t_i) - Energy\ consumption\ at\ time\ i\ including\ simultaneous\ usage$

$n - type\ of\ day$

To account for the effect that the total energy consumption during different days might differ, the integrated energy consumption at a specific day is divided by the sum of the energy consumption during all days. That factor is multiplied by the number of different days and the aggregated energy consumption during an average day The total energy consumption for each type of day is calculated as depicted in Equation 3.3.

Equation 3.3

$$E_{day\ n} = n * \left[\int E_{average\ day}(t_i)dt\right] * \frac{\int E_{day\ n}(t_i)dt}{\sum_{i=0}^{n} \int E_{day\ n}(t_i)dt}$$

$E_{day\ n} - Aggregated\ energy\ consumption\ for\ day\ n$

$E_{average\ day}(t_i) - Energy\ consumption\ at\ time\ i\ for\ an\ average\ day$

The aggregated energy consumption during a specific day is multiplied by the normalized curve for that specific day. This results in a curve for every day which describes the energy consumption of all households on a specific day in the city. Finally, the types of days occurring during the year are matched with the energy consumption for different days as calculated above.

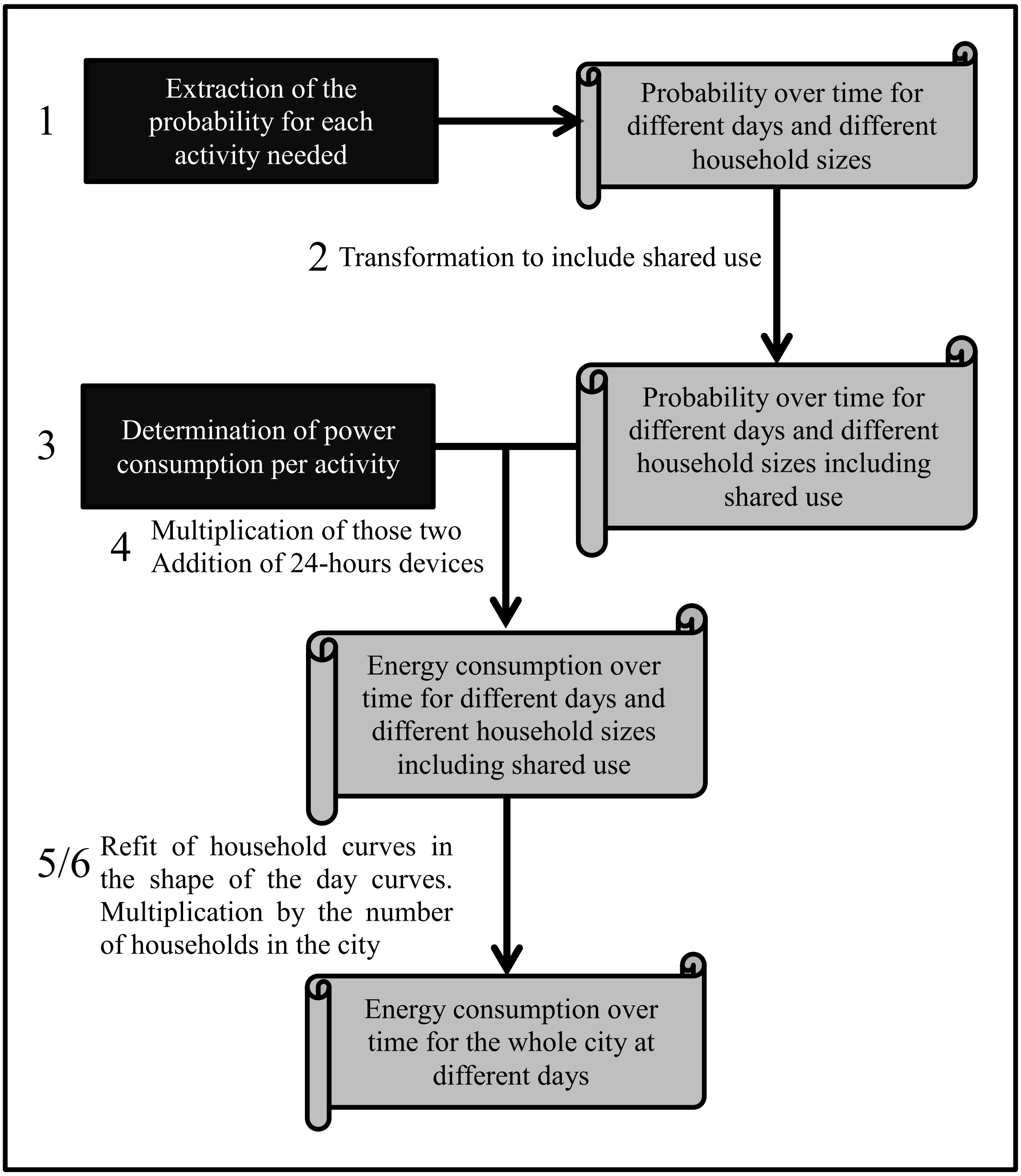


Figure 3.3: Illustration of the methodology to derive load curves for different days during a year in an entire city (own diagram).

3.1.3 Transformation of daylight availability

The third relevant input data set is the daylight availability during one year. Occupants switch on the lights in case they are active at home and the daylight availability is perceived as too low. To model this effect, the daylight availability over time for one year is extracted from a data base. The type of data and quality is explained and assessed in section 4.1.3.

In case there is sufficient daylight for activities, it is assumed that no electrical lighting is needed. In Figure 3.4, the algorithm to estimate the lighting electricity demand is depicted. If the occupant is at home, the level of illuminance is compared to a threshold value. For each time interval i at which the illuminance level falls under a certain threshold value, a temporary value is set to 1. This indicates that electrical lighting is needed for that time interval. For each time interval where the natural lighting is higher than the threshold value, the temporary value is set to 0, indicating that electrical lighting is not needed. Finally, the temporary value for each time interval is multiplied with the power consumption of the light source and the probability of being active at home at that time interval.

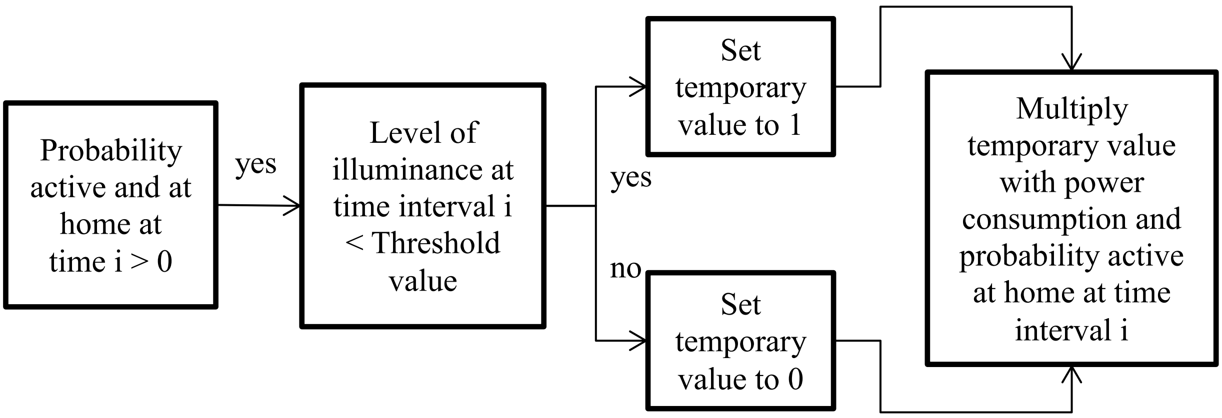


Figure 3.4: Algorithm to include the effects of daylight coming into the room on the lighting demand.

3.2 Energy for space heating

The third energy service that has been modeled is the demand for rooms at a certain temperature T_i. Equation 3.4 below has to be calculated to derive the required heating input. If this equation holds, the internal temperature T_i is constant over time. The equation includes several terms. The heating input $\dot{q}_h$ is the term symbolizing the energy demand for space heating over time. The other terms are the internal heat gains $\dot{q}_{is}$, heat losses over the building envelop $\dot{q}_{component}$ as well as over the window $\dot{q}_{win}$. The last factor is the heat flow caused by ventilation $\dot{q}_V$.

Equation 3.4 based on *(De Rosa, et al., 2014)*:

$$C_i \frac{dT_i}{dt} = \dot{q}_h + \dot{q}_{is} + \dot{q}_v + \dot{q}_{solar} + \dot{q}_{component} = 0$$

$T_i - internal\ temperature$

$C_i - thermal\ capacitance\ of\ the\ internal\ air$

$\dot{q}_h - heating\ input$

$\dot{q}_{is} - internal\ heat\ gain\ (e.g. electrical\ devices)$

$\dot{q}_v - heat\ losses\ due\ to\ ventilation$

$\dot{q}_{solar} - solar\ gains$

$\dot{q}_{component} - heat\ flow\ through\ different\ components$

The surplus heat caused by internal heat gains $\dot{q}_{is}$ consists of metabolic heat emitted from occupants as well as the use of electrical devices and lighting. The heat emissions from electrical appliances and lighting are assumed to equal their electricity consumption. The load curves of their consumptions, as derived previously, can simply be negated to get their heat production.

The metabolic heat of a person can range between 100 and 400 watt, depending on the activity (Varkie, et al., 2009). For the surplus heat of people, the probability of an activity is matched with a certain value for the metabolic emission that corresponds it. This is done with the same method that is used to model the electricity and hot water consumption.

The heat flow $\dot{q}_V$ caused by ventilation can be divided into two parts. Firstly, the heat flows caused by airing the room due to an uncomfortable indoor climate like bad smell or high humidity. That is also called sanitary ventilation (Mata & Kalagasidis, 2009). The second contribution is the heat flow occurring due to airing the room because the internal temperature exceeds a certain comfortable level. Thus, that occurs mostly in summer. In some countries where temperatures reach high levels, air conditioning is installed. That causes additional electricity consumption. However, in the present report, it is focused on sanitary ventilation as cooling is excluded from the study.

The exact calculation of the sanitary ventilation can be found in Equation 3.5. In this equation, the density and the specific heat capacity are matter constants of air. The heated floor area in the building and the temperature of the supply air as well as the internal temperature are dependent on the dwelling. The ventilation rate is measured in volume per time and area. In the European standard CEN Standard EN15251, typical ventilation rates for different rooms can be found. However, it can be recommended to assume an average value when modeling a city as it probably evens out over the whole set of buildings.

Equation 3.5 based on (Mata & Kalagasidis, 2009)

$$\dot{q}_v = \frac{V_c * A * (\rho c_p)}{1000} * [T_{vent}(t) - T_i(t)]$$

$V_c - ventilation\ rate\ \left(\frac{volume}{time * area}\right)$

$A - heated\ floor\ area\ in\ the\ building$

$\rho - density\ of\ air$

$c_p - specific\ heat\ capacity\ of\ air$

$T_{vent} -\ \ temperature\ of\ supply\ air$

A third phenomenon that influences the heating demand is the heat flows through the different components in a building. In this report the floor, external walls, the roof and windows are taken into consideration.

The heat transfer over the components is dependent on thermal convection. As can be seen in Equation 3.6, the driving factor is the temperature difference between the external and the internal temperature. The thermal resistance of the building parts is represented by the thermal transmittance and is measured in watt per kelvin and m^2. Hence, the surface of the building component also plays an important role.

Equation 3.6 based on (De Rosa, et al., 2014)

$$\dot{q}_{component} = (T_e - T_i) * \sum_j U_{component,j} * S_{component,j}$$

$T_i - internal\ temperature$

$T_e - external\ temperature$

$U_{component,j} - Thermal\ transmittance\ of\ the\ component\ j$

$S_{component,j} - Surface\ of\ the\ component\ j$

In the present report it is assumed that in a European city, a sufficient correlation between the thermal transmittance factor and the year of construction exists (see section 2.3). Thus, the values for different years of construction are collected and listed. Furthermore, data about the number of houses built in a certain period is gathered. With the latter dataset, the percentage of houses from a certain construction period can be calculated.

To apply Equation 3.6, the surface areas of the different components are expressed in relation to the living area. The living area in a city can be considered as available information. For the window, the window surface per living area can be found in literature. It is usually given as window surface per living area ore per external wall area depending on the literature considered (Sveriges Centrum för Nollenergihus - SCN, 2012), (Trainings- & Weiterbildungszentrum Wolfenbüttel e.V. TWW, n.d.). Thus, in some cases it has to be recalculated to get the relation to the living area.

The data found on the surface areas of the roof, floor or external wall area is very detailed for specific types of houses. However, to estimate the situation in an entire city, detailed data about the housing stock would have to be accessible. It has not been possible to find such data for the present case study and the availability of it for other cities is questionable. Hence, own estimations are done. It can be expected to find data about the living area in a city. To derive a relation between the living area and the area of the components, some geometric relations are derived.

It is assumed that a building is a perfect cube and that all rooms are squares. Furthermore, all walls are supposed to have the standard height of two and a half meters. Accordingly, the surface of all (internal/external) walls equals $10 * \sqrt{A_{living}}$. A further assumption is that two of those walls are external walls. This leads to a factor of $5 * \sqrt{A_{living}}$ for external walls which is derived in Equation 3.7. The measurements used in the calculations are depicted in Figure 3.5 A.

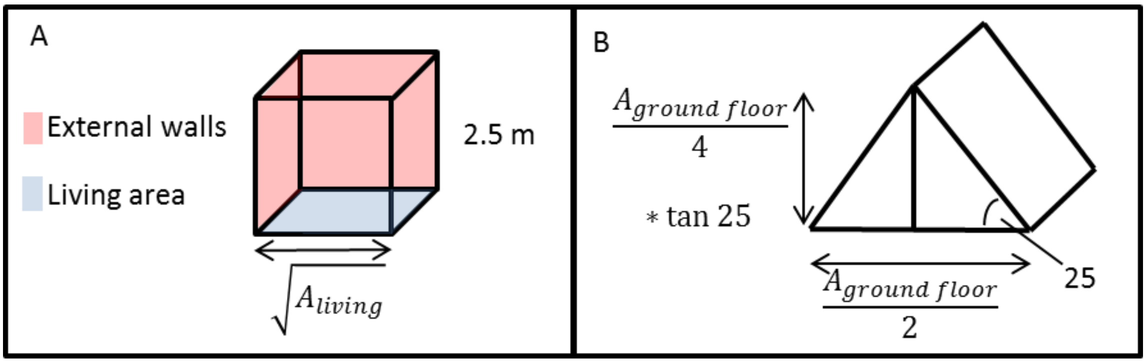


Figure 3.5: Dimensions for a cubic building: A) Derivation for the expression for external walls. B) Derivation for the roof area.

It is assumed that a building has on average a certain number of storeys. The living area is divided by that number to calculate the floor area as presented in Equation 3.8. It is assumed that the area of the roof equals the area of the ground floor. However, the roof pitch has to be taken into consideration. It is assumed that the angle between the base area and the roof area equals 25 degrees, as depicted in Figure 3.5 B. This leads to an estimation for the relation between the roof and the ground floor area, presented in Equation 3.9. Furthermore, the additional external wall area on the sides can be calculated, which can be seen in Equation 3.10.

Equation 3.7

$$A_{external\ walls} = 2 * 2.5m * \sqrt{A_{living}}$$

Equation 3.8

$$A_{ground\ floor} = \frac{A_{living}}{N_{average\ number\ of\ stories}}$$

Equation 3.9

$$A_{roof} = \frac{A_{ground\ floor}}{\cos 25}$$

Equation 3.10

$$A_{additional\ external\ wall} = \frac{A_{ground\ floor}}{2} * \frac{A_{ground\ floor}}{4} * \tan 25$$

The relations derived above have been tested against real values (see Appendix). The equations deliver reasonable values for the ground floor (maximum error 13 %) and the roof (maximum error 10 %). However, for the external walls the values are significantly too low. Since the values are highly uncertain a sensitivity analysis on the areas of the external walls t is done in section 4.5.2.

Using the previously explained equations and apply it on the information about the living area in a city, the aggregated surface per component can be calculated. Hence, the result of this step is data about how many m^2 of window/roof/floor or external walls exist. Knowing, the percentage of houses built in a certain period, estimation about how much window/roof/floor or external wall area was built in that specific period can be made. Since it is previously derived which heat transmittance coefficients correspond to these periods, Equation 2.1 can be calculated for the whole city. The entire method to derive the heat losses in a city is presented in Figure 3.6 below. In that figure input data sets are depicted as grey and outputs as white boxes.

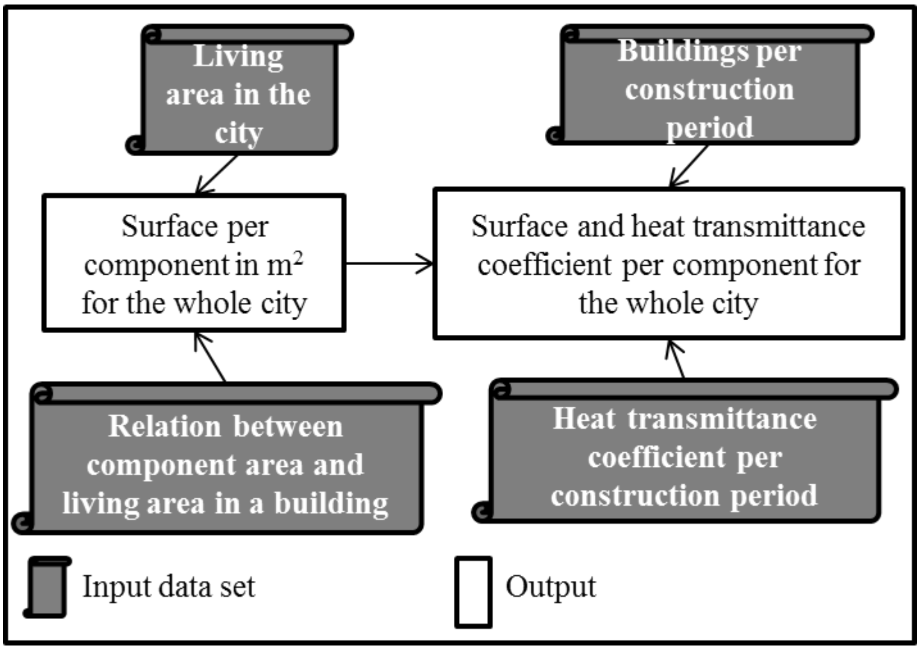


Figure 3.6: Methodology to calculate the heat losses in a whole city.

The last factor influencing the amount of heating energy in a city is the solar gain through transparent components. The energy of the sun enters the building through glass windows which leads to a reduction of the heat load in winter and an increased indoor temperature in summer. The heat flow due to solar gain is calculated as described in Equation 3.11, on the next page.

Equation 3.11

$$\dot{q}_{solar} = f_{Shadow} * g * S_{window} * I_{global} * f_{horizontal}$$

$f_{Shadow} - Shadow\ factor$

$g - Transmittance\ coefficient$

$S_{window} - Window\ surface$

$I_{global} - \ Global\ irradiation\ orthogonal\ to\ ground$

$f_{horizontal} - Factor\ to\ compensate\ windows\ not\ being\ horizontal$

In Equation 3.11, the factor f_{Shadow} stands for the area of the window that is covered by shadow. This can occur due to neighboring buildings or sun blinds. It ranges between zero and one and represents the non-shadowed area divided by the entire window area (De Rosa, et al., 2014). The g-value is a measurement for the transmittance of the windows for the energy in solar radiation. It is unit-less, ranges between zero and one and is the quotient between the energy transmitted through the surface and the energy reaching it. The window surface S_{window} in the whole city is derived similarly as explained in the section about heat transmittance losses. I_{global} represents the global radiation flux. It is measured in watt per square meter.

The present model describes a whole city. As a simplification, it can be assumed that all windows are vertical windows. The factor $f_{horizontal}$ compensates for differences in the orientation of the windows. Mata, et al. (2013) state that this “constant differs according to the latitude of the geographic region studied”.

4 CASE STUDY OF GOTHENBURG

The methodology described in the previous chapter is applied on the city of Gothenburg. In the following chapter, case-specific characteristics or issues are explained and strategies to solve them are explained. To use the model on a specific city, a long list of input parameters and data sets is needed. Those are listed and assessed in the next section. Finally, the main results are presented which is followed by a validation of the model as well as the identification of hot spots including a sensitivity analysis.

4.1 Input data sets and parameters

A large part of the work of the on-hand report is the data collection and assessment. Hence, a separate section for the input data sets and parameters exists. In the following sections, the input data are explained, the quality is assessed and the transferability to other cities is briefly described.

4.1.1 Time use survey

In 1990/01, 2000/01 and 2010/11, Statistics Sweden (Statistiska centralbyrån – SCB) conducted time use surveys – TUS. The main goal of the surveys and their evaluation is to analyze the equality between women and men on a time use base. The data is gathered via phone interviews and diaries. The diaries were filled in for a weekday and a weekend day consisting of 24 hours divided in ten-minute intervals. The participants had to write down in their own words what they were doing, if they were doing anything on side and if they had company. Further background data was compiled by phone interviews (Statistiska centralbyrån, 2012). An example for a filled-in diary can be found in the appendix.

In 2000/2001, 3980 individuals (living in 2138 households) took part in the survey. The participants aged 20-84 were all officially registered in Sweden while the survey was conducted. Occupants under 20 were excluded from the survey (Statistics Finland, n.d.).

The above described way to collect time use data is proved. The survey conducted by Statistics Sweden follows the guidelines of Eurostat. Thus, the data used in this model, can be found in a similar format for other European countries. To apply the model to other countries, it is recommended to look at the "Harmonised European Time Use Survey". This is an initiative of Eurostat where several EU countries conducted time use survey. At https://www.h2.scb.se/tus/tus/default.htm, tables can be extracted for the different countries (Statistics Sweden, n.d.).

Many different types of information were surveyed during the study. That included for example the size of household, the type of diary day, the participant's income and age. However, it is not possible to extract data combining several of those criteria from the data base. It is impossible to get data combining the size of household, the type of diary day and the percentage of participants doing an activity in the same data set. Hence, two data sets for each energy-consuming activity are extracted: one for the household size (one to five people) and one for the type of diary day (weekday and weekend day). Below, a list of the different groups of activities can be seen. A more detailed list of activities extracted can be found in the appendix.

- Energy consuming activities: TV, food preparation, cleaning…
- Active at home (only relevant for lighting): resting, reading books…
- Non-active at home: sleeping
- Away from home: main and second job, gardening, walking the dog…
- Neglected activities due to low percentage: caring for pets, handicraft…

The above described restriction on the usage of the data base might be to ensure universality of the data and the participants' privacy. If many cross-sections are combinable, the number of participants fulfilling those criteria decreases which can lead to wrong information as the influence of aberration increases. Furthermore, it might be possible to draw inferences about single participants.

As the TUS applied in this report is relatively old, a comparison between older and newer TUS has been briefly done, including estimations of how that influences the energy consumptions. To see how the behavior of people changes on the long-term, the results of the 1990/91 and 2010/11 survey have been compared.

According to Statistiska Centralbyrån (2012), the time spent on housework has slightly decreased. This could lead to lower energy consumption for water heating. However, the time spent with paid work increased. This is mostly due to the fact that more women conduct paid work (Statistiska centralbyrån, 2012). Hence, the time spent away from home might decrease and lower the lighting and electricity consumption.

Both genders have more spare time compared with the 1990/91 survey. The section spare time includes social activities, hobbies and outdoor activities. It can be seen that social activities as meeting friends, talking on the phone or going out to bars and restaurants has decreased. One explanation for that might be that social activities have been partly replaced by internet activities (for example the phone calls). This idea is supported by the fact that the time spent on the internet and on the computer has increased relatively much. Woman spent 20 minutes more with computers and men 40 minutes compared to the 1990/91 survey (Statistiska centralbyrån, 2012). These effects probably increase electricity consumption in the household. A further finding is that the time spent with TV and radio has increased as well (for both genders is has increased about 10-15 minutes) which might be correlated to a decreasing amount of time spent with reading. This shift from TV consumption instead of reading could also lead to an increase in electricity consumption.

One activity in the TUS is called “personal needs”. This section includes personal hygiene, naps but also eating snacks like candy or coffee breaks. Time spent with these activities has increased over the years. For women it has increased by 10 minutes and for man by 5 minutes (Statistiska centralbyrån, 2012). In case the time spent in the bathroom is a big contribution to the increase, the energy consumption for hot water might have increased.

The time when Swedish people eat and sleep as well as how long they do it basically stayed constant over time. Generally, it can be said that the shape of the curves during a day is similar in different years. The peaks mostly occur at the same time. However, they are higher or broader (Statistiska centralbyrån, 2012).

Finally, it can be said that changes in behavior are relatively minor. Nevertheless, the use of computers and TV has increased. Between the two surveys that are compared, the internet has become available for everyone. This is the reason why the time spent on the internet has increased and a further probable reason for the increase of time spent with computers. As example for this development, the amount of men spending time on the internet during the course of a weekday is compared between different years in Figure 4.1 (Statistiska centralbyrån, 2012).

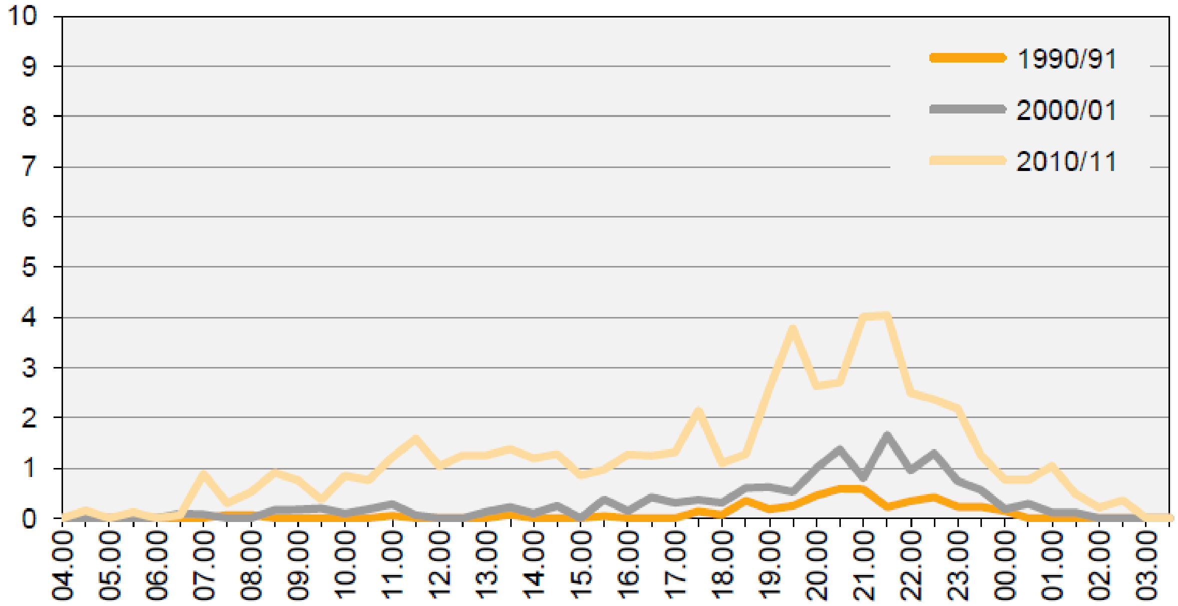


Figure 4.1: Percentage of men using computer/ internet at different times of an average weekday in the years 1990/91, 2000/01 and 2010/2011. Participants between 20-64 years old. Statistics from September to May (Statistiska centralbyrån, 2012).

In the on-hand report data is used from 2000/01 as this is the most detailed data available for the public. However, more general data is available from 2010/11 and was compared with the 2000/01 data to estimate the changes in behavior over time.

4.1.2 External temperature and solar irradiation

The external temperature and the solar radiation are extracted from the webpage of the Swedish Meteorological and Hydrological Institute – SMHI. Both data sets are available on an hourly distribution over the whole year. The values are specifically from Gothenburg but data for other places in Sweden can be collected as well. The same data exists probably for other European countries on national data bases.

The external temperature is extracted for the year 2000 to be consistent with the other data sets. It is used to calculate the heat leakage over the building envelope. The solar radiation is needed to calculate the amount of solar gain through transparent surfaces. The recording of the global radiation in Gothenburg has started quite recently. Hence, the only data set that contains a full course of a year is data from 2014. As the solar radiation and the daylight availability highly correlate, there is certainly a mismatch between the radiation data (from 2014) and the data about daylight availability (from 2000).

The temperature as well as the solar radiation data sets can be considered credible as SMHI is a reliable source. However, it only covers Sweden and the availability about the solar radiation in other countries might be limited.

4.1.3 Daylight availability

The data about daylight availability is taken from "S@tel-Light - The European Database of Daylight and Solar Radiation". On that webpage, data about daylight intensity for Europe between the years 1996 and 2000 can be found. The data is taken from measurements by a Meteostat satellite on a half-hourly resolution. Those satellites take picture of the earth and measure the reflected radiation (Hammer, et al., n.d.).

As the data base is not as established as the other data bases and as there is no official Institute behind it, the data quality is assessed according to (Harris, 2015). The author supplies a checklist to test internet sources against credibility, accuracy, reasonableness and support. As the data set is taken form the internet, the checklist is considered to be a suitable assessment tool for the quality of data. The input data assessment can be found in the appendix. It can be considered suitable as input data. However, the reliability can be considered lower than for the other data sets used in the model.

For the present model, data for Gothenburg Sweden (latitude 57°43′12″N, longitude 11°58′12″E, average altitude 2 m) is extracted from the data base. Data is available for several other highly populated areas in Europe. The data used is the illumination measured in lux on a work plane at 0.8 m height. The data supplies measurements on a half-hourly distribution for the years between 1996 and 2000 but in this case only the data from 2000 is taken to be consistent with the available time use data (see section 4.1.1). All data is based on the assumption that the glazing is standard double panel (70% normal transmittance and 10 % diffuse reflectance). Furthermore, the distribution of the surfaces is assumed to be: Ceiling 30%, Walls 40%, Floor 30%. There are twelve data sets in total as there are three options for different building types four possible orientation of the building. For the model the average of the four data sets describing windows at the façade (N-E-S-W) are taken. Thus, the average illumination on a work plane in Gothenburg over the whole year on a half-hourly distribution is derived (Hammer, et al., n.d.).

4.1.4 Threshold values for temperature and lighting

To derive the heating demand as well as the demand of electricity for lighting, threshold values for a comfortable indoor climate have to be set. Firstly, the illuminance value at which people are assumed to switch on the lights is determined. Secondly, the temperature that occupants in Sweden perceive as comfortable is defined.

The threshold values or the lighting vary between different studies. According to a study on the correlation between indoor office environment and office workers' performance conducted by Vimalanathan & Babu (2014), an optimal level for indoor room illumination is 1000 lux. However, in other studies 500 lux are suggested (e.g. (Commission Internationale de l'Eclairage, 1986)). Richardson, et al. (2009), even state the threshold value as solar irradiation reaching the earth in W/m^2 and assume a value between ten and sixty. In Table 4.1, an overview of different threshold values from literature is given. The guidelines depicted in Table 4.1 are regulations for minimum illuminance on a work plane (horizontal), for drawing and conference rooms (IEA International Energy Agency, ECBCS Energy Conservation in Buildings and Community Systems, 2010). However, it is likely that residents in private homes perceive the same illuminance levels as comfortable.

Table 4.1: Overview of threshold values from different articles and guidelines

Article/ guideline	**Threshold value**
(Commission Internationale de l'Eclairage, 1986)	500 lux
(Newsham, 1994)	150 lux
(Reinhart, 2005)	500 lux
(Richardson, et al., 2009)	10-60 W/m^2
(Vimalanathan & Babu, 2014)	1000 lux
(Yao & Steemers, 2005)	150 lux
DIN EN 12464-1	300-500 lux
ISO-CIE Standard Europe	500-750 lux
International Standard ISO 8995-1 – CIE S 008/E	500-750 lux

The present model is based on the ISO-CIE Standard for Europe. This guideline requires 500 lux of minimum illuminance on a work plane and for conference rooms and 750 lux for drawing. To generalize or extend this model, it may be interesting to consult (IEA International Energy Agency, ECBCS Energy Conservation in Buildings and Community

Systems, 2010) available at http://www.lightinglab.fi/IEAAnnex45/guidebook/4_lighting%20and%20energy%20standards%20and%20codes.pdf where other international guidelines can be found.

In addition to weather input parameters, the internal temperature is needed to start the simulation. As stated in a European directive on energy performance in buildings, the indoor temperature is decided on national level (BS EN 15251:, 2007). Thus, it can be assumed that the indoor temperatures that are accepted by the residents differ between countries. In the present model an acceptable temperature for Sweden has been chosen. However, this has to be replaced if the model is applied for another location. According to the study on the correlation between indoor office environment and office workers' performance conducted by Vimalanathan & Babu (2014), and optimal level for indoor room temperature is 21 degrees C. This temperature is assumed to be the internal temperature in Gothenburg as well.

4.1.5 Load curve of devices

The values for the power consumption and duration of electrical devices is mostly taken from (Widén, et al., 2009a) and (Widén & Wäckelgård, 2010). However, the data is cross-checked with internet sources and rectified in case the majority of those contradicted the findings from the main journal articles. That is the case for the clothes dryer and the dishwasher which are underestimated in Windén, et al. (2009a) and corrected based on (Draft Logic, 2014), (EnergyUseCalculator, 2015) and (Wholesale solar, n.d.).

To calculate the energy consumption for water heating, the desired volume and temperature are needed. Those are taken from (Widén, et al., 2009a) (see section 2.1.). The detailed values for the load curves of electrical devices and water-consuming activities can be found in the appendix. For the water consumption during the time spent in the bathroom an imaginary but realistic bathroom routine was developed in section 4.2.1.

The values extracted from the journal articles can be considered quite uncertain. However, they have also been cross-checked with other commercial online sources. Thus, the values used in the case study are considered to be suitable for the modeling purpose. The bathroom routine is highly uncertain. For other locations the same values can be assumed as no specific assumptions for Gothenburg or Sweden have been made.

4.1.6 Emission from people and electrical devices

To calculate the internal gains in the building, emissions from technical devices as well as from people are needed. Heat emissions from people are caused by metabolic activities and depend on the intensity of the movement. For electrical devices it is assumed that the emissions equal the electricity consumption.

In Table 4.2, typical heat emissions from people for several activities are depicted. Even though data for the activities done in households are not found, the information leads to some conclusions for the on-hand model. Except for the activities “Light bench work”, “Dancing” and “Heavy work”, the heat emission per person is in the same range. Looking at the activities done in a household, only cleaning can be considered to cause higher heat emissions. However, this effect is assumed to be negligible. Hence, the heat emission from people is regarded to be an average value of 125 watt per person.

Table 4.2: Heat emission of different activities (Varkie, et al., 2009)

Level of Activity	Typical Application	Heat gain/ person in watt
Seated at rest	Theater	103
Seated, light work	Office	117
Moderate office work	Office	132
Standing, walking slowly	Retail Sales	147
Light bench work	Factory	220
Dancing	Nightclub	249
Heavy work	Factory	425

4.1.7 Heat transmittance coefficient

The heat transmittance coefficients are needed to calculate the heat losses over the building envelop. The different components considered are: roof, floor, external walls and windows.

For roofs, floors, windows and external walls, the heat transmittance coefficients are extracted from a report by Boverket. Boverket is the Swedish central office for construction. The heat transmittance coefficients in Sweden, were measured and studied by them in the framework of a project to map the current building stock and their energy consumption (BETSI). It is assumed that the existing building stock in Gothenburg corresponds in a sufficiently to the measured values. As BETSI is commissioned by the Swedish government, the data is considered to be reliable.

In the BETSI report, the coefficients can be found for different construction periods. Those are matched with the information about the years of construction of the building stock in Gothenburg. In Table 4.3, in the section 4.1.8, the groups of input parameters, their sources as well as how they match to the construction years can be seen. All detailed input parameters can be found in the appendix.

The last coefficient that has to be determined is the g-value for windows. It is a measure for the solar energy transmitted through transparent components and is assumed to be 0.77. The factor can range between 0.69 and 0.86 depending on the glazing and type of window (Trainings- & Weiterbildungszentrum Wolfenbüttel e.V. TWW, n.d.). The age of the building does not correlate with the characteristics of the window as those are exchanged on a regular basis and no data on the types of windows for the city of Gothenburg exists. Thus, an average value for all windows is assumed.

The heat transmittance values for the roof, floor and external walls can be considered reliable. Nevertheless, for the windows average values are assumed that could differ in reality.

4.1.8 Type of building

To extend the model from one household to the whole city, information about the size of the households (one to five members) as well as the living area is needed. This information is taken from city municipalities in Gothenburg. A further data set taken from there is the construction date of buildings in Gothenburg. This data is needed to make conclusions about the heat transmittance coefficients of the different components in the buildings since it can be assumed that they correlate with the age of the building. As the city of Gothenburg is an official instance in the municipality, the data extracted from there can be considered reliable.

As discussed in section 3.2, for the factors for external walls, the ground floor and the roof, no general data can be found. The data available is very detailed for specific types of houses. Thus, the equations derived in section 3.2 are used in the model of Gothenburg. These are valid under the assumption that a building is a perfect cube with square rooms. Furthermore, it is presumed that an average house consists of three storeys and that one storey is typically two and a half meters high.

In Table 4.3, the input parameters of the on-hand case study and their sources can be seen. All values can be found for single as well as multifamily houses. The information about the living area is depicted in the first column and is collected from the homepage of the city of Gothenburg. This data set is combined with the relations of the component surface, as derived in section 3.2. Thus, information of the aggregated area per component in the whole city is obtained. The information about the number of houses in a certain period, as presented in the second column, is also collected from the city of Gothenburg.

Table 4.3: Input data from different sources for the calculation of heat losses in Gothenburg.

Numbers of households of a certain surface area in m^2	**Numbers of building from different construction periods**	**Heat transmittance coefficient for all components from different construction periods**
< 51	Before 1930	Before 1960
51-70	1931-1940	1960-1975
71-90	1941-1950	1976-1985
91-110	1951-1960	1986-1995
111-140	1961-1970	1996-2005
141-170	1971-1980	
>170	1981-1990	
	1991-2000	
	2000-2010	
	After 2011	
(Göteborg Stan, 2012)	(Göteborg Stan, 2012)	(Boverket, 2010)

4.1.9 Validation and comparison data

To validate the model, different data sets are taken depending on the part of the model to be validated. For the hot water heating, no suitable data is found. Generally, it is hard to find suitable data as there hardly exists data on the timing of energy consumption. Thus, the output of the model has to be adapted to be comparable to the validation data.

To validate the space heating consumption, data from the district heating system in Gothenburg is taken. This data includes the consumption of all clients in MW on a one-hour resolution for the years 2010-2014. As in the on-hand report only the year 2000 is modeled, the model has to be adjusted. Furthermore, only the shape of the curves can be compared as the data also includes the consumption of industrial clients. However, it is assumed that the industrial consumption is quite constant.

For the validation of the consumption for lighting, data from a model for the UK developed by (Richardson, et al., 2009) is taken. This model is described in the literature study, section 2.2. However, this model is limited to the generation of data on single households. The selectable options are the kind of household (1-5 persons household) and the month of the year. It is only possible to extract the curve for an average day per month. Thus, one summer day and one winter day for a one person household is taken from the present model and compared to the data from (Richardson, et al., 2009). Nevertheless, the data sets are neither from the same year nor from the same country

(Widén, et al., 2009a) constructed load curves for household electricity. They used data from EL-SEA-2007 to validate their model. This data set includes “preliminary electricity measurements of household electricity on individual appliance” conducted by the Swedish Energy Agency. The measurements were done between 2005 and 2007 and included 217 households. The diagrams on this are taken from the paper and compared with the derived model.

4.2 Application of the model on Gothenburg

In this section, the application of the method on the city of Gothenburg is described. The electricity demand (electrical appliances and lighting) and the hot water demand are modeled in a similar way. Hence, they are summarized in one section followed by the explanation of the space heating demand.

4.2.1 Electricity and water heating

As explained in section 3.1, the load curves for electrical devices, lighting and hot water are determined by combining the power/water consumption per activity with the time-use data. In the following paragraphs, case-specific characteristics of this procedure are explained and special features for Gothenburg and Sweden are highlighted.

In section 3.1, the energy consumption per activity was described. Moreover, the procedure to transform the time-use data and the daylight availability were explained. The same structure is followed to explain case-specific aspects for Gothenburg.

4.2.1.1 Estimation of power consumption per activity for Gothenburg

To derive the power consumption of each activity, data from journal articles is taken. For the electrical appliances those values can directly be found in most cases. The data derived is the watt consumption per activity (e.g. 1500 watt for cooking).

For the fridge and the freezer a lower amount of power is taken as input for the model. In reality the devices cycle and do not consume at maximum capacity during 24 hours. As suggested in (Wholesale solar, n.d.), the time that the device is plugged in should be divided by three. This leads to the assumption that one third of the maximum capacity runs 24 hours in this model.

The calculation for the energy for water heating is based on Equation 3.1 (see section 3.1). To apply that equation, the desired volume and temperature are needed. Those data is taken from Widén, et al (2009). However, some activities are left out as their consumption is quite small (Hand wash 0.7 l, wash face 1.3 l).

For the water used to clean the apartment or to wash the hair, no required temperature is found in literature. Thus, for the cleaning water the same temperature as for washing the hands is taken. It is assumed that this water is mostly in contact with peoples' hands and the same temperature is considered to be comfortable. The water to wash the hair is assumed to be the same as for showering.

The estimation of the power consumption of the activity "other personal care" is more complex. It is assumed that most of the activities included in this section are taken place in the bathroom. Hence, a possible average bathroom routine is derived. As academic studies about people's behavior in the bathroom are hard to find, own estimations are made. Those are based on one survey made by IKEA (IKEA, 2014) and one extracted from yalaphc.net (http://www.yalaphc.net/viewer/A4sf). IKEA published the typical morning routine of inhabitants of Stockholm, Paris, Berlin and London.

Based on those two studies the distribution presented on the next page for the bathroom routine is assumed. In Equation 4.1, it is depicted how the energy consumption during the activity "other personal care" is calculated.

- Total time spent in the bathroom - $t_{bathroom}$: integration of the curve describing "other personal care" extracted from the time use surveys
- Shower routine:
  - Chance that an occupant showers in the morning:57 %
  - Duration: 14 minutes
  - Volume: 40 liters
  - Temperature: 40 degrees
- Additional water used from the tap:
  - Chance that an occupant takes water from the tap:100 %
  - Duration: 3 minutes
  - Volume: 6 liters
  - Temperature: 36 degrees
- Hair washing routine:
  - Chance that an occupant washes her/his hair: once a week (1/7 → 14 %)
  - Duration: 14 minutes
  - Volume: 10 liters
  - Temperature: 40 degrees

Equation 4.1:

$$q_{bathroom\,routine} = \frac{c_p * \rho}{t_{bathroom}} * \sum_j \left(T_{output,j} - T_{input}\right) * \ p_j * V_j * t_j$$

$t_{bathroom} - Total\ time\ spent\ in\ the\ bathroom$

$c_p - Specific\ heat\ capacity\ of\ water$

$\rho - Densitiy\ of\ water$

$T_{output,j} - Desired\ temperature\ of\ activity\ j$

$T_{input} - Input\ temperature\ in\ the\ pipe\ system$

$t_i - Time\ for\ activity\ j\ in\ seconds$

$V_i - Volume\ of\ water\ for\ activity\ j\ in\ liter$

$p_i - Probability\ for\ activity\ j$

According to the study from yalaphc.net, 88 % of people use electrical devices when they are in the bathroom. It is assumed that people use an electrical device for 5 minutes during an hour spent in the bathroom. As a representative for electrical devices the power consumption of a hair dryer is taken. This is multiplied by 5/60 to reduce the consumption due to the time-limited use.

For the power consumption for light bulbs 75 W is assumed. In previous works from the UK (see section 2.2), statistical data on lighting sets in houses was used. However, this kind of data could not be found for Sweden. Hence, a first guess is made and the power consumption of light bulbs is investigated further in a sensitivity analysis.

4.2.1.2 Transformation of time-use data for Gothenburg

For Sweden, data sets on several kinds of households and days are extractable from a time-use data base. The time-use survey on which the data is based was conducted in 2000/01. The data sets gathered distinguish between five different household sizes. Those are measured in people per household (“one person”, … “five persons or more”). There is a list of different days available. However, only data sets for an “ordinary working day” and a “day off” are collected. The other options are very dependent on individuals (“sick leave day”, “vacation day”…) and hard to assign to days during the year.

Even though the participants of the time use survey had to fill in if they were doing an activity with someone else, it is not extractable from the data base. Thus, for this model some assumptions on simultaneous activities are made.

All activities that are assumed to be done alone are multiplied by the number of household members. However, in the present model it is only multiplied by two. This is done as the time use survey did not include participants who are under 20 years old. It is assumed that every household consists of two grown-ups and their children. In Gothenburg every fourth household with children consists only of one adult and her/his children (Göteborg Stad, 2012). Nevertheless, it is assumed that this is evened out by the households with grown-up children or households that consist of more than two adults.

It is likely that the energy consumption of small children is quite low. The majority of their activities are probably done in company with a grown-up. Thus, this would not lead to a significant increase in energy consumption. However, occupants in their teens have considerable energy consumption. Their user patterns might look very different from the older survey participants. They probably do less housework and consume more entertaining media. Nevertheless, no data on this exists and it is not covered by the model.

For the hot water consumptions the activities that are relevant are:

- Other personal care
- Food preparation
- Dish washing
- Cleaning

It is assumed that “Food preparation” is a shared activity. The hot water consumption for food preparation can be considered to increase non-linear and in a negligible amount if two people cook together. Furthermore, the load curves for the activities derived in 3.1.1 are average values. It is assumed that they even out over the whole city (a person cooking for a five persons household might use more and a person cooking for a one person household might use less energy/water than derived in 3.1.1).

The following categories of activities present in the time-use survey were considered relevant for modeling the use of electrical appliances:

- Other personal care
- Dish washing
- Cleaning
- Laundry
- Ironing
- Computer and video games
- Other computing
- TV and video
- Radio and music

Only “TV and video” as well as “Radio and music” are considered to be shared activities. Hence, the power consumption of the other activities is multiplied by two.

For lighting a long list of activities conducted at home is derived. This detailed list can be found in the appendix. For shared use of lighting sources the relevant activities are:

- Food preparation
- Radio and music
- TV and video
- Teaching, reading, talking with the child

The results of the previous steps are typical curves for the energy demand of hot water heating, electricity for lighting and electrical devices. Those are derived for the different kinds of households and a weekend and weekday each. Finally, those are multiplied by the number of households of that type in Gothenburg (available from City of Gothenburg) and matched with the weekend and weekdays in 2000. The detailed values for the power consumption per activity can be found in the appendix. For a further description of the sources see section “4.1.5 Load curve of devices”.

4.2.1.3 Transformation of daylight availability data in Gothenburg

For the daylight availability the data is taken from from “S@tel-Light - The European Database of Daylight and Solar Radiation” for the year 2000. The data set describes the level of illumination on a work plane of 0.8 m height in Gothenburg for different kinds of windows. For this case, the illumination level through façade windows is considered the most suitable one. Data on this is available in lux and for the four different cardinal sections. Since it is assumed that the orientation of the window evens out over the city, the average of north, east, south and west is taken. Finally, the algorithm explained in 3.1.3, is used to model the effect of the daylight on the lighting demand. The threshold value for Gothenburg is set to 500 lux. The derivation of the threshold value can be read in section 4.1.3.

4.2.2 Space heating

In the following paragraphs the factors influencing the energy demand for space heating are explained. This includes internal heat gains, ventilation, heat losses due to transmittances over surfaces and solar gains.

As described in section 3.2, the internal heat gain consists of heat emissions from lighting, electrical appliances and metabolic heat from the occupants. The emissions from lighting and electrical appliances are assumed to equal their electricity consumption. Thus, the load curves for electrical devices and lighting derived in previous sections are aggregated. The sum of the two is subtracted from the heating load. The heat emissions from people are regarded to be an average value of 125 Watt during the whole day. Further information and the derivation of this value can be found in section 4.1.6.

In section 4.2.1, the probability of people being at home is derived. The results of that section are two curves, one describing a day off and another describing an ordinary working day. However, the activity “sleeping” is not included in those curves. Since occupants also emit heat during sleep, the probability of this activity is added to the existing curves. Both curves are multiplied by 125 Watt to obtain the surplus heat from people over time.

Adding up the curves for the heat emission from people, the heat emission from electrical appliances and the heat emission from lighting, a full load curve for the surplus heat in Gothenburg is obtained for a day off and an ordinary working day. Finally, it should be emphasized that this is valid under the assumption that each household contains of two adults, like for the other energy services.

As mentioned in chapter 3.2, the heat flow from ventilation consists of natural and sanitary ventilation. For the Swedish case, it is assumed that there is no natural ventilation. The outdoor temperature is regarded to hardly reach a level that makes air conditioning necessary for households. Furthermore, it is considered that airing due to high temperatures mostly occurs during the warm seasons when no heating is needed. Therefore, the effect of the natural ventilation on the energy demand for space heating is neglected in this model.

To assess the relevance of the sanitary ventilation, its value is calculated according to Equation 3.5. For all input parameters high values are chosen in order not to underestimate the energy demand. The ventilation rate is set to of 1.4 $l/s*m^2$ which is regulated in the CEN Standard EN15251. That guideline is valid for non-residential buildings but is considered to give a first estimation on the range of sanitary ventilation. However, the value for the ventilation rate in residential buildings can be assumed much lower. The calculation leads to values lower than 5 kilowatt for heat losses due to sanitary ventilation. A detailed calculation can be found in the appendix. The heat flow is rather low when considering that people only air their rooms during a very short time of the day. Thus, ventilation in general is neglected in this model.

As described in chapter 3.2, heat flows over surfaces like windows, walls and the roof cause heat loss in the building. Data about the temperature difference, the size of the components in buildings and the heat transfer coefficients in Gothenburg are needed. The components considered in the on-hand model are: the windows, external walls, the roof and the ground floor. For the ceiling as well as for internal walls it is assumed that the temperature is equivalent on both sides and thus no heat flow exists.

The driving factor of the heat flows is the temperature difference between the external and the desired internal temperature. In the present an acceptable indoor temperature for Sweden is set to 21 degrees Celsius which is motivated in section 4.1.4. The external temperature is available on the homepage of Swedish Meteorological and Hydrological Institute - SMHI (http://opendata-download-metobs.smhi.se/explore/?parameter=3 accessed: 2015-04-20). The data set extracted is from 2000 so consistency between the data about daylight availability and the time use surveys is given.

The area of the different components is the last relevant parameter. Data about the living area in Gothenburg exists for single-family and multi-family houses. All houses that could not be allocated to one of those groups are summarized in “others”. The exact data available is the number of households in different intervals of flat sizes (<50 m^2, 51-70 m^2…). Multiplying the number of households with the mean value for the living area in each interval gives an estimation of the aggregated area in Gothenburg. The aggregated area for multi-family homes is distinguished from single-family houses whereas “others” are assumed to be 50 % single- and 50 % multi-family houses.

In a second step, the relation between the living area and the area of the different components has to be obtained. For the windows, it is measured in two different ways depending on the literature and studies considered. In (Sveriges Centrum för Nollenergihus - SCN, 2012), it is measured in window surface per living area and estimated as 0.37 for multifamily houses. In (Trainings- & Weiterbildungszentrum Wolfenbüttel e.V. TWW, n.d.), it is declared in window surface per external walls and the values are between 0.05-0.2 for multifamily and 0.05-0.3 for single-family houses.

For the Swedish case, the first source is considered more suitable as the second based on German conditions. However, it only provides the value for multifamily houses. Observing the data from (Trainings- & Weiterbildungszentrum Wolfenbüttel e.V. TWW, n.d.), it can be seen that the value for single-family houses is approximately in the same range as for multifamily houses. Thus, the value is considered to 0.37 for both cases.

As discussed in section 3.2, for surface areas of external walls, the ground floor and the roof, no general data can be found. The data available is very detailed for specific types of houses. Thus, the equations derived in that section (3.2) are used in the model of Gothenburg. These are valid under the assumption that a building is a perfect cube with square rooms. Furthermore, it is presumed that an average house consists of three storeys and that one storey is typically two and a half meters high.

The final data input set needed is the heat transfer coefficients. All values for that are extracted from a report by the Swedish official office for construction (Boverket). The coefficients are available for the different components and for different construction dates. Furthermore, it is distinguished between multi-family and single-family houses. A list of all available data and further explanation were done in section 4.1.7.

Information about the number of houses in a certain period is gathered from Gothenburg city. With the help of that the percentage of buildings from different construction periods is derived. This is done by dividing the number of houses built in a certain time interval by the total amount of houses in Gothenburg. Subsequently, the percentages can be combined with the different heat transmittance coefficients to produce and average. As the time intervals for the heat transmittance coefficients and the construction of the buildings do not perfectly match, the average of the heat transmittance coefficients of two periods is taken. All detailed input parameters can be found in the appendix.

As explained in chapter 3.2, there are five relevant input parameters to calculate the additional heat flow in the building due to solar radiation. The first factor is the shadow factor representing the non-shadowed area of a building. In Sweden, this value is assumed to equal 0.5. It is extracted from SVEBY (Standardisera och verifier energiprestanda för byggnader) which is a project initiated by the construction and real estate industry. It supplies typical modeling input data for energy balance calculations to actors within the industry (SVEBY - Branschstandard för energi i byggnader, 2012).

The transmittance for solar energy of windows is assumed to be 0.77. The aggregated window surface in Gothenburg is approximately 7477138.6 m^2. This value was derived before when the losses due to heat flows through different components was modeled. As for the external temperature the source for the global radiation in Sweden is the Swedish Meteorological and Hydrological Institute - SMHI (http://opendata-download-metobs.smhi.se/explore/?parameter=3 accessed: 2015-04-20). A detailed derivation of those input values can be found in “4.1.7 Heat transmittance coefficient”, “4.1.2 External temperature and solar irradiation”.

The last input parameter of the model is the factor that compensates for differences in the orientation of the window. A very detailed derivation of this factor being 0.68 for Sweden can be found in (Mata & Kalagasidis, 2009) and is approved a couple of years later by (Mata, et al., 2013)

4.3 Results

In this chapter, the results of the case study are presented. The differences in modeled energy demand between different days and seasons are analyzed.

As a winter weekday, Thursday, 21st December 2000 is taken because it is the day with the shortest daylight availability. Moreover, it can be assumed to be representative for the colder season. The winter weekend day is Saturday, 23rd December 2000 since it is the first weekend day following the winter weekday. For the summer days Wednesday 21st June 2000 and Saturday 24th are taken. The 21st June is the day with the longest daylight availability.

The dependencies of the modeled energy demand on the input factors are studied. An attempt on the reduction of input data and the simplification of the model is made. Furthermore, the results from the model are compared to real data to validate the model. Based on that, factors for the sensitivity analysis are identified and the transferability to other cities is discussed.

4.3.1 Electricity for electrical appliances

For the modeled electricity demand for electrical appliances, seasonal differences are not noticeable. However, the modeled curves differ between a weekday and a weekend day. In Figure 4.2, the modeled load curves for those days are depicted. The dotdashed line represents the modeled electricity demand on a weekday. During that day two peaks can be seen, one in the early morning of about 80 megawatt and one in the evening of about 100 megawatt. The weekend day is indicated by the solid line. The increase of the curve occurs later than on weekdays and the modeled demand rises directly to 110 megawatt where it approximately stays until the evening.

As a simplification, a constant electricity demand of 60 megawatt during a weekday with two peaks could be assumed. The first one at 6:00 h of 80 megawatt and one of 100 megawatt at about 19:00 h. For a weekend day a constant electricity demand of 60 megawatt could be assumed that increases to 110 megawatt at about 08:00 h and keeps that level until 19:00 h.

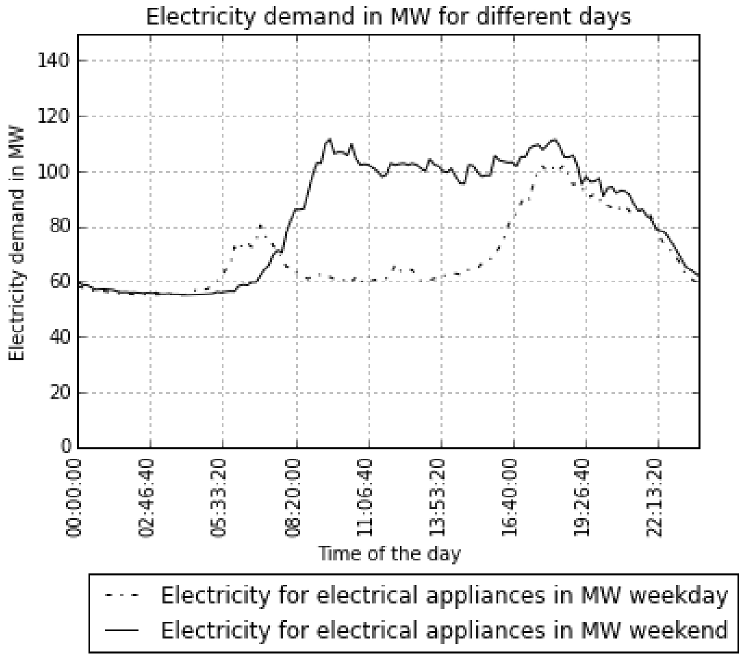


Figure 4.2: Electricity demand in megawatt for a weekday (dashdotted line) and a weekend (solid line).

To simplify the model further and decrease the amount of input data, the activities with the highest contribution to the modeled electricity demand are identified. Therefore, the modeled electricity consumption per person of on an average weekday and weekend day are studied. The activities that contribute most to the modeled electricity demand on both days are: watching TV, dish washing, food preparation and cleaning.

In Figure 4.3, the modeled electricity demand of the different activities can be seen in a stacked area diagram. The four identified activities are represented by the colors blue, red, green and cyan. The magenta area represents the sum of all other activities. Thus, a comparison of the contributions of the different activities can be made.

The modeled electricity for “food preparation” has a major contribution to the peak in the morning, at lunch time and in the evening. The “dish washing” shows the highest contributions directly after the food preparation. The modeled load curve for cleaning is relatively constant compared to other activities. The activity “watching TV” leads to a continuation of the evening peak.

The contribution from other activities is relatively low. Thus, the sum of all four activities reflects the total modeled electricity demand quite well. A higher divergence can be noticed during the morning and the evening peak. However, using only the information of food preparation, cleaning, dish washing and watching TV could be sufficient to build a load curve for a weekday.

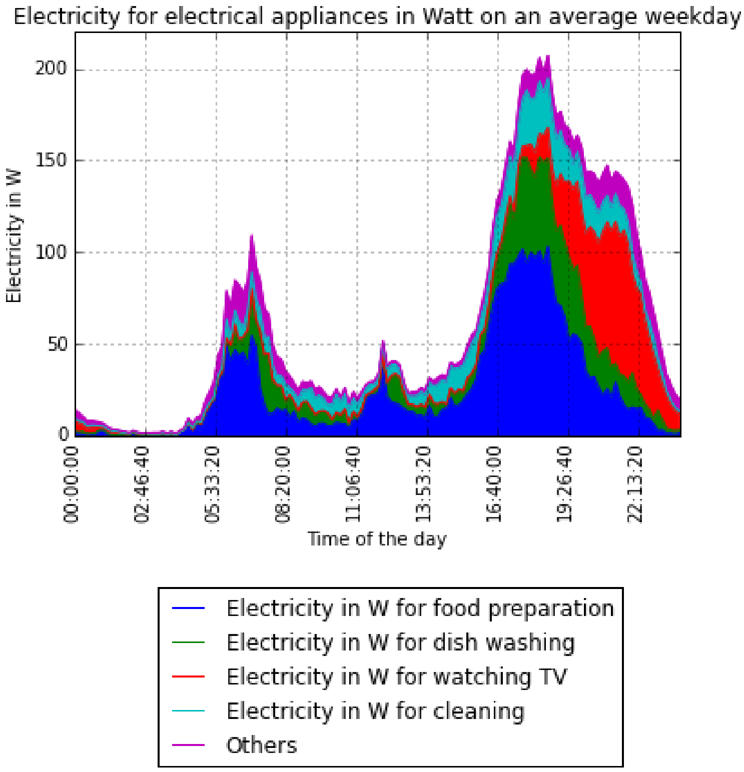


Figure 4.3: The four main contributions to the electricity demand on a weekday in comparison with the other activities for electrical appliances.

The same figure is determined for the modeled electricity consumption per person on a weekend day. As can be seen in Figure 4.4, the modeled electricity for “food preparation” has the main contribution to the modeled electricity demand. This demand as well as the modeled demand for “cleaning” and “dish washing”, increase rapidly in the morning, rise further during the day and fall down quickly in the evening. However, the modeled electricity for “watching TV” that increases during evening hours leads to continuing high modeled electricity demand.

During the day especially at about 11:00 h the contribution of other activities (magenta) is relatively high. Thus, it is questionable if the information about food preparation, cleaning, dish washing and watching TV is sufficient to derive the electricity load curve during a weekend day.

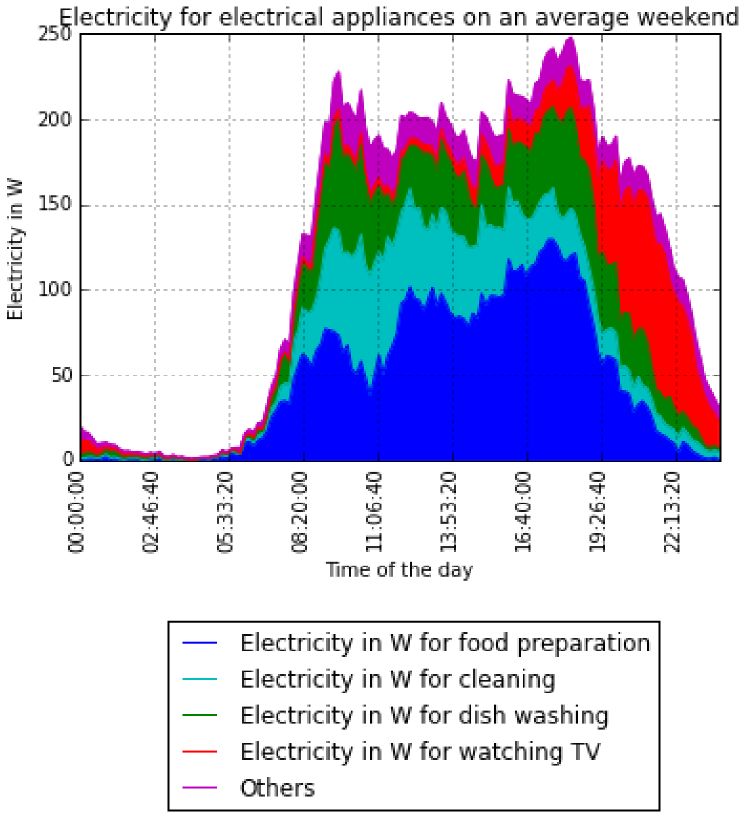


Figure 4.4: The four main contributions to the electricity demand (left) on a weekend day in comparison with the aggregated electricity demand (right) for electrical appliances appliances.

Summarizing, for weekdays the curve can be developed with data about food preparation, cleaning, dish washing and watching TV. However, this relation is questionable for weekend days.

4.3.2 Electricity for lighting

The modeled electricity for lighting is dependent on the availability of daylight and the probability that people are at home. The first factor is highly dependent on the season and the second on the type of day. Hence, in this section four days are compared with each other to analyze and simplify the model. Those are a weekend and weekday in summer and winter.

In Figure 4.5 A), the modeled electricity demand for lighting on a weekday is depicted for summer and winter. For both cases exists a peak in the morning and one in the evening. However, the modeled electricity demand in winter is higher, especially during the morning peak. The maximum modeled electricity demand due to lighting on a weekday is 16 megawatt.

In Figure 4.5 B), the modeled demand is shown for a weekend. In summer, it falls down to zero during the middle of the day. For the winter day it increases in the morning, falls down slightly right after noontide and shows a constant higher modeled demand during the afternoon with a peak in the evening. Generally, the modeled peaks on weekend days are lower than on weekdays by 4 megawatt. The shapes of the modeled curves are relatively irregular. Thus, it is hardly possible to derive a general rule for it. In the next paragraphs, the dependencies of the model on the relevant input parameters are analyzed.

A) B)

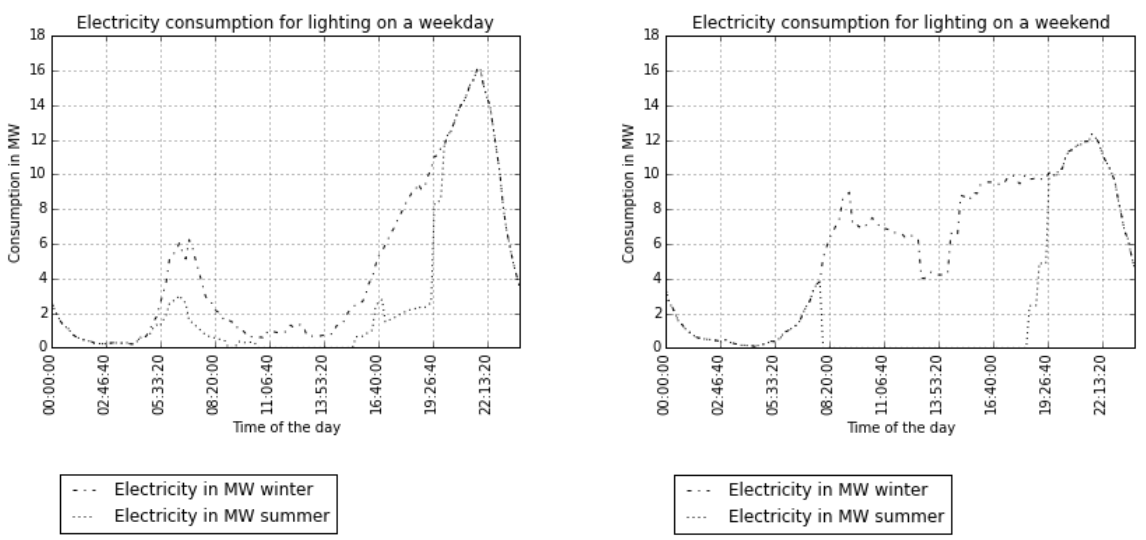


Figure 4.5: Electricity demand for lighting on different days during different seasons.

A) B)

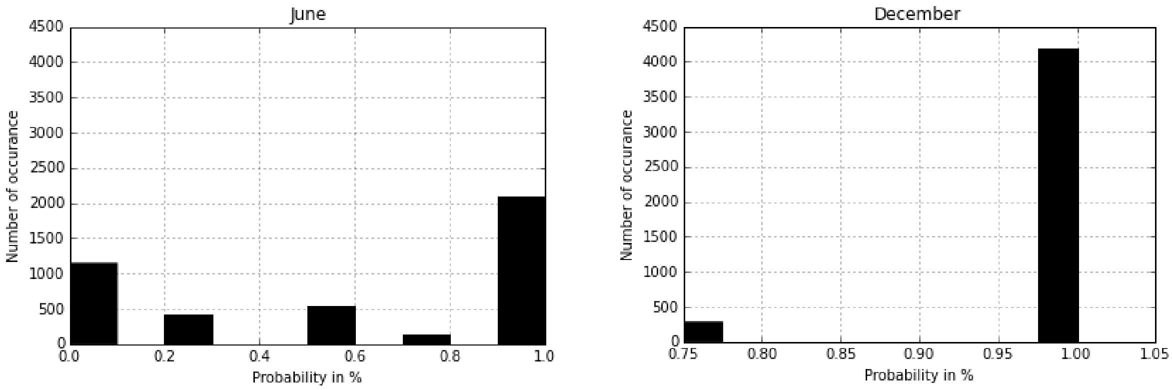
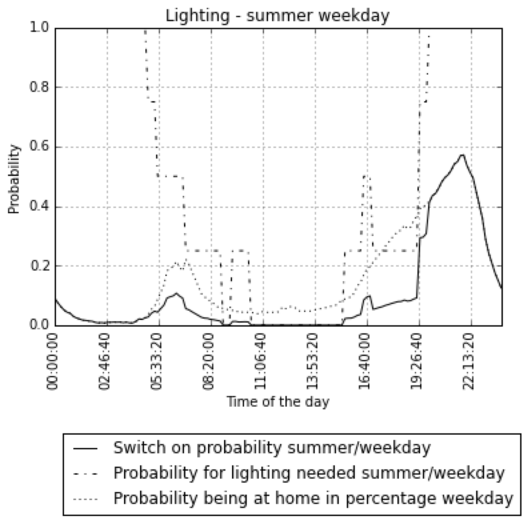


Figure 4.6: Distribution of the probability that the daylight availability in a room is lower than the threshold value in June (A) and December (B).

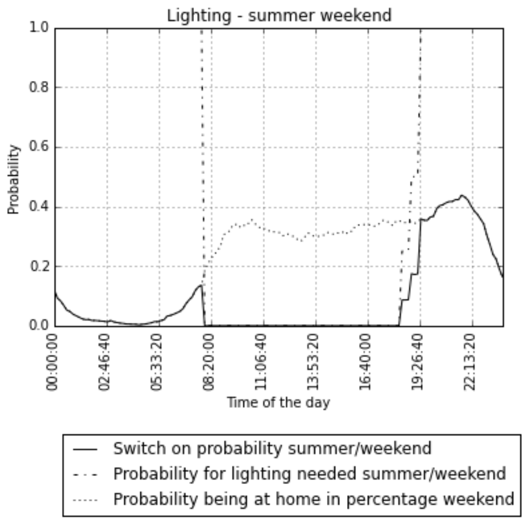
The daylight availability differs between the seasons. In the year 2000, two seasons can be identified. The first one is from April to September and the second one is from October to March. This is done based on the distribution of the probability that artificial lighting is needed (daylight in the room lower that the threshold). In Figure 4.6 A), this can be seen for June. It can be noticed that the values that occur the most are a probability of 0 % and of 100 %. For December, almost only the value 100 % occurs during the whole month as can be seen in Figure 4.6 B). Hence, in this section one weekend and weekday of June and December are analyzed further. For a whole year it could be assumed that the electricity demand for lighting from April to September is very similar to June and from October till March similar to December.

To derive the dependencies between the input parameters and the modeled electricity demand three factors are compared to each other. The first one is the probability that people are at home depending on the type of day. The second one is the probability that artificial lighting is needed. The third factor is the switch on probability. This is the product of the first two. Based on that factor, the electricity demand can be modeled by multiplying with the number of households and the consumption of light bulbs. However, this does not change the shape of the curve.

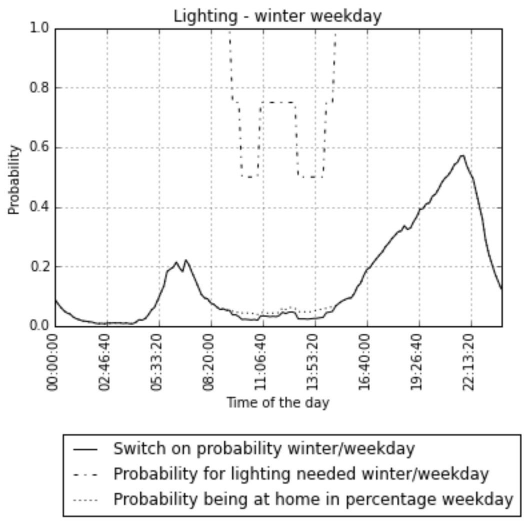
A)



B)



C)



D)

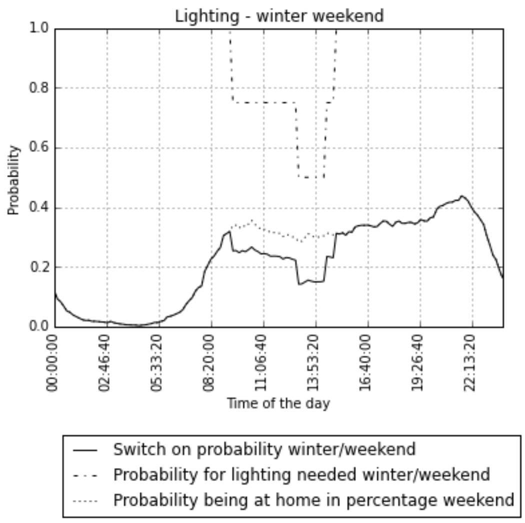


Figure 4.7: The relation between probability of being active at home, the probability that artificial lighting is needed and the switch on probability for A): summer weekday, B): a summer weekend, C): a winter weekday, D): a winter weekend

In Figure 4.7, the three different factors are depicted for the four different days (21st Jan, 23rd Jan, 21st Jun, 24th Jun). The switch on probability is the solid line and the probability of being at home is the dotted line. The third line represents the probability that artificial lighting is needed. Based on that, some correlations are identified.

For both days in summer, there is a timeframe between approximately 07:00 and 19:00 where the modeled electricity demand for lighting equals zero. During the rest of the day it is linear to the probability of being active at home.

For the working day in winter, the modeled electricity demand is linear to the probability of being at home. This is due to the fact that the lighter hours occur during times when people are not at home. Hence, the effect of lighter hours during the middle of the day in winter does not influence the modeled electricity demand. The modeled electricity demand from lighting during a weekend day in winter is linear to the possibility of being active at home. Nevertheless, at a certain time frame during the middle of the day the modeled demand is decreased due to higher daylight availability.

The derivation of the shape can be conducted based on credible data that can be gathered for other European cities as well. However, the factor that influences the level of the peak is rather uncertain. Thus, a sensitivity analysis on it is done in section 4.5.2.

4.3.3 Heat for water heating

In Figure 4.8, the modeled energy needed to heat water in Gothenburg on a weekend day and on a weekday can be seen. On a weekday, a high morning peak occurs followed by a lower modeled energy demand until the late afternoon which is only interrupted by a small peak during lunch time. At the late afternoon and evening two additional peaks occur during a weekday. On a weekend day, the morning peak is higher and occurs later than on a weekday. After that the modeled energy demand for water heating fluctuates a lot until it falls down to low values during the late evening. Generally, the modeled energy demand for water heating is higher on weekends than on weekdays.

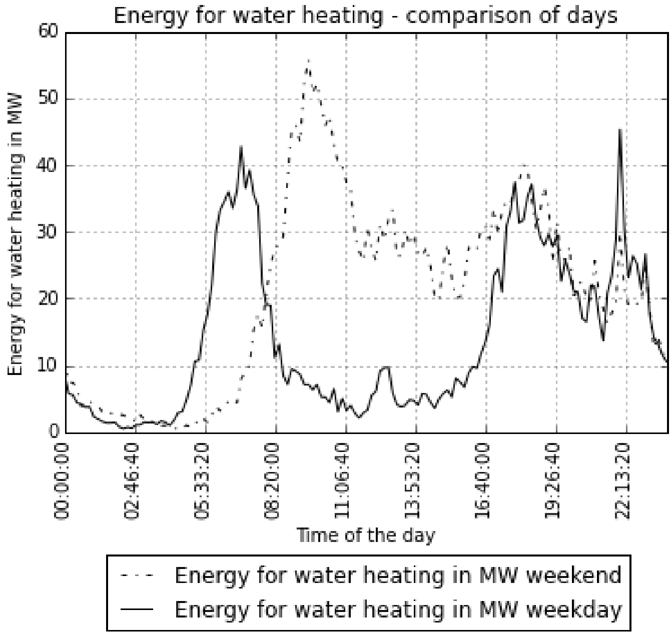


Figure 4.8: Energy for hot water heating during a weekend day and a weekday.

As major contribution to the modeled energy demand for hot water, the activities "other personal care" and "dish washing" are identified. Their relation to and influence on the total demand are analyzed. Therefore, the modeled energy demand in watt per person on an average weekday and weekend day are studied.

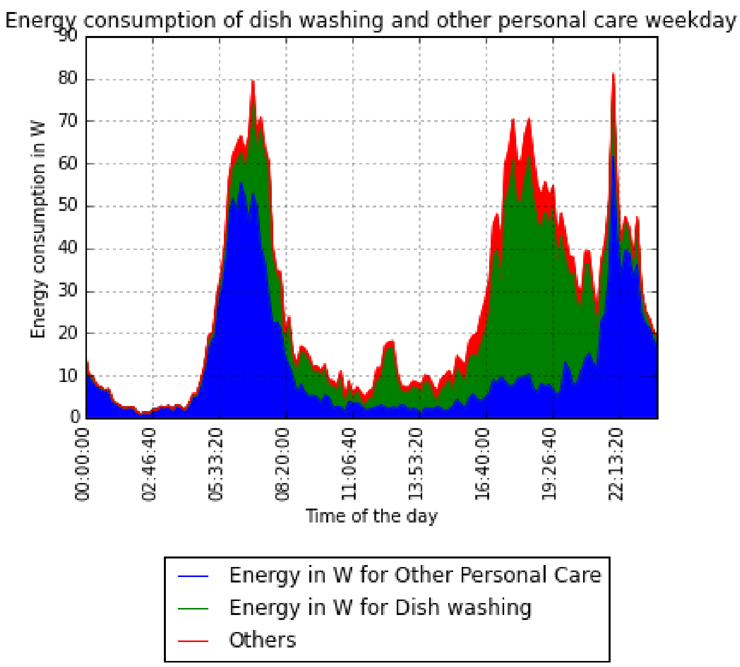


Figure 4.9: Contributions of the activities „other personal care" and "dish washing" on the total energy demand for heating on a weekday.

In Figure 4.9, the modeled energy needed to heat water for other personal care is depicted in blue and for dish washing in green. The sum of all other activities is represented by the red area. Both activities give a relatively good estimation on the shape and the amount of the total modeled energy demand for hot water heating. The modeled energy demand of the other activities (red) shows the highest divergence during the afternoon peak. However, there exist a close correlation between “other personal care”/”dish washing” and the total modeled demand during weekdays although higher peaks should be expected.

For the weekend day, the same figure is derived as for the weekday. In Figure 4.10, the modeled energy demand for hot water heating of other personal care is depicted in blue and for dish washing in green. For the weekend day the sum of the other modeled activities is higher than on weekdays, especially in the middle of the day. However, it can be possible to model the hot water heating demand on a weekend only with information on “other personal care” and “dish washing” even though there should be a higher demand expected from noontide till late afternoon.

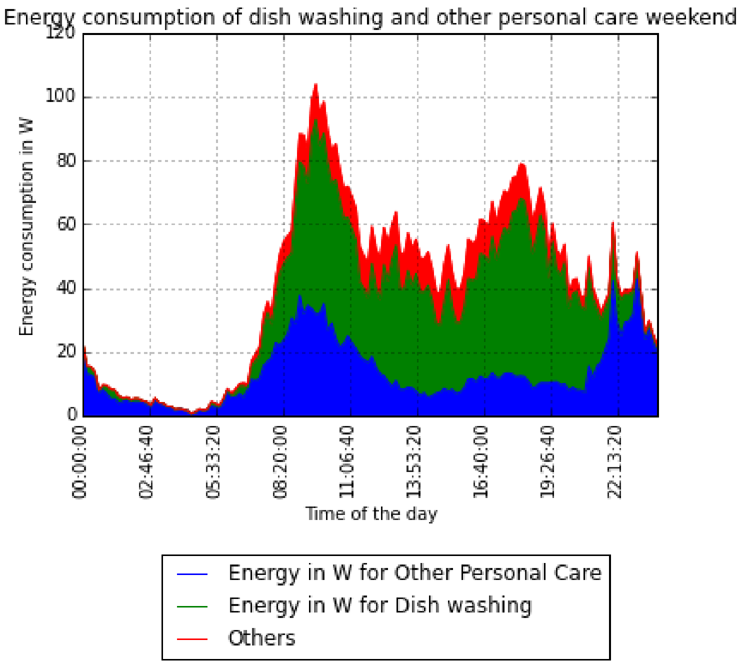


Figure 4.10: Contributions of the activities „other personal care” and “dish washing” on the total energy demand for heating on a weekend day.

Summarizing, the heat demand for hot water can be modeled with information on the activities “other personal care” and “dish washing”. Some exceptions occur during peak hours on weekdays and a constant slightly higher energy demand is noticed during the day time for weekends.

4.3.4 Heating

The heating demand in Gothenburg can be modeled as shown in Equation 4.2 below. As can be noticed the heat losses can be compensated by the solar gains and the internal gains in case they are large enough. However, it is assumed that the space heating demand cannot be negative as cooling is excluded from the study. Thus, in cases where the space heating demand falls under zero this term equals zero and only the hot water heating is added.

Equation 4.2:

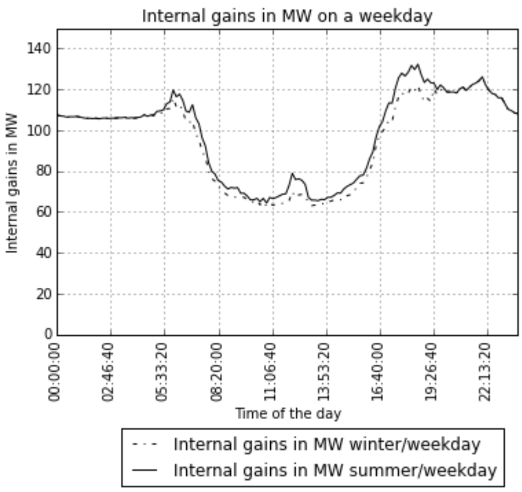
$$Heating\ demand =$$

$$\max \{ \quad heat\ losses - solar\ gains - internal\ gains, \qquad 0 \quad \} + hot\ water\ heating$$

The internal gains are composed of the emissions from electrical appliances and light bulbs as well as the emissions from metabolic activities of people. It is assumed that the emissions from electrical appliances and light bulbs equal their consumption. This consumption is sufficiently explained in previous sections.

The emissions from people are dependent on the probability of being at home and thus on the time use data. In Figure 4.11, the modeled internal gains are compared between seasons on a weekend day and a weekday. There are no significant differences between seasons. The modeled heat emissions in summer are slightly lower due to fewer emissions from light bulbs during that season.

A)



B)

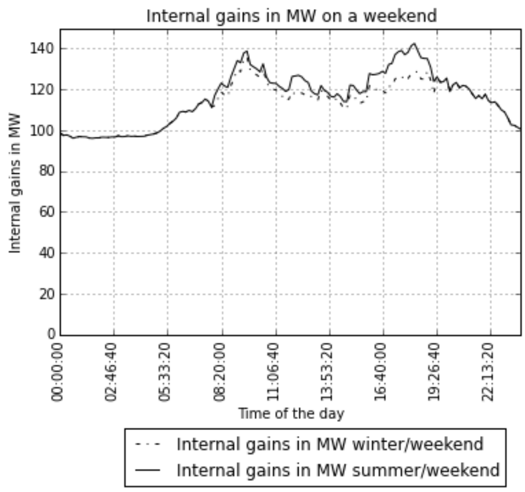


Figure 4.11: Internal gains in MW. A) comparison between summer and winter on a weekday. B) Comparison between summer and winter on a weekend day

The next two aspects that influence the modeled heating demand are the modeled solar gains and the modeled heat losses. Those are highly dependent on the solar irradiation and the external temperature but not on the occupant’s time use. Thus, in Figure 4.12, only the seasonal differences of those two factors are depicted. It can be noticed that the modeled solar gain in summer is significantly higher than in winter. Furthermore, the shape of the modeled peak is much broader. The modeled heat losses are higher in winter than in summer. Nevertheless, the daily fluctuations in winter are not as large as in summer. In winter, the modeled heat losses increase from 500 to around 620 megawatt. In summer, it decreases from 50 megawatt in the morning to -200 megawatt during lunch time. This means that cooling would be needed to keep the desired temperature of 21 degrees in the room.

A) B)

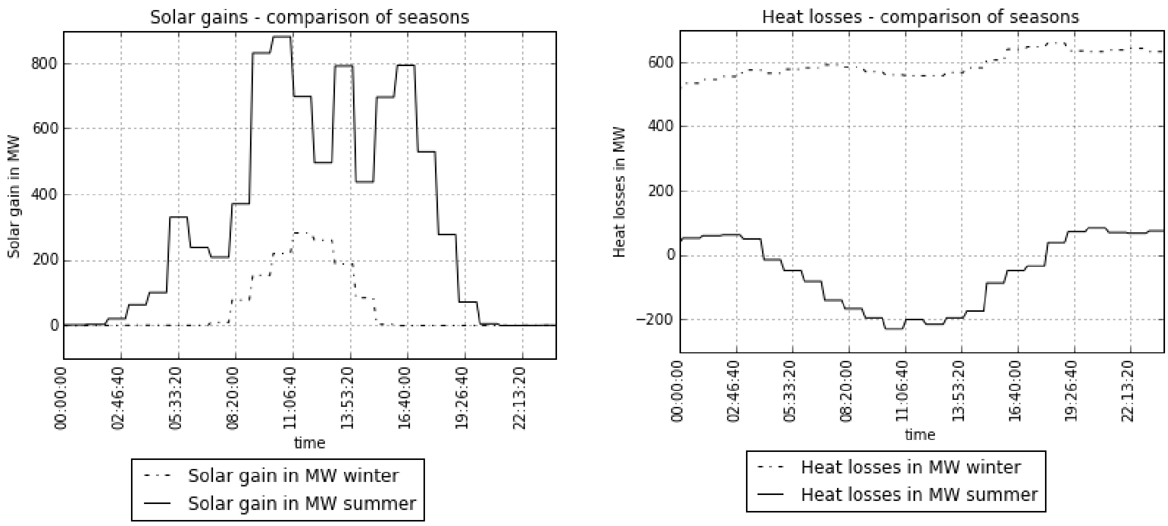
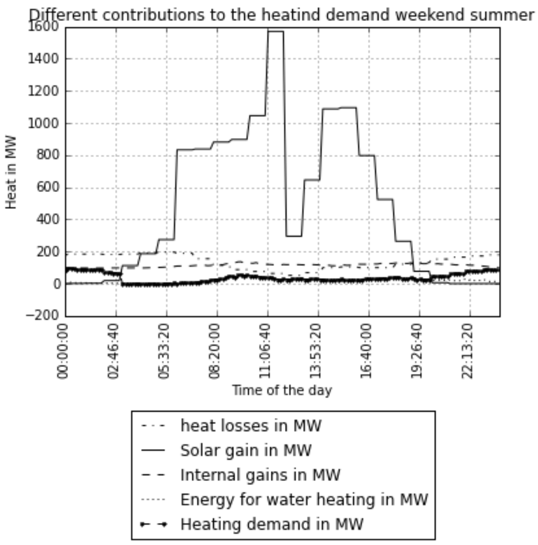


Figure 4.12: A) Solar gain in MW in summer and winter. B) Heat losses in MW in summer and winter.

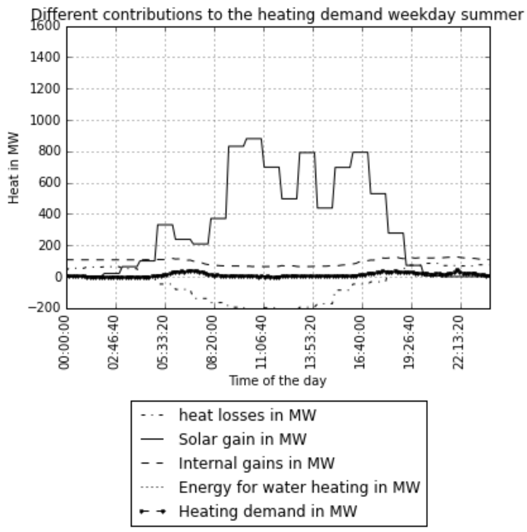
The last factor is the modeled energy for water heating. This aspect and how it is influenced by different input parameter as well as how it can be simplified has already been described in section 4.3.3. Thus, in the following it is focused on how the modeled heating demand is composed and on how relevant the different aspects are.

In Figure 4.13, the different contribution to the modeled heating demand during different seasons and days can be seen. In figure A) and B) the different days for summer are depicted. As the weekend is the 21st June and the weekend is the 24th June, the modeled solar gain and heat losses differ due to different solar radiation and external temperature on those days. However, in both pictures, it can be seen that in summer the modeled heating demand equals the modeled hot water heating. However, the correlations between the different contributions during winter are more complex.

A)



B)



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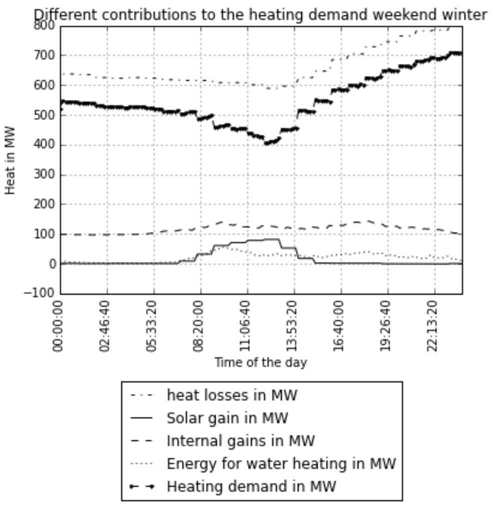

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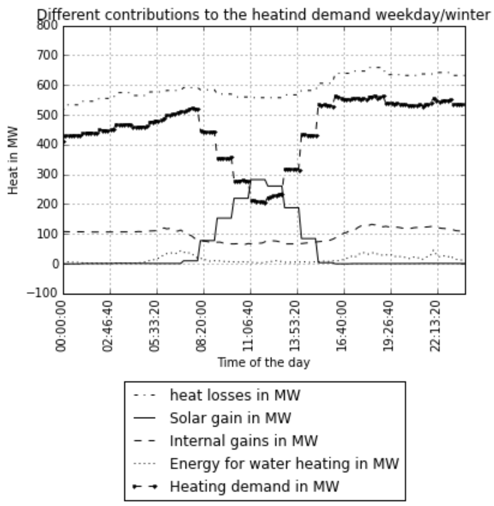


Figure 4.13: The relation between the different contribution to the heating demand and the total heating demand for A): summer weekend, B): a summer weekday, C): a winter weekend, D): a winter weekday

During winter (pictures C) and D)) the contributions of the modeled hot water heating and the modeled internal gains seem to be relatively small. Therefore, the distributions of the values for them are studied. For the hot water heating a constant value of around 5 MW can be assumed. This assumption is supported by how the values are distributed. In Figure 4.14 (A), it can be seen that a value around 5 megawatt is met most often. As this is a relatively small contribution to the total modeled heat demand, the fluctuation in the modeled water heating demand can be neglected for the total heat demand in winter. For the internal gains, two values between which the emissions fluctuate could be defined. Those are around 65 megawatt and 115 megawatt which can be noticed in Figure 4.14 B). The lower value should be assumed during the late morning and afternoon when the majority of people is not at home.

A) B)

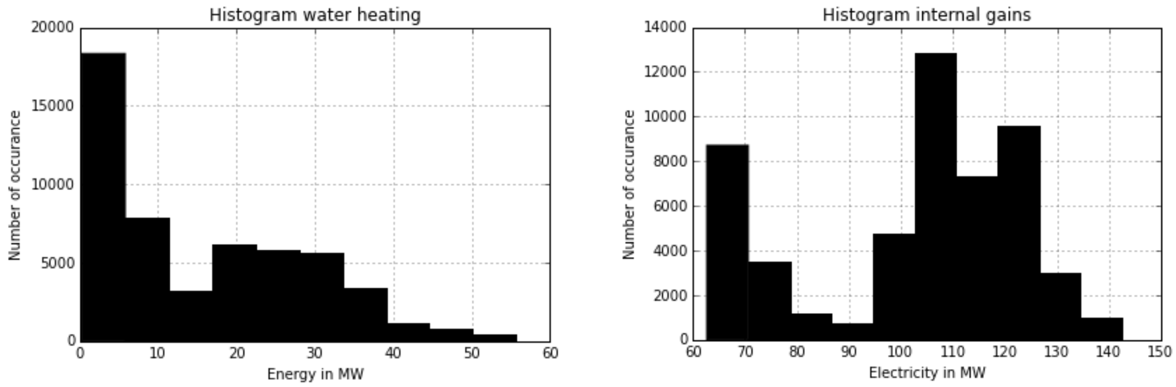


Figure 4.14: Distribution of the values for the water heating (A) and the internal gains (B) in megawatt.

In Figure 4.13 C) and D), it can be seen how the modeled curve for the heating demand for the winter follows the modeled curve of the heat losses only to be lowered by the modeled solar gain in the middle of the day. Summarizing, it can be said that the heat demand in winter could be determined as:

$$Heating\ demand = X * (21 - T_{external}) - Y * I_{solar} - Constant$$

For Gothenburg the X value equals around 25 MW*K^{-1} and is a product of different heat transmittance coefficients and areas. The Y value equals 1.96*10^{6} m^{2}. The constant equals either 60 or 110 megawatt which is the sum of the modeled water heating and the modeled internal gains. As the X and the Y value are uncertain, a sensitivity analysis on them is done.

4.4 Validation

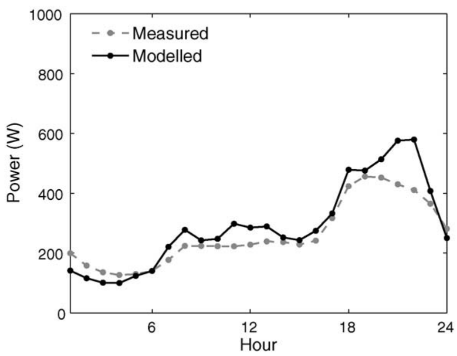
Data to validate the model is hard to find. However, some data that have been found during the literature study are used for a comparison to the model. In all cases the model has been adjusted to be comparable to the input data. Nevertheless, it is still questionable if a comparison is possible after all.

4.4.1 Validation – electricity for electrical devices

In Figure 4.15, data extracted from Widén, et al (2009a) and the modeled data is compared. In the figure from Widén, et al (2009a) on the left side, measured values from the Swedish Energy Agency – SEA are represented by the grey line. That line describes the electricity consumption per person in an apartment. This is compared with the modeled electricity consumption on a weekday in a one person household. From the options extractable from the model, the one person household is considered to correspond to an apartment the best.

It can be seen that the measured and the modeled data are relatively similar. Nevertheless, in the morning the measured data is lower than during the rest of the day. In contrast to that the modeled electricity shows a slight peak. This might be due to the fact that people eat cold food for breakfast and do not use the stove in the morning. However, in the model an average electricity consumption for "food preparation" is used.

A)



B)

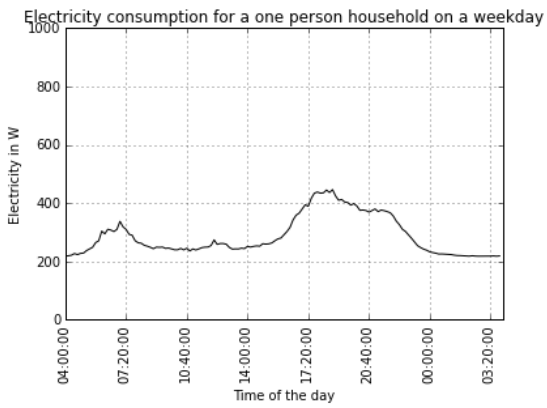


Figure 4.15 A) diagram extracted from (Widén, et al., 2009a) measured consumption per person of electrical devices in an apartment during a weekday, B) Modeled electricity consumption per person of electrical devices in a one person household on a weekday.

In Figure 4.16, the comparison of the measured electricity consumption per person in a detached house on a weekday can be seen. As comparison, the modeled electricity demand of a five persons household is depicted. It can be assumed that the number of occupants is higher in detached houses. Hence, the five persons household is considered to be a suitable comparison for the measured data from Widén, et al. (2009a). The measured data represents the electricity consumption for one person in the household on a weekday. With the model, curves for whole households are derived. Thus, it is questionable if the curves are comparable in that way. However, some conclusions can be drawn from the comparison.

It can be seen that the power consumption in both diagrams corresponds relatively well. However, the modeled peak is about 200 watt lower. Since the measured values are from 2007 and thus are more recent than the values used in the model (2000), it might be that the electricity consumption during the evenings is higher due to more activities computers.

Generally, it can be questioned how comparable the measured and modeled data are. They are not from the same year. Furthermore, the measured data represents only a few households and the modeled data is based on TUSs averaged over the whole country.

A) B)

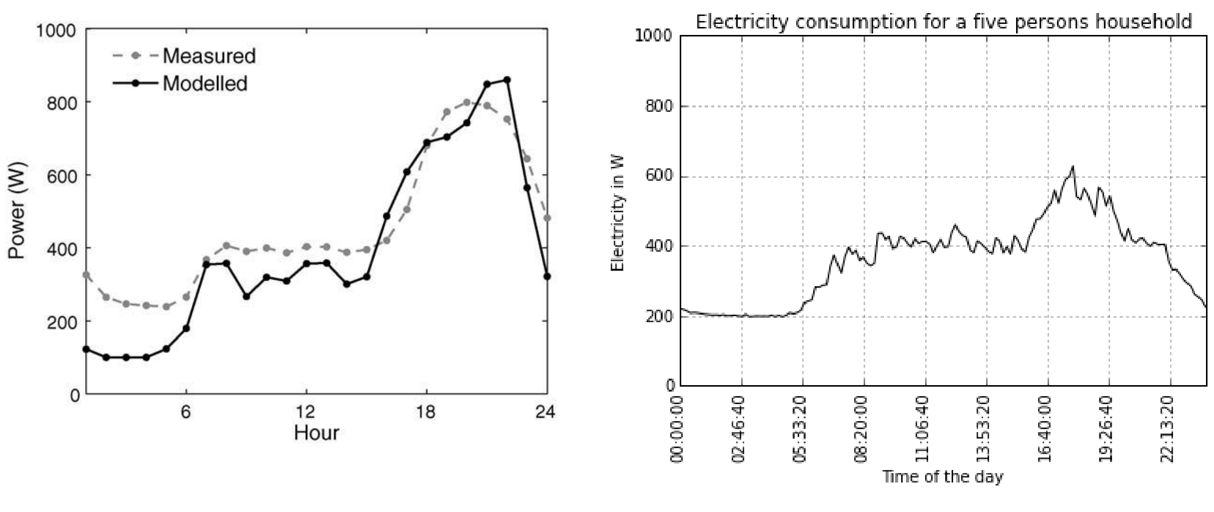


Figure 4.16 A) diagram extracted from (Widén, et al., 2009a) on the power consumption per person of electrical devices in a detached house during a weekday from measured and modeled values, B) Power consumption per person of electrical devices in a five persons household on an average day extracted from own model.

4.4.2 Validation for electricity for lighting

The validation for lighting is done with another model derived for the UK by (Richardson, et al., 2009). From that model, data on the electricity consumption for different kinds of household sizes can be extracted. The type of day that can be chosen are a weekend and a weekday for each month of the year. However, no specific date can be extracted.

For the validation a weekend day in October and a weekday in March for a single household is extracted. From the model derived in this report, the 08/10/2000 and the 10/04/2000 are taken as comparison. The modeled consumption in this model is so low that it is not comparable to the model from the UK. Thus, the power consumption per light bulb is increased to 450 watt to be comparable to the UK model at least to some extent.

As can be seen in Figure 4.17, the modeled peaks in the morning on a weekend in October is relatively similar. However, there are immense differences in the evening. The modeled electricity consumption in the late evening is about 400 watt higher in the model from the UK. Furthermore, it can be seen that the peak is shifted to a later time.

A weekday in March is depicted in Figure 4.18. The shape of the modeled curve is quite alike, with a morning and an evening peak. However, the modeled electricity consumption in the UK model is much higher.

The model could not be validated with the available data as the levels of the peaks differ immensely. Nevertheless, it is questionable if the two days are comparable as the year and the country are not the same. Furthermore, the validation of a model with another model might not be suitable. However, it can be concluded that the assumption for the power consumption of lightbulbs is significantly higher. Thus, a sensitivity analysis on that is done in the next chapter.

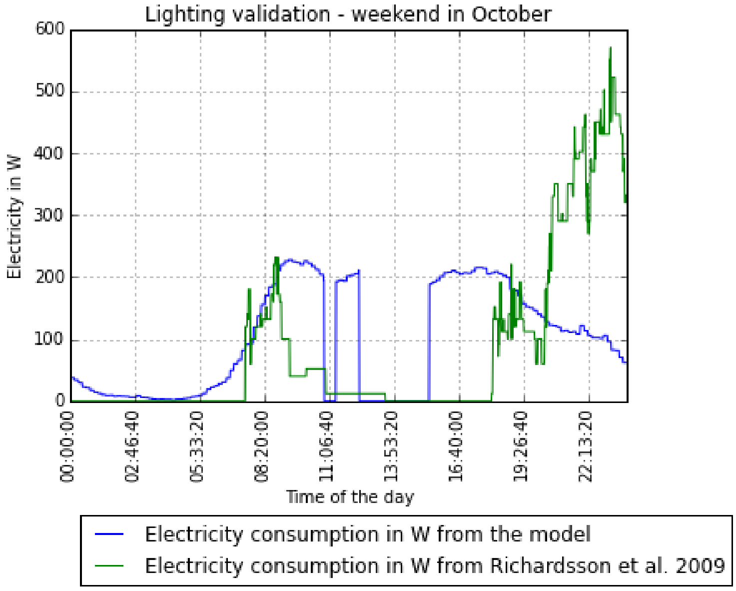


Figure 4.17: Validation of electricity for lighting in a single household on a weekend in October.

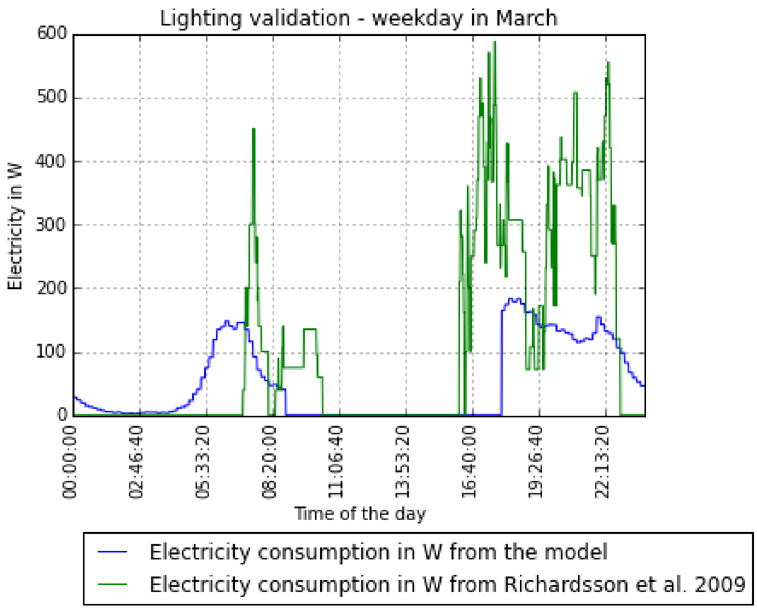


Figure 4.18: Validation of electricity for lighting in a single household on a weekday in March.

4.4.3 Validation for heating

To validate the modeled heating demand, the results of the model are compared to data from the district heating system in Gothenburg. The data for the district heating system included the years 2010-2013 and parts of 2014. The data for 2000 was not available. Thus, the model is run with input data from 2013 where possible. Additionally, the data from the district heating plants is reduced by 10 % due to losses in the grid.

In Figure 4.19, the comparison of the two graphs is plotted. The district heating data is represented by the blue graph and the modeled data by the green. As can be seen the difference between the two is up to 200 MW. This might be due to the fact that the district heating data includes all clients in Gothenburg. Thus, also industry is included. In contrary, the model only takes into consideration residential areas. Furthermore, the data from the model fluctuates a lot, especially from March to April.

In the model, the actual on-time heat demand is modeled. However, it is possible that people do not adjust their heating system if it is slightly colder or warmer than the assumed, desired 21 degrees. Additionally, it is likely that people accept colder temperatures during the night when they are asleep. Thus, in reality the heating demand is more constant during the course of the day and does not correlate as closely to the temperature as the modeled results do.

Furthermore, it is possible that the district heating system includes storage system that can buffer the curves for the heating demand and might smoothen the curve. The district heating data describes the aggregated production and the model the modeled consumption. Thus, it can be questioned if the two are comparable. Summarizing, it can be said that the model could deliver a sufficient first estimation for the behavior of the curve when compared with the district heating data. Nevertheless, the level of the peaks might be too low.

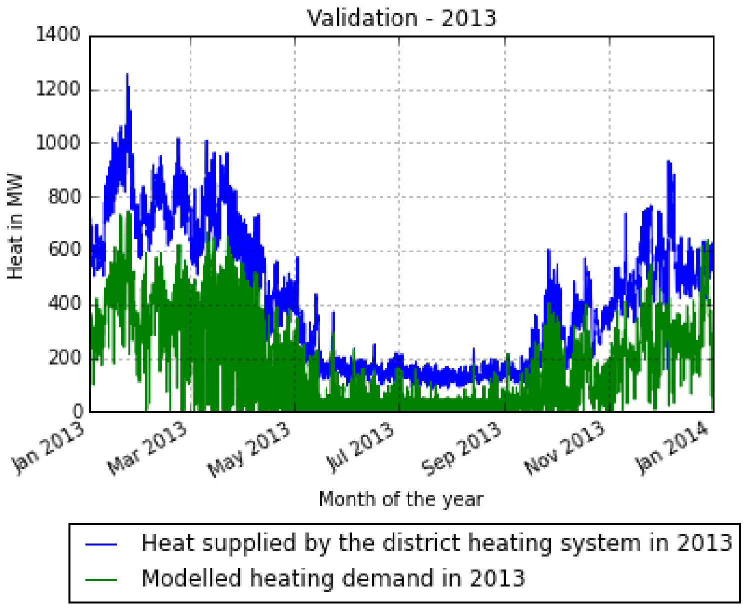


Figure 4.19: Comparison of the modeled data and data from the district heating system in Gothenburg.

4.5 Hot spots

One goal of the study is to identify hot spots. Hot spots are areas of uncertain data or parameters that have a big influence on the results. Generally, the time use data has a high influence on the results. Especially, the activities food preparation, cleaning, dish washing and watching TV are important for the modeled electricity demand of electrical appliances. For the modeled hot water demand, the most influencing activities are the information about the activities other personal care and dish washing.

The modeled electricity for lighting is moreover dependent on the daylight availability. The modeled space heating demand shows high correlations to the external temperature and the solar irradiation.

4.5.1 Lack of data and uncertain data

The data for the external temperature, the solar irradiation and the time use surveys are gathered from official data bases. Hence, this data is credible. However, the use of the time use surveys can be questioned in several ways. This has previously been discussed in section 2.1. Most crucial for this model is that it is not extractable which activities are done in company with another household member. Furthermore, it can be discussed how realistic the time use data is since the procedure is complicated for the participants.

The power consumption of light bulb is another factor of high uncertainty in the model. Statistical data on how dwellings in Sweden are equipped with light bulbs have not been found. As could be seen in the validation section, the assumed power consumption is probably too low. Thus, a sensitivity analysis on this part is conducted.

As derived in section 4.3.4, the modeled heat losses are proportional on a factor describing the product of the different heat transmittance coefficients and areas in the city. Especially, the areas of the different components in the buildings are uncertain. Furthermore, the heat transmittance values of the windows could differ in reality as well. It is not known when and how often home owners change the window glazing. The correlation between the age of the window and its heat transmittance coefficient might be wrong. Hence, a sensitivity analyses on specifically on the window age and the area of external walls is done.

Another factor influencing the heat demand is the solar radiation. The only data set that included an entire year is the data from 2013. Using the data from 2000 would have been more suitable for the model since all other data sets are from 2000.

The power consumption of electrical devices is taken from journal articles and is cross-checked with other sources. Thus, it can be considered to be certain. However, the energy consumption of activities demanding hot water includes more factors. For some of them a reasonable value had to be assumed. Nevertheless, the real value could be different. This is briefly discussed in the next section.

Even though the model could be validated to some extent, there is still a lack of suitable data sets for the validation. The model has shown correlation to the validation data. However, data to conduct a more precise validation would make a more detailed analysis and adjustments of the model possible.

4.5.2 Sensitivity analysis

There are some input parameters that have been identified as uncertain. Some of them have a large contribution to the final result. Those parameters are further investigated in this section.

To model the energy for hot water heating, the activities dish washing and other personal care have been identified as large contributor. However, the activity “other personal care” might have a higher or lower hot water demand in reality. The activities included in that section are rather unspecified. Taking a coffee break, doing a manicure or meditating could also be part of it and would not be correlated to energy consumption. For the second major contribution, the dish washing, it could be possible that people spend some time with wiping and putting the dishes in the cupboards. This would not lead to lower energy consumption during the entire activity. In the model it is assumed that there is a constant water use during the activity dish washing. As all relations are linear, changes for those activities would lead to a different level of the peak but would not change the shape. However, if the real energy consumption of those activity is lower, the influence of them on the total energy demand is also lower.

The activities that contribute most to the modeled electricity demand are “watching TV”, “dish washing”, “food preparation” and “cleaning”. However, the real electricity demand for food preparation might be lower as it could also include the preparation of cold dishes in the morning and evening which would not lead to further energy consumption. Thus, also the influence of this activity might be lower.

For the electricity for lighting, ta power consumption of 75 watt per light bulb is assumed. However, this assumption is not based on literature. Furthermore, in the validation phase it came clear that the value has probably been chosen too low. It can be concluded that the consumption is not lower than calculated in the model. Nevertheless, it is considered that people have several lights on and that some occupants stay in different rooms when they were assumed to be in the same. Thus, an electricity consumption of 250 watt is modeled in the sensitivity analysis.

In Figure 4.20, the two different, modeled cases for summer and winter can be seen. On the left a weekday is depicted and on the right a weekend day. Especially during the evening peak on weekdays the electricity demand rises immensely. The peak consumption increases from 14 megawatt to almost 55 megawatt. The average modeled electricity demand on a winter weekday increases from 4 to 14 megawatt. On a weekend day, the average modeled electricity demand rises from 3 to 9 megawatt. Thus it can also be concluded that the difference in aggregated electricity consumption during a weekend day and a weekday is higher for the higher power consumption.

In Figure 4.20, on the right side, the differences on a weekend day can are depicted. Generally, the modeled electricity demand increases immensely. The evening peak rises from around 12 to 40 megawatt. On average the modeled electricity demand on a weekend day increases from 6 to 20 megawatt during winter and from 2 to 7 megawatt in summer.

Summarizing, the shape of the modeled curve does not change but the level of the peak increases a lot. However, the increase is not in a range that would influence the modeled heat demand through increasing the internal gains. The modeled heat demand is about several 100 megawatt high. Thus, an increase by maximum 40 megawatt at some peaks for the internal gains will not change the result about the modeled heating demand significantly.

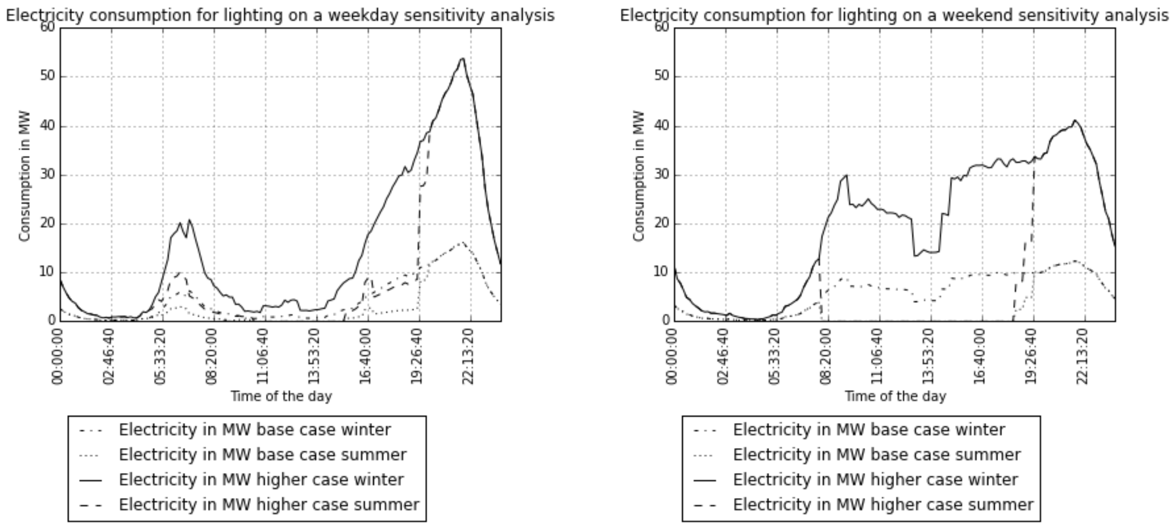


Figure 4.20: Different cases for the power consumption of light bulbs in winter and summer and on a weekend day and a weekday.

As is explained in section 4.3.4, the modeled heating demand in summer equals the modeled water heating demand. However, in winter the heating curve follows the heat losses over surfaces subtracted by the solar gains. As a general rule the equation below, was derived:

$$Heating\ demand = X * (21 - T_{external}) - Y * I_{solar} - Constant$$

The Y value is the product of the shading factor, the g-value of windows, the area of windows and a factor for compensating for different window orientations. For Gothenburg this value equals about $1.96*10^6$ m^2. In Table 4.4, the individual factors that lead to the Y factor can be seen. The g-value of windows can lie between 0.69 and 0.86 (Trainings- & Weiterbildungszentrum Wolfenbüttel e.V. TWW, n.d.). All other factors are decreased or increased by an imaginary but reasonable amount but are not based on ranges found in literature.

Table 4.4: Input parameters of the sensitivity analyses on solar gain for the base case, case I and case II

	Case 1	**Base case**	**Case 2**
Shading factor	0.3	0.5	0.7
G-value windows	0.69	0.77	0.86
Window area in Gothenburg	0.27*Living area= 5456290.33	0.37*Living area= 7477138.6 m^2	0.47*Living area= 9497986
Factor to compensate for different orientations	0.48	0.68	0.88
Product (factor Y)	$0.54*10^6$ m^2	$1.96*10^6$ m^2	$5.03*10^6$ m^2

In Figure 4.21, the solar gain for the different cases in winter can be seen. Especially the assumptions underlying case 2 have a big influence on the modeled solar gain. In Figure 4.22, it can be seen how the modeled heating demand changes based on the two different cases. Both cases show huge differences compared to the base case during noontide. The modeled solar gain has a big influence on the modeled heating demand. However, the new input parameters for case 1 and case 2 are relatively extreme. It can be concluded that the variation of input parameter does not change the shape of the modeled curve put the level of the peak. Furthermore, it can be said that the heat demand will not be higher than case 1 and not lower than case 2.

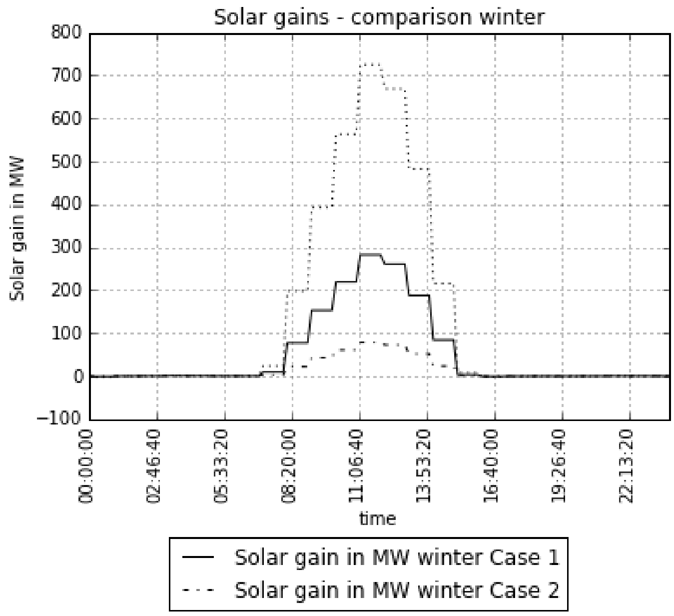


Figure 4.21: Comparison of three different cases for solar gain in winter. The base case is indicated by the solid line.

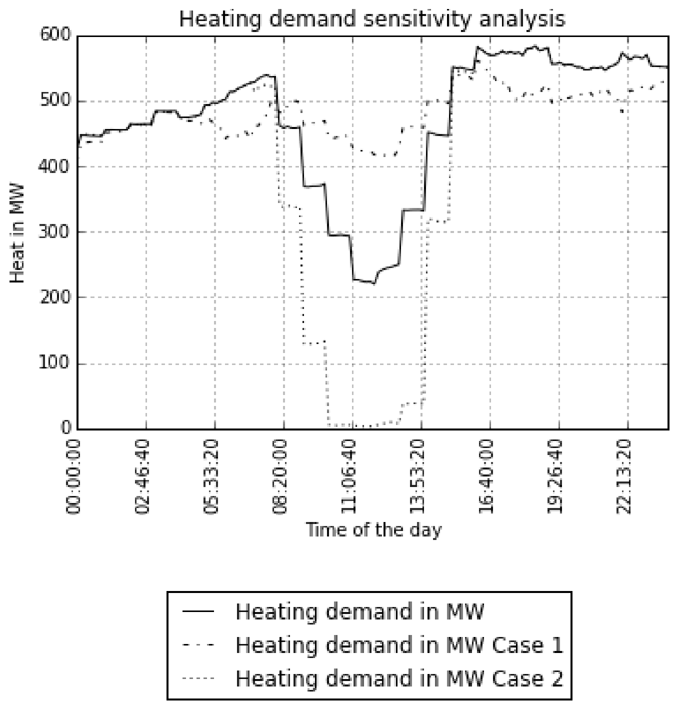


Figure 4.22: Comparison of the influence on the heating demand of the different cases for solar gain in winter.

The modeled heat demand is highly dependent on the modeled heat losses over the surfaces of the different components in the building. Those losses are dependent on the external temperature, the heat transmittance coefficients of the components and their area. The external temperature is extracted from a credible source. However, the heat transmittance coefficients and the area of the components in particular are uncertain. Hence, some scenarios for them are derived and studied.

Previously, it has been mentioned that especially the area of the external walls might be assumed too low. Hence, it is multiplied by 3 and the changes in the modeled heat demand are studied. A lower case is not considered since it is very unlikely that the external wall area is lower than assumed.

In Figure 4.23, the difference between the base case and the case with a larger area for the external walls on a weekday and a weekend day can be seen. For both cases, the modeled demand for the base case is about 50 megawatt lower than the demand in the modified case. Since the modeled heat demand is at least 400 megawatt in winter, the 50 megawatt change is not significant. Thus, even though the estimation of the area might be incorrect, the influence is rather low.

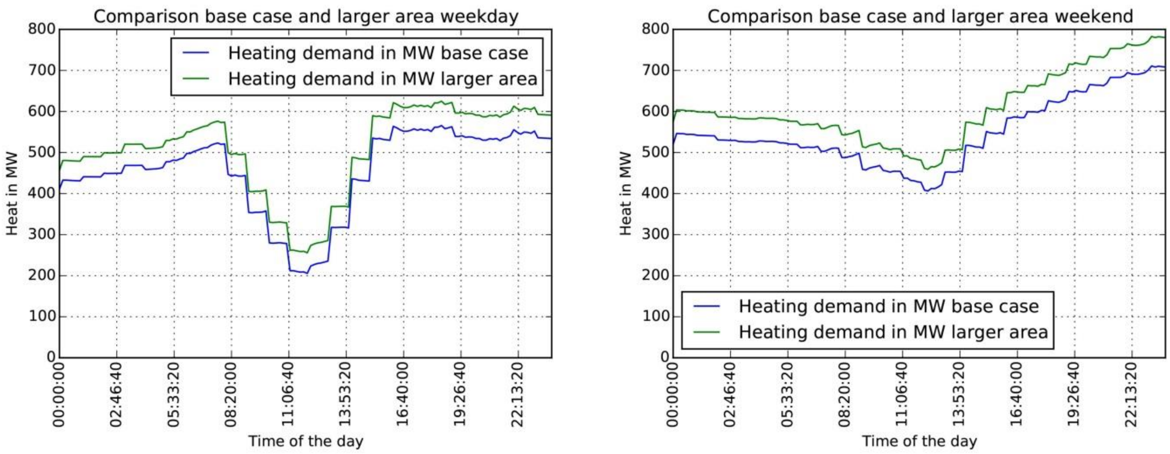


Figure 4.23: Comparison between the base case and a case with a larger area for external walls for a weekday (left) and a weekend day (right).

The heat losses over the building envelop are dependent on the sum of the different components' area multiplied by their heat transmittance coefficient. For this model, it can be calculated as presented in the equation below.

Equation 4.3:

$$Heat\ loss\ = \Delta T * [U_{window} * A_{window} + U_{walls} * A_{walls} + U_{roof} * A_{roof} + U_{floor} * A_{floor}]$$

The surface areas of the components range between 67 and $77*10^6$ m^2. Although the area of the external walls is the highest with $77*10^6$ m^2, all values lie in the same range. Despite the heat transmittance coefficient for the windows all other coefficients are on average lower than 0.3 W/K*m^2. For the external walls it is about 0.2 W/K*m^2 (all values are depicted in detail in the appendix). Thus, the multiplication of the area of the external walls by three, only leads to an increase of the heating demand by around 15 %.

Due to their low heat transmittance coefficients, it can be concluded that an increased area for the walls, the roof and the floor only slightly influences the outcome. Nevertheless, the heat transmittance value of the windows can equal up to 2.35 W/K*m^2. Thus, an increased window area might lead to a more significant change.

The last sensitivity analysis that is studied is the difference in heat transmittance coefficients for windows. It is highly unpredictable how and when home owners exchange their windows. Thus, the correlation between the age of the building and the characteristics of the windows might be incorrect. In a first case, it is assumed that all buildings are equipped with old windows. This leads to a heat transmittance of 2.35 W/K*m^2 for single-family and 2.22 W/K*m^2 for multifamily houses. For the second case, all windows are modeled as new windows. This leads to a heat transmittance of 1.87 W/K*m^2 for single-family and 1.885 W/K*m^2.

In Figure 4.24, the results of the different window scenarios are depicted. It can be seen that for the case that all windows are old windows, the modeled heating demand only increases slightly. The modeled heating demand in the case that all windows are new windows is decreased by about 50 megawatt. Nevertheless, as for the changes in external wall area, that difference is relatively low.

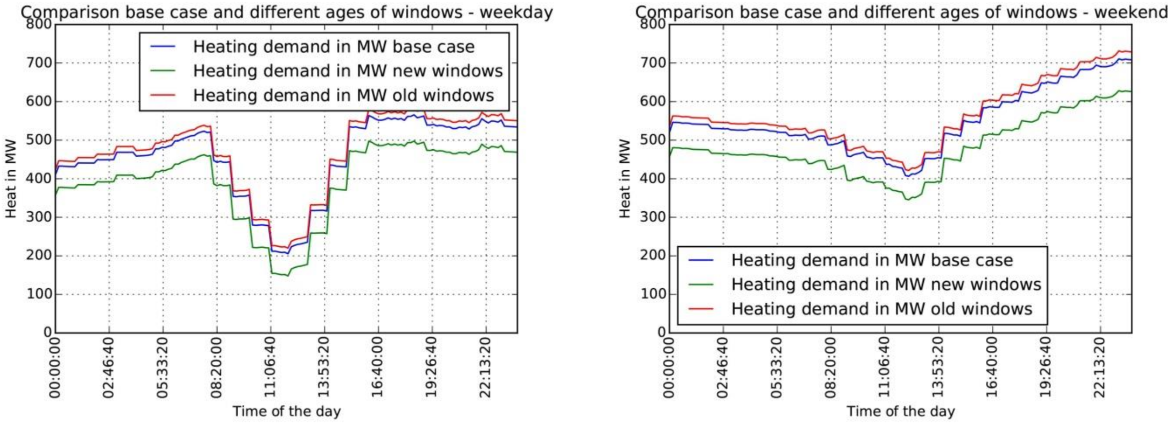


Figure 4.24: Comparison between the base case and a case with different window ages for a weekday (left) and a weekend day (right).

In Table 4.5, the heat transmittance coefficients of windows from different years as extracted from Boverket (2010) are presented. Before 1985, the values are relatively similar to each other. In Gothenburg, most of the buildings were built before 1980. Especially in the period from 1961 to 1970, a lot of houses were constructed (see table in the appendix). Thus, the assumption that all windows are old windows has a minor influence on the total modeled heating demand.

Table 4.5: Heat transmittance values for single- and multifamily houses for different construction years (Boverket, 2010)

Construction year	Single-family houses in $W/(m^2*K)$	Multifamily houses in $W/(m^2*K)$
<1960	2.34	2.22
1961-1975	2.3	2.22
1976-1985	2.01	2.04
1986-1995	1.94	1.8
1996-2005	1.87	1.97

Summarizing, the power consumption of light bulbs can change the modeled electricity demand significantly if it is higher and has probably been assumed to low in this model. Furthermore, the factors influencing the solar gain can lead to immense changes of the modeled load curve of the heating demand during the middle of the day in winter. However, the heat transmittance coefficients and the external wall area that have been considered to be rather uncertain parameters do not influence the outcome of the model significantly.

4.5.3 Transferability to other cities

To model the electricity consumption for lighting the daylight availability and the probability of being at home is needed. These can be extracted from (Hammer, et al., n.d.) and (HETUS, 2006) which are credible sources. However, the power consumption of light bulbs is highly uncertain for Gothenburg and it is questionable if statistics on it exist for other European cities.

The modeled electricity demand for electrical devices correlates with the activities “food preparation”, “cleaning”, “dish washing” and “watching TV” at least for weekdays. The modeled energy demand for hot water heating is dependent on “other personal care” and “dish washing”. Nevertheless, occupants in other countries might have different user patterns. Thus, the relevance of those activities could be lower.

On the next page, in Figure 4.25, the probability that people do the above mentioned activites is compared between Sweden (left) and Spain (right). Spain is chosen since it is assumed that Spanish people differ a lot in behavior from Swedes due to a different culture and climate. As can be seen, the timing of the activities is different between the countries. In Spain the peaks are much more definite. However, it seems that the total amount of time people spend with those activities are the same in both countries. Thus, the model could still be applied even in a different country.

The modeled heating demand is mostly dependent on the solar irradiation and the external temperature. Furthermore, factors by which the temperature and radiation are multiplied are needed. The temperature and the radiation values can probably be gathered for other cities as well. However, even after a long data gathering and assessment phase the correct factors for the multiplication could not be found. Thus, it is highly questionable that those values are easy to gather for other cities. Nevertheless, the shape of the curve can still be sufficiently modeled.

Finally, it can be said that the model can be transferred to other cities and deliver sufficient results for the shape of the curves. However, it the correct level of the peaks is hard to model.

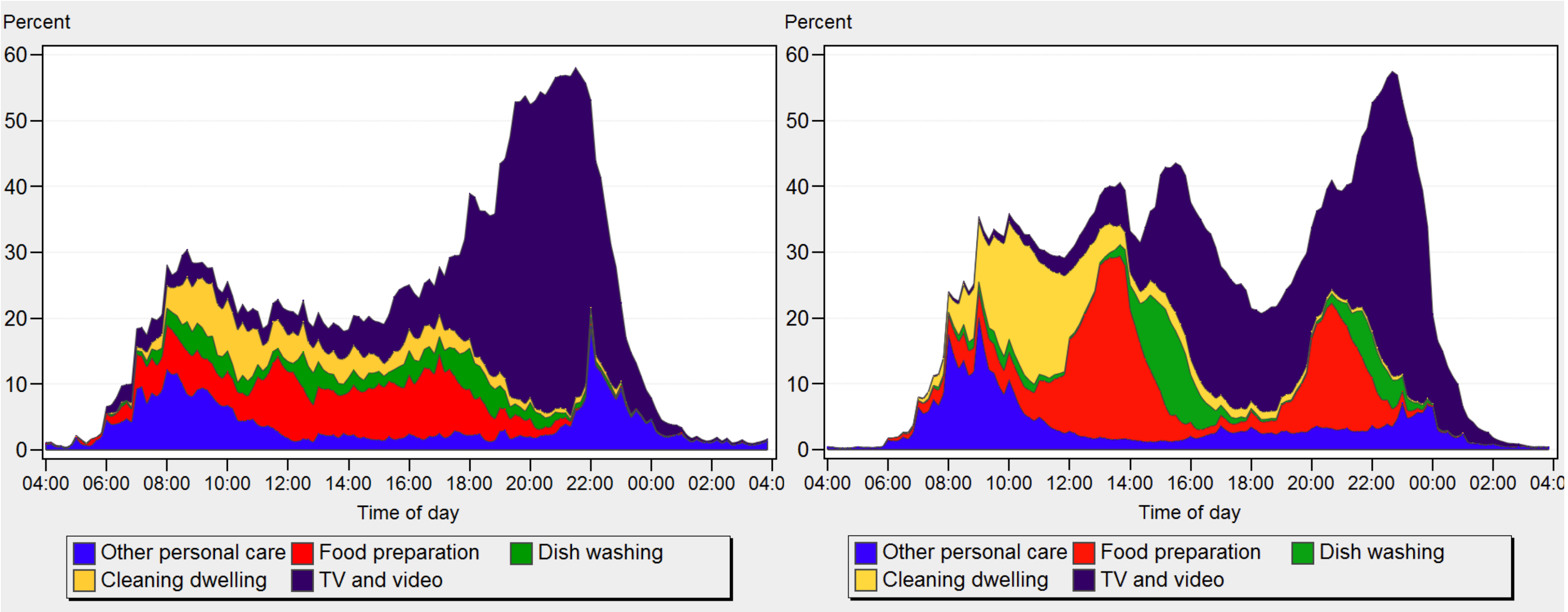


Figure 4.25: Comparison of probability that people do a certain activity in Sweden (left) and Spain (right) (HETUS, 2006).

5 DISCUSSION

In this section the final outcome of the report is discussed and analyzed. It is referred to the goal and scope and the main research questions are answered. One goal was to identify “hot spots”. These include areas where the available data is limited or uncertain.

Statistical data on how dwellings in Gothenburg are equipped with light bulbs are unobtainable. Nevertheless, that data is available for the UK (Richardson, et al., 2009) and could have been a starting point to derive a better estimation for Sweden. Furthermore, detailed investigations on European Directives for lightbulbs could also have resulted in assumptions closer to reality. The assumption for the power consumption of lightbulbs in this model is probably far from reality. However, a more realistic value could easily be implemented in the code. Thus, it is an issue about the input data research and conclusions on the quality of the model cannot be drawn.

Another area of low data availability is the surface area of different components. The geometric model derived in this report could have been further developed and validated. To do so, the modeled heating demand could be integrated over the whole year and compared with measured, annual heat consumption of buildings. That could be taken from the energy certificates of multi-family houses or from a data base called TABULA (http://webtool.building-typology.eu/). In the TABULA database different houses and their yearly heat consumption are listed. However, it is questionable if the modeled annual heat demand can be compared with specific individual buildings and if it is possible to draw conclusions from that for a whole city. Furthermore, as shown in the sensitivity analysis, an increase of the surface area for e.g. external walls does not lead to a severe increase of the modeled heating demand. Thus, it might not be relevant to derive an exact value for the surface areas.

A further hot spot is the data on the time use. The time use surveys are a promising if not the only tool to model timing of energy use. Nevertheless, they could be adjusted for energy demand modeling or the model could be further developed to include more aspects. In this report a method has been developed on how to model shared use of appliances. However, it is not taken into consideration that occupants might still use the appliances alone. This phenomena could be included by assuming how long people do activities in company and how long they do them alone. Additionally, the effect that people might forget to switch off appliances is not covered by the model.

Occupants who are under 20 years old are not included in the time use surveys. However, especially teenagers could have a considerable energy demand. In the present report, inhabitants under 20 are not modeled. The effect of their energy demand could have been estimated by extracting time use data for the youngest possible peer group (20-25 years old) and assuming that teenagers behave similar. However, this correlation is questionable. It has been identified that especially the activities “food preparation” and “dish washing” have high contributions to the modeled energy demand. Since those activities are mostly done by the grown-ups in the family, it is debatable if teenagers’ behavior can be assumed to be similar to the youngest peer group’s behavior.

Most of the time-dependent data is extracted from credible sources. Due to that, the general shape of the modeled demand curve delivers relatively good results for a first estimation about an energy system. However, the data that is needed to derive the level of the peaks is rather uncertain. From data bases used for the time-dependent data, data sets for other cities are extractable. However, the availability of the factors for the level of the peaks in other cities is questionable. Thus, the model can be transferred to other cities to derive the general of the demand curves but not to derive the level of the peaks. Information of the aggregated energy demand of cities is often available. The combination of that information and the model allow estimations about the level of the peaks.

It can be concluded that it is possible to derive a simple model with a small number of input parameters depending on the purpose on the model. If a first rough estimation on the energy demand is required the model can be sufficient. In combination with information about the aggregated energy consumption in the city, even the level of the peaks could be estimated. However, the model cannot be used to predict future developments of urban energy systems or to make detailed simulations.

6 OUTLOOK, LIMITATIONS AND RECOMMENDATIONS

As explained in the previous chapter, the model delivers quite realistic results for the general shape of the load curves. However, the level of the peaks is relatively uncertain. Thus, it is suggested to study the factors influencing this further. Especially, the surface areas in the building as well as more detailed information on the time use would be worth further investigations. Furthermore, an actual attempt to transfer the model to another city and assess the quality of the results could be made. Another possible option would be the application of the model on a city in a warmer climate and the inclusion of cooling.

The time use surveys have been identified as promising tool to derive the timing of energy demand. However, they also lead to limitations of the model and provide options for further studies and optimizations of the model. Occupants under 20 years old are excluded from the model which leads to the fact that a whole peer group in their teens is not considered. It could be estimated how high their energy consumption is and if this has an influence on the results of the model. Additionally, the modeling of shared use is a challenging attempt. In the present model, it is assumed that some activities, e.g. watching TV are always done in company. However, the majority of people certainly still watches TV alone at some times. This is not covered by the model. Strategies could be developed on how to model shared use more detailed and to account for the effect that occupants might still do shared activities alone.

A third aspect that is not included in the time use surveys is individual behavior and preferences. It is possible that people leave the lighting on despite they are not at home or leave their computer on while they are at work. Additionally, personal preferences like people that consider a higher/lower temperature or illuminance level as assumed are not included. In a future study it could be estimated how big these effects are.

Finally, it can be recommended that the time use surveys are extended to younger participants and include more information about activities in the bathroom. Additionally, information about shared activities should be made available. Additionally, the actual energy consumption in some dwellings could be measured to assess the correlation between the activities and the consumption further. Another suggestion is better data assessment in the energy system itself.

For example, measurements of the energy consumption in disaggregated areas. During the data research for the validation of the model, it became obvious that this data hardly exists.

It can be concluded that the highest development potential lies in the derivation of the factors for the peaks. Additionally, further validation of the model and its application to other cases can be suggested. Finally, the adjustment of time use surveys for energy demand modeling could increase the quality of the model.

7 CONCLUSION

The goal of the report was to develop a simple model for the timing of energy demand in an urban energy system. The amount of input data is required to be as low as possible. The transferability of the model to other cities should be ensured. Furthermore, areas of high data uncertainty and high contributions to the energy demand should be identified.

To do so, four energy end uses are modeled for the city of Gothenburg. Those are electrical appliances, lighting, warm rooms and hot water. A suitable method is derived based on a literature review and the relevant input data is collected and assessed. In the methodology, input parameters about time use, weather, power consumption of appliances, building characteristics and households in Gothenburg are used and connected with linear relations. Additionally, the model is validated and a sensitivity analysis is conducted.

The case study showed that the modeled electricity demand for electrical appliances is mainly dependent on four activities and the demand for hot water on two activities. The modeled lighting demand is highly correlated to the probability that an occupant is active and at home. However, during summer the modeled electricity demand equals zero during lunchtime and is slightly decreased during lunchtime in winter. The modeled heat demand in summer equals the hot water demand. Nevertheless, in winter it is highly correlated to the temperature and the solar irradiation.

Based on the results, the validation, input data assessment and the sensitivity analysis, it can be concluded that there can be a good estimation made on the general shape of the demand curves. However, the levels of the peaks are harder to model and demand more detailed information especially about the building stock. Used in combination with information about the aggregated or annual energy demand in a city the model can be used to get a first idea on how the energy demand in that city could look like. When applied for this purpose the model can be transferred to other European cities as well.

Finally, it can be recommended that certain parameters are investigated in more detail and are quantified more precisely. Furthermore, the model could be developed further regarding the adaption of the time use data.

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APPENDIX

Assessment of daylight availability data from satel (Hammer, et al., n.d.)

Criteria	Sub-criteria	Fulfillment
Credibility	Author's Credential	The full name, title, position, picture and e-mail address of the authors is accessible from the webside All authors are from universities or research institutes
	Evidence of Quality Control	The project was funded by the European Union from 1996-1998 (Directorate General XII). Hence, some kind of quality control can be assumed
	Metainformation	The database is referred to in some papers
Accuracy	Timeliness	The data is rather old as it is from 1996-2000.
	Comprehensiveness	The comprehensiveness is a bit limited for non-experts but this is more due to a not very user-friendly webpage structure than due to the quality of the information.
	Audience and Purpose	The purpose is to make data about daylight availability easier available for the public.
Reasonableness		not really applicable for data sets as no opinions are presented
Support	Source Documentation or Bibliography	It is explained that the data comes from six Meteostat satellites that are operated by the EUMESAT organization.
	Corroboration	Not assessed
	External Consistency	Cannot be assessed as I do not have previous knowledge on the data. However, the data seems reasonable from my own experience on daylight availability in Gothenburg.

Load curves of electrical devices

Device	Watt consumption	Source
TV	200	Windén et al 2009
Radio	100	Windén et al 2009
Cooking	1500	Windén et al 2009
Cleaning	1000	Windén et al 2009
Dryer	3000	Windén et al 2009 http://energyusecalculator.com/electricity_clothesdryer.htm
Iron	1000	Windén et al 2009
Washing machine	490	Windén et al 2009
Tablet	0	
Phone	0	http://energyusecalculator.com/electricity_cellphone.htm
Dishwasher	1800	http://energyusecalculator.com/electricity_cellphone.htm
Fridge	50	
Freezer	80	
Stand by	66	Widén & Wäckelgård 2010
Hair dryer	1500 (125*)	http://www.wholesalesolar.com/StartHere/HowtoSaveEnergy/PowerTable.html
Computer	100	Windén et al 2009
Laptop	50	http://www.daftlogic.com/information-appliance-power-consumption.htm

* Under the assumption that a person uses an electrical device 5 minutes per hour spent in the bathroom, the consumption is reduced to 125 Watt.

Load curves of water consuming activities

Device	Water consumption amount in l	Source	Temperature in degree C	Source	Guestimation about time span
Sink	16	Widén et al 2009	55	Yao & Steemers 2005	1800
Hot water for cooking	3	Assumption	40		3600
Bucket	3,3	Widén et al 2009	35		3600
Shower	40	Widén et al 2009	40	Yao & Steemers 2005	
Bath	100	Widén et al 2009	40	Yao & Steemers 2005	
Tap	2	Widén et al 2009	35	Yao & Steemers 2005	
Wash hair	10	Widén et al 2009	55		

Number of houses of a certain size in Gothenburg 2012 (Göteborg Stad, 2012)

	Single family houses							**Multi family houses**						
SDN	< 51 kvm	51-70 kvm	71-90 kvm	91-110 kvm	111-140 kvm	141-170 kvm	>170 kvm	< 51 kvm	51-70 kvm	71-90 kvm	91-110 kvm	111-140 kvm	141-170 kvm	> 170 kvm
Göteborgs stad	1 100	1 982	5 245	8 005	19 464	10 245	5 999	44 814	78 109	50 341	16 389	5 696	1 244	719

	Others						
SDN	< 51 kvm	51-70 kvm	71-90 kvm	91-110 kvm	111-140 kvm	141-170 kvm	>170 kvm
Göteborgs stad	906	1 026	587	431	215	46	39

Number of houses from a certain construction period in Gothenburg 2012 (Göteborg Stad, 2012)

SDN	Single-family houses										
	-1930	**1931-1940**	**1941-1950**	**1951-1960**	**1961-1970**	**1971-1980**	**1981-1990**	**1991-2000**	**2001-2010**	**2011-**	**No data**
Göteborgs stad	5 191	4 222	4 661	4 219	7 975	11 269	5 110	4 002	4 556	722	113

SDN	Multifamily house										
	-1930	**1931-1940**	**1941-1950**	**1951-1960**	**1961-1970**	**1971-1980**	**1981-1990**	**1991-2000**	**2001-2010**	**2011-**	**No data**
Göteborgs stad	21 302	20 520	19 562	33 672	53 553	23 285	8 300	4 696	6 908	3 685	1 829

SDN	Others										
	-1930	**1931-1940**	**1941-1950**	**1951-1960**	**1961-1970**	**1971-1980**	**1981-1990**	**1991-2000**	**2001-2010**	**2011-**	**No data**
Göteborgs stad	548	84	55	215	701	564	202	120	184	11	566

U-values for floors (Boverket, 2010)

Construction year	Single-family houses in W/(m2*K)	Multifamily houses in W/(m2*K)
<1960	0.28	0.36
1961-1975	0.32	0.28
1976-1985	0.27	0.29
1986-1995	0.24	0.26
1996-2005	0.18	0.22

U-values for external walls (Boverket, 2010)

Construction year	Single-family houses in W/(m2*K)	Multifamily houses in W/(m2*K)
<1960	0.47	0.07
1961-1975	0.31	0.07
1976-1985	0.21	0.17
1986-1995	0.17	0.03
1996-2005	0.2	0.05

U-values for roof (Boverket, 2010)

Construction year	Single-family houses in W/(m2*K)	Multifamily houses in W/(m2*K)
<1960	0.37	0.46
1961-1975	0.25	0.24
1976-1985	0.18	0.99
1986-1995	0.16	0.16
1996-2005	0.14	0.18

U-values for windows (Boverket, 2010)

Construction year	Single-family houses in W/(m2*K)	Multifamily houses in W/(m2*K)
<1960	2.34	2.22
1961-1975	2.3	2.22
1976-1985	2.01	2.04
1986-1995	1.94	1.8
1996-2005	1.87	1.97

Principle diary (HETUS, 2006)

Diary/person ID	Starting time	Ending time	Main activity	Parallel activity	Who with:				Where/ mode of tranport
					Alone	Spouse	Small child	Other pers.	
A	04:00	07:20	Sleep						At home
a	07:20	07:50	Shower						At home
a	7:50	08:30	Had breakfast	Read newspaper			Ch		At home
a	08:30	08:40	Walked to bus		A				By foot
a	08:40	09:00	Bus to job					OP	By bus
a	09:00	11:20	Paid work					OP	At work
a	11:20	11:50	Lunch break: meal	Talked with colleag.				OP	At work
a	11:50	12:00	Lunch break: walk	Talked with colleag.				OP	By foot
a	12:00	12:30	Lunch break: walk		A				By foot
a	12:30	16:30	Paid work					OP	At work
a	16:30	16:50	Bus to home	Read newspaper	A				By bus
a	16:50	17:00	From bus by foot		A				By foot
a	17:00	17:40	Cooked supper	Talked with children			Ch		At home
a	17:40	18:20	Had supper	Talked with family		Sp	Ch		At home
a	18:20	19:10	Dish washing	Listened to radio	A				At home
a	19:10	21:00	TV			Sp	Ch		At home
a	21:00	22:10	Took a walk	Talked with spouse		Sp			By foot
a	22:10	22:20	Shower						At home
a	22:20	04:00	Sleep						At home

Activities extracted from the time use survey

Energy-consuming activities:

- Other personal care
- Food preparation
- Dish washing
- Cleaning dwelling
- Laundry
- Ironing
- Computer and video games
- Other computing
- TV and video
- Radio and music

Active at home (only relevant for lighting)

- Construction and repairs
- Teaching, reading, talking with child
- Other domestic work
- Reading books
- Other reading

In-active at home

- Sleeping

Away from home

- Main and second job
- Activities related to employment
- Eating*
- School and university
- Freetime study
- Gardening
- Tending domestic animals
- Walking the dog
- Shopping and services
- Informal help to other households
- Participatory activities
- Visits and feasts
- Other social life
- Entertainment and culture
- Walking and hiking
- Other sports and outdoor activities
- Other hobbies and games

*) It could be guessed that eating should be done at home. This was assumed in a first version of the model and led to unreasonable results. Hence, in the final version it was assumed that people eat at work or away from home.

Neglected activities (very low percentage)

- Other household upkeep
- Handicraft
- Caring for pets
- Organizational work

Calculation of sanitary ventilation in Sweden

$$\dot{q}_v = \frac{V_c * A * (\rho c_p)}{1000} * [T_{vent}(t) - T_i(t)] =$$

$$\frac{1.4 \frac{l}{s * m^2} * 90m^2 * 1.2 \frac{kg}{m^3} * 1.005 \frac{kJ}{kg * K}}{1000 \frac{l}{m^3}} * (-10 - 21)K = 4.7\ kW$$

Factor	Assumed value
$V_c - ventilation\ rate\ \left(\frac{l}{s * m^2}\right)$	1.4 l/s*m^2 – European standard (Centre for Renewable Energy Sources and Savings - CRES, 2006)
$\rho - density\ of\ air$	1.2 kg/m^3 - approximate density at 20 degree Celsius (engineering toolbox, n.d. a)
$c_p - specific\ heat\ capacity\ of\ air$	1.005 kJ/(kg*K) - heat capacity at 20 degree Celsius (engineering toolbox, n.d. b)
$A - heated\ floor\ area\ in\ the\ building$	90 m^2 - average size of a dwelling in Gothenburg calculated based on data from (Göteborg Stad, 2012)
$T_{vent} - \ temperature\ of\ supply\ air$	-10 degree Celsius - Rather low assumption to make a conservative estimation
$T_i - internal\ temperature$	21 degree Celsius - as set as desired internal temperature in 4.1.2

Validation of the model

Equation 7.1

$$A_{external\ walls} = 2 * 2.5m * \sqrt{A_{living}}$$

Equation 7.2

$$A_{ground\ floor} = \frac{A_{living}}{N_{average\ number\ of\ stories}}$$

Equation 7.3

$$A_{roof} = \frac{A_{ground\ floor}}{\cos 25}$$

Equation 7.4

$$A_{additional\ external\ wall} = \frac{A_{ground\ floor}}{2} * \frac{A_{ground\ floor}}{4} * \tan 25$$

	Living area	Number of storeys	Ground floor	Roof	External walls
Validation data I	3208	5	737.5	764	1320
Model	3208		641.6	707.93	333.06
Error			13 %	7.3 %	
Validation data II	200	2	n.d.	100	240
Model	200		100	110.37	70,71
Error				-10.4 %	

Validation data I: (Mata & Kalagasidis, 2009): Data on a multi-family building in Köping

Validation data II: (De Rosa, et al., 2014)