NTNU – Trondheim
Norwegian University of
Science and Technology

Validation of user profiles for building energy simulations

Eline Rangøy

Master of Energy and Environmental Engineering
Submission date: June 2013
Supervisor: Vojislav Novakovic, EPT
Co-supervisor: Igor Sartori, SINTEF
Usman Ijaz Dar, EPT

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

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Norwegian University
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MASTER THESIS

for

Stud.techn. Eline Rangøy

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Validation of user profiles for building energy simulations

Validering av brukerprofiler for bygnings energisimulering

Background and objective

Building energy simulation software are able to calculate the demand for building related energy services such as heating, cooling and ventilation, as well as generation from on-site renewables (e.g. photovoltaic and solar thermal) with the desired time resolution. On the other hand, knowledge on user profiles in Norway is lacking or is not understood in enough detail. Furthermore, in building performance simulations it is preferable to use stochastic – yet statistically meaningful – user profiles in order to better represent user behaviour variability.

The main objective of this work is to generate stochastic, yet statistically representative user profiles for residential buildings in Norway and validate them against existing metered data. The term user profiles indicates the daily profiles (with sub-hourly resolution) of energy services that are mainly driven by the user, i.e. domestic hot water (DHW), lighting, and electric plug loads.

User profiles will be generated starting from Time of Use Surveys (TUS) and using the methodology identified by the student in her previous project assignment. Validation of such user profiles will be made mainly by comparison with existing metered data from the 'Eldek' project. Other data sources for validation may be considered if necessary.

This assignment is closely related to The Research Centre on Zero Emission Building at NTNU and SINTEF (FME ZEB) that has the vision to eliminate the greenhouse gas emissions caused by buildings. The main objective of FME ZEB is to develop competitive products and solutions for existing and new buildings that will lead to market penetration of buildings that have zero emissions of greenhouse gases related to their production, operation and demolition.

The following tasks are to be considered:

1. Identify discrepancies in Norwegian TUS compared to UK and/or Sweden that may have an impact on the user profiles, and discuss ways to overcome it.
2. Implement the methodology for generating user profiles as an Excel (64 bit) based program. This work will build upon the routines already developed by Usman Dar (co-supervisor)

3. Generate user profiles with sub-hourly resolution for: occupancy, DHW draw offs, lighting, plug loads dived in subcategories, e.g. cooking, washing, leisure, etc.
4. Acquire data from Eldek project (metered user profiles); analyse and organise them in a way suitable to be compared with the generated user profiles. If necessary consider other data sources than Eldek.
5. Compare generated vs. metered user profiles, and assess their validity. Try to find ways to calibrate the generation algorithm in order to increase the match with metered profiles. Discuss and motivate the calibrations performed.

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Within 14 days of receiving the written text on the master thesis, the candidate shall submit a research plan for his project to the department.

When the thesis is evaluated, emphasis is put on processing of the results, and that they are presented in tabular and/or graphic form in a clear manner, and that they are analyzed carefully.

The thesis should be formulated as a research report with summary both in English and Norwegian, conclusion, literature references, table of contents etc. During the preparation of the text, the candidate should make an effort to produce a well-structured and easily readable report. In order to ease the evaluation of the thesis, it is important that the cross-references are correct. In the making of the report, strong emphasis should be placed on both a thorough discussion of the results and an orderly presentation.

The candidate is requested to initiate and keep close contact with his/her academic supervisor(s) throughout the working period. The candidate must follow the rules and regulations of NTNU as well as passive directions given by the Department of Energy and Process Engineering.

Risk assessment of the candidate's work shall be carried out according to the department's procedures. The risk assessment must be documented and included as part of the final report. Events related to the candidate's work adversely affecting the health, safety or security, must be documented and included as part of the final report. If the documentation on risk assessment represents a large number of pages, the full version is to be submitted electronically to the supervisor and an excerpt is included in the report.

Pursuant to "Regulations concerning the supplementary provisions to the technology study program/Master of Science" at NTNU §20, the Department reserves the permission to utilize all the results and data for teaching and research purposes as well as in future publications.

The final report is to be submitted digitally in DAIM. An executive summary of the thesis including title, student's name, supervisor's name, year, department name, and NTNU's logo and name, shall be submitted to the department as a separate pdf file. Based on an agreement with the supervisor, the final report and other material and documents may be given to the supervisor in digital format.

☐ Work to be done in lab (Water power lab, Fluids engineering lab, Thermal engineering lab)
☐ Field work

Department of Energy and Process Engineering, 16. January 2013

Olav Bolland
Department Head

Vojislav Novakovic
Academic Supervisor

Research Advisors: Igor Sartori, Postdoc, Usman I. Dar, PhD candidate

Preface

This master's thesis documents the work done by Eline Rangøy working on her thesis assignment during the spring of 2013 at the Department of Energy and Process Engineering at the Norwegian University of Science and Technology.

I will thank the people who have helped me finding data for this project. Signe Kroken and her colleagues at UMB and Hanne Sæle at SINTEF.

A special thanks goes to Ian Richardson and Usman Ijaz Dar for sharing the source code of their work. And to my supervisors Igor Sartori and Vojislav Novakovic.

I will also thank my beautiful friends and family, and my wonderful husband Gunnar Rangøy for help and support. Looking back on the time at NTNU it has been five years with blood, sweat and tears. But all the wonderful memories make up for that. Still can't believe I made it.

Mahay ny zavatra rehetra aho ao amin'ilay mampahery ahy.

Eline Rangøy

Eline Rangøy
Trondheim, Thursday 27th June, 2013

Abstract

To make Zero Energy Buildings (ZEB) commercially competitive as dwellings the energy supply and on-site generation has to be thoroughly planned. The optimal mix of energy sources depend on the demand profiles for the building. Detailed load calculation for HVAC installation is implemented in many building energy simulation software whereas the main user dependent loads are greatly simplified.

In this assignment models for generating stochastic and statistical representative user profiles for Norwegian households have been made. The work is a continuation of the literature study where a methodology of Richardson et al. was recommended for further work. This model uses national time of use survey data (TUD) which have some discrepancies compared to Norwegian TUD.

The objective has been to adjust Richardson's model with Norwegian data and assess the validity of the generated user profiles. Thereby determine if the Norwegian TUD can be used despite the discrepancies with the existing simulation methodology.

Four models have been made generating data for occupancy and electricity demand for lighting, non-HVAC appliances and water heater (DESWH). The generated profiles have 10-minute resolution for the occupancy model and 1-minute for the other three.

With limited access to measured data only superficial validations of the output could be made. From the comparison it is found that the generated demand profiles for lighting and appliances can be used in building simulation software if calibrated separately for each household size. The occupancy is considerably underestimated in the model and the profile for DESWH should be based on more detailed TUD. No model have been made for domestic hot water draw-off events because too little data was available for both adjusting the model input and validating the output. Without more data the existing model of Widén or Jordan and Vajen is recommended to use as is.

Sammendrag

For å gjøre Zero Energy Buildings (ZEB) kommersielt konkurransedyktige som boliger må energiforsyning og selvprodusert energi planlegges nøye. Den optimale kombinasjonen av energikilder avhenger av lastprofilen for bygningen. Detaljerte lastningberegninger for HVAC-installasjoner er implementert i mange energisimuleringsprogrammer for bygninger, men de viktigste brukeravhengige lastene er sterkt forenklet.

I denne oppgaven er det laget modeller for å generere stokastiske og statistisk representative lastprofiler for norske husholdninger. Arbeidet er en videreføring av litteraturenstudien der en metodikk av Richardson et al. ble anbefalt for videre arbeid. Denne modellen benytter data fra en nasjonal tidsbrukundersøkelse (TUD) som har noen ulikheter i form sammenlignet med data fra den norske undersøkelsen.

Målet med oppgaven har vært å justere Richardsons modell med norske data og vurdere gyldigheten av de genererte brukerprofilene. For dermed å finne ut om de norske tidsbrukdataene kan brukes til tross for uoverensstemmelsene, sammen med den eksisterende simulerings metoden.

Fire modeller er laget, som generer data om når folk er hjemme og behov for elektrisk energi til belysning, apparater og varmtvannsbereder. Profilene har en oppløsning på 10 minutter for når folk er hjemme og ett minutt for de tre andre.

Med begrenset tilgang til måledata er kun overfladiske vurderinger av profilenes gyldighet kunnet gjort. Sammenligningen viser at profilene for belysning og elektriske apparater kan brukes i bygningssimuleringsprogram hvis de blir kalibrert separat for hver husstandstørrelse. Profilen for når folk er hjemme er betydelig lavere enn den burde, og profilen for DESWH bør baseres på mer detaljert tidsbrukdata. Det er ikke laget en modell for tappevannforbruk fordi for lite data er tilgjengelig til både å justere modellens input data og å validere output data. Uten mer data anbefales det å bruke den eksisterende modellen av Widén eller Jordan og Vajen som de er.

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List of Abbreviations

AO Active occupant

DESWH Domestic electric storage water heater

DHW Domestic hot water

E-INST Electric instantaneous water heater

HVAC Heating, Ventilation and Air Conditioning

NVE Norwegian Water Resources and Energy Directorate

RE Renewable energy

SEA Swedish Energy Agency

SSB Statistics Norway

TUD Time of Use Data

ZEB Zero Emission/Energy Building

Chapter 1

Introduction

The awareness of the human impact on the climate changes have increased all over the world for the last decades. Consequently renewable energy sources and energy efficiency have become a greater political target. In Norway this have among other things resulted in increasingly stricter national building codes for energy efficiency in buildings. In addition to this the Norwegian government enterprise Enova SF was established in 2001 to promote further reduction in energy consumption and shifting towards more renewable energy sources by providing information and economic incentives.

Passive house and low-energy buildings have long been the stretch goal in the building sector, but with more and more passive houses successfully built this is no longer as great a feat. The new challenge is Zero Energy Buildings (ZEB) and plus houses, which imposes stricter requirements for collaboration across disciplines. A ZEB produces as much energy over a year as it consumes and on-site energy generation from renewable energy sources (RE) is thus necessary.

Much remains before these buildings are commercially competitive especially for dwellings. To reduce the costs the optimal mix of energy supply to the building both delivered and from on-site generation is being investigated. The best combination is highly dependent on the load profile for the building and the local storage capacity. Detailed load calculation for HVAC installation is implemented in many building energy simulation software whereas the main user dependent loads are greatly simplified. More knowledge on this gives a better base for calculating the optimal mix of energy solutions and can thus decrease both the investment and operation cost for the building making it more commercially competitive.

1.1 Background

This work is a continuation of the work done in the project assignment by the author during the fall of 2012. In that project a literature survey was carried out and proposals made for how to generate user profiles for the main user dependent energy loads in buildings: domestic hot water, lighting and non-HVAC electrical appliances. It was concluded to use an existing model made for UK by Richardson et al. and adjust it with Norwegian data. The main issue is the discrepancy in the national Time of Use Survey Data (TUD) for Norway and UK that are the main input for the model.

1.2 Objective

The objective of the work presented in this report is to adjust Richardson's model with Norwegian data and assess the validity of the generated user profiles. Thereby determine if the Norwegian TUD can be used despite the discrepancies with the existing simulation methodology.

1.3 Outline

Richardson's energy demand model is described in Chapter 2 with simulations results. Different methods of generating DHW profiles are also presented.

In Chapter 3 relevant data and statistics for Norway are presented. The type of data is similar to the ones used in Richardson's model in addition to measurements that will be used in validation of the simulation output. Here the discrepancies in the Norwegian TUD compared to the UK and Sweden are presented.

In Part II each of the energy demand models and the occupancy model are presented separately. Adjustments are described and the simulation output presented. The generated profiles are compared to measured data and discussed.

Part III includes a description of further work and the final conclusions drawn for the validity of the generated user profiles.

No work have been done in the lab etc. thereby no risk assessment has been carried out.

Part I

Existing models and data

Chapter 2

Existing models for generating user profiles

In the project assignment five different energy load profile models were presented and discussed [11]. All the models are made mainly "bottom-up" and are developed by Richardson et al. [15], Widén et al. [29], Armstrong et al. [4], Yao and Steemers [33] and Jordan and Vajen [9]. A proposal for how a Norwegian model should be made is given in the project report. It is stated that the one made for the UK by Richardson et al. should be used as base for both lighting, electrical appliances and domestic hot water, implementing features from the other models. The proposal also include a recommendation of Norwegian data sources to be used.

In this chapter the different models are presented. For Richardson's models the methodology is more thoroughly explained as it will be used for the Norwegian model. Simulation output with the original UK data is presented to better evaluate the output of the Norwegian model. A more detailed description of the other models, limitations and evaluations can be found in the project report.

2.1 Occupancy

Richardson's occupancy model is used in both the lighting and appliance model. It generates a profile with number of active occupants for every 10-minute from household specified time of use survey data (TUD). An active occupant (AO) is defined as a person who is in the house and not asleep. Richardson uses seven occupancy states; from zero to six active occupants.

A Markov-chain technique [28] is used to calculate the state for each time step. The next state is only dependent on the current state and the different probabilities of the state changing as is shown in Equation (2.1).

$$AO(t+1) = \begin{cases} 0 & \text{with probability } P_0(AO(t), t) \\ 1 & \text{with probability } P_1(AO(t), t) \\ 2 & \text{with probability } P_2(AO(t), t) \\ \vdots & \\ 6 & \text{with probability } P_6(AO(t), t) \end{cases} \tag{2.1}$$

These probabilities of changing of states for each step is calculated from the TUD as shown in Table 2.1 and is organized in matrices. The transition probability matrices have five dimensions:

- Household size [1 to 5]
- Weekday and weekend
- Time step [1 to 144]
- Active occupancy state in current time step [0 to 6]
- Active occupancy state in next time step [0 to 6]

An easier way of getting occupancy profiles would be to for each time step calculate the probabilities for the seven occupancy states and disregard the state in the previous or the next time step. For this method the probability of the state changing in the next time step will be higher giving a more volatile and less representative profile.

An overview of how the profiles are generated in the model is given in Appendix A.1

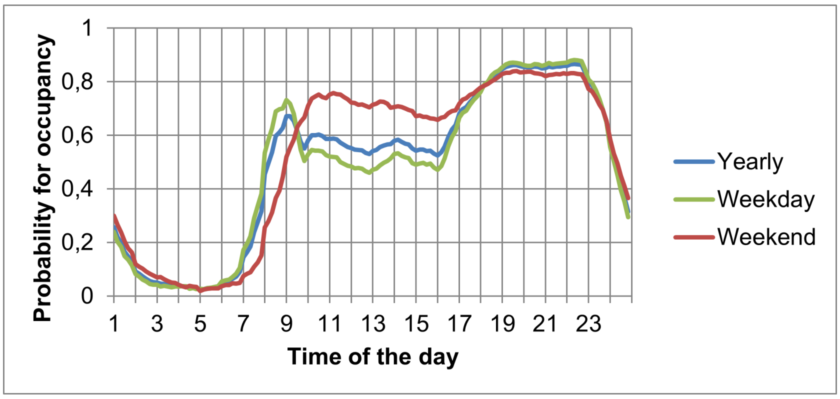
2.1.1 Simulation output

The output data is generated as an average of simulations of 20 households for one year for each household size. Figure 2.1a shows the probability that the household has one or more active occupants (AO) during the day for weekday, weekends and for the whole year. It is an equally weighted average of the five household sizes. From this simulation the average occupancy is 0.496 but the value found by Richardson and used in the appliance model is 0.459. This is then probably the average weighted for household strata. The profile shows the expected two main peaks for the morning and the evening and low activity during the night. The occupancy increases later in the weekends but the decreases at the same time for all days.

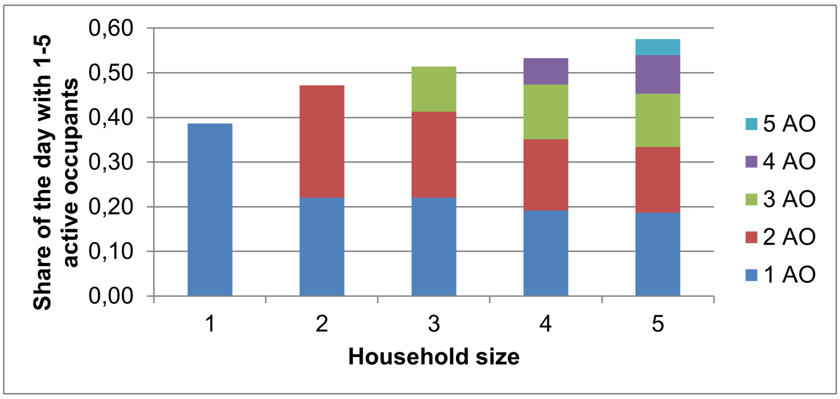
Figure 2.1b shows the distribution of number of active occupants for the different households. Both the occupancy and the probability for higher number of active occupants increases with the household size as expected.

Table 2.1: Example calculation of the transition probability matrix at 00:00–00:10 for 2-person households on weekdays [17].

Number of active occupants		Number of occurrences in the TUD		Transition probability $P_x(AO(t), t)$
At 00:00	At 00:10			
0	0	1251	1251+8+3 = 1262	1251/1262 = 0,991
0	1	8		8/1262 = 0,006
0	2	3		3/1262 = 0,002
1	0	435	435+1021+29 = 1485	435/1485 = 0,292
1	1	1021		1021/1485 = 0,687
1	2	29		29/1485 = 0,019
2	0	414	414+69+1244 = 1727	414/1727 = 0,239
2	1	69		69/1727 = 0,039
2	2	1244		1244/1727 = 0,720



(a) Daily probability that the household has one or more active occupants.



(b) Active occupancy distribution for each household size.

Figure 2.1: Simulation output for Richardson's occupancy model. 100 units for one year.

2.2 Lighting

Richardson's lighting model generates an energy demand profile for lighting with a 1-minute resolution [16]. An overview of how the profiles are generated in the model is given in Appendix A.2

Initially the household is assigned a set of bulbs with different rating among 100 example bulb sets. Because some bulbs are switched on more often than others each bulb is assigned a relative use weighting from a natural logarithmic distribution. The selection of the bulb sets and the use weighting is independent of the household size.

From a normal distribution with a mean of 60 W/m^2 and a standard deviation of 10 W/m^2 a threshold outdoor irradiance is found. A switch-on event can only occur for 5% of the time when the outdoor irradiance is above this value.

It is assumed that the lighting demand increases with the number of active occupants, but that the relation is not linear. Because of this "effective occupancy" (EO) is introduced as the ratio between use of lighting for the number of active occupants and the use by one active occupant. This factor is calculated from annual energy demand for lighting per household size, N_{res}, as shown in Equation (2.2).

$$\mathrm{EO(AO)} = \frac{\text{Energy use}(N_{res} = \mathrm{AO})}{\text{Energy use}(N_{res} = 1)} \tag{2.2}$$

To adjust the model such that the mean overall annual lighting energy demand equals a specific value the probability for any switch-on event is multiplied with a calibration scalar. This has been determined by running simulations for 100 dwelling for one year, ten times, using one minute resolution irradiance data specified for each day.

The switch-on probability is calculated as shown in Figure 2.2. For each time step and each bulb the probability is calculated and compared to a random number to decide if a switch-on event occurs. If so a duration is picked randomly from the distribution shown in Table 2.2 found by Stokes et. al. [25]. Regardless of this value, the lighting unit will be switched off if the number of active occupants becomes zero.

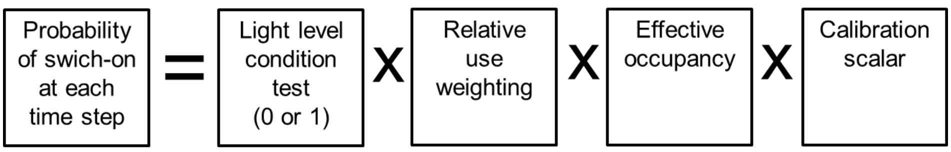


Figure 2.2: Probability for switch-on event for each time step and bulb [19].

Table 2.2: Distribution of lighting event duration in minutes. Each interval has equal probability [25].

1	2	3-4	5-8	9-16	17-27	28-49	50-91	92-259

2.2.1 Simulation output

The results of a simulation of 500 households for one year are shown in Figure 2.3. These show the annual energy demand for lighting, average daily and annual profile. There is a clear peak in the demand in the morning and the evening. And the morning peak in the weekend appears later than for weekdays. The monthly variations are also significant. For the annual demand there is a clear increase for larger households.

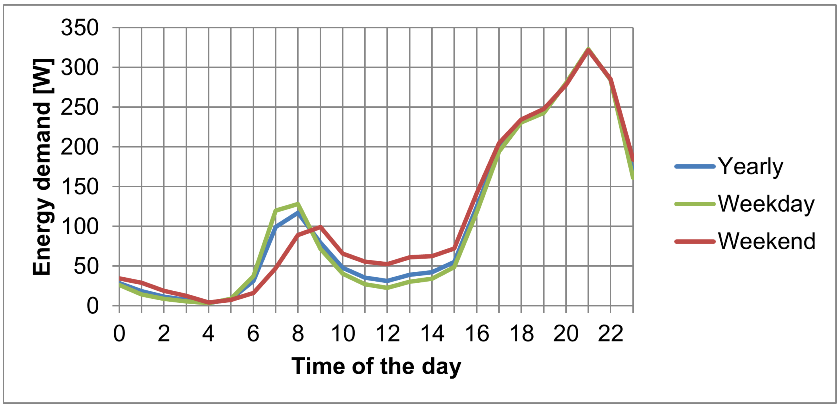
2.3 Electrical appliances

Richardson's model for electrical appliances generates user profiles with a one-minute resolution [18]. As for the two previously described models the inputs to this model are number of residents in the dwelling, whether it is a weekday or weekend and the month of the year. An overview of how the profiles are generated in the model is given in Appendix A.3.

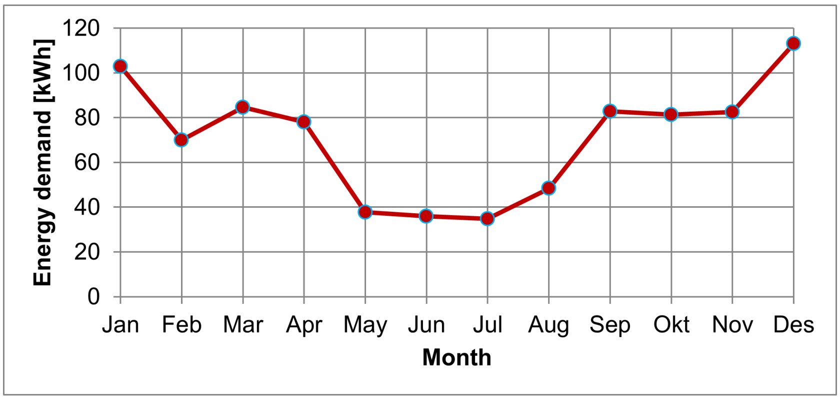
For each simulation the occupancy model is run and a set of electrical appliances is assigned to the dwelling. The appliances are chosen randomly from a list of 33 different appliances including electrical water and space heating. The ownership probability for an appliance is the same for all household sizes but it varies for each appliance. In addition to the ownership probability several parameters are needed for the different appliances such as:

- Number of uses per year
- Mean cycle length [min]
- Mean cycle power [W]
- Standby power [W]
- Delay restart after cycle [min]

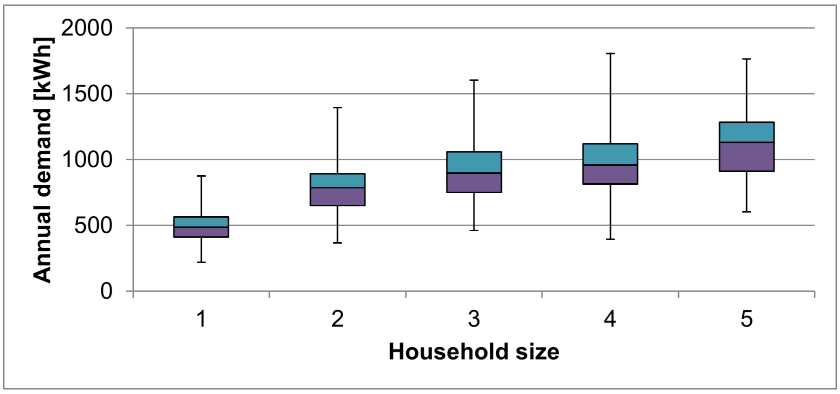
These parameters describe switch-on events and the use of each appliance. Standby power and restart delay is used directly in the simulation, but the mean cycle length and power is calculated in different matters for the various appliances as described in Section 2.3.4. The number of uses per year is used to calibrate the model as described in the next sections.



(a) Daily energy demand profile.



(b) Average monthly profile.



(c) Annual energy demand for each household size.

Figure 2.3: Simulation output for Richardson's lighting model. 500 units for one year.

2.3.1 Activity probability

For each appliance the use can depend on certain activity, only active occupancy or none of the two. For example the microwave can only be used if at least one person in the dwelling is engaging in the activity *Cooking*. Further the phone is only depending on active occupancy while the freezer will be independent of both occupancy and activity to run.

For the appliances linked to a certain activity the probability for a switch-on event depends on the activity profile derived from the TUD. The profile gives the probability that at least one of the occupants is performing the activity. Profiles are made for six different activities, for each active occupant state and for weekdays and weekend. The resolution is as for the TUD 10 minutes.

2.3.2 Annual energy demand calibration factor

The generated user profiles is supposed to represent the total electricity demand for the household. To do this without including every conceivable appliances that could exist in a household the model is calibrated to meet a target annual energy demand. With the parameters listed in Section 2.3 the annual energy demand for each appliance can be found. Multiplying this with the ownership probability gives the average annual electric energy demand for multiple runs with the model. In the model an overall calibration factor is used to change this target demand by increasing the number of cycles for each appliance.

2.3.3 Appliance specific calibration factor

An other way the model is calibrated is with the appliance specific calibration factor. It gives the relation between the number of times the appliance should start in a year and the average number of minutes in a year were all the criteria for a switch-on event to occur is met. The criteria being that the dwelling is occupied and at least one of the residents is doing the activity linked to the appliance. To calculate for how many minutes this complies for the average occupancy probability and the average activity probability is used as shown in Equation (2.3). Unlike the overall calibration factor this value is calculated individually for each appliance.

$$f_c = \frac{n_{cyc}}{P_a(n_{min,yr}\bar{P}_{occ} - n_{cyc}(t_{cyc} + t_{del}))} \tag{2.3}$$

$$
\begin{aligned}
f_c &= \text{Appliance specific calibration factor,} \\
n_{cyc} &= \text{Number of cycles per year,} \\
P_a &= \text{Average probability for the actual activity,} \\
\bar{P}_{occ} &= \text{Average occupancy probability,} \\
n_{min,yr} &= \text{Number of minutes in a year,} \\
t_{cyc} &= \text{Cycle length,} \\
t_{del} &= \text{Time delay before restart,}
\end{aligned}
$$

The average activity probability P_X is found from the activity probability matrix using Equations (2.4) and (2.5). For every activity and weekday the average is found and the final activity probability is weighted 5/7 and 2/7 for weekday and weekend to get the average over a week.

$$P_X = \frac{5P_{X,wd} + 2P_{X,we}}{7} \tag{2.4}$$

$$P_{X,wd} = \sum_{n=1}^{n_{max}} \sum_{t=1}^{t_{max}} \frac{p_{wd}(t,n)}{n_{max}t_{max}} \tag{2.5}$$

$$
\begin{aligned}
n_{max} &= \text{Highest number of active occupants (5),} \\
t_{max} &= \text{Total number of time steps (144),} \\
X &= \text{Activity category } X\text{,} \\
p_{wd}(t,n) &= \text{Probability for activity } X \text{ for weekdays at (t, n),} \\
P_{wd} &= \text{Average probability for activity } X \text{ for weekdays}
\end{aligned}
$$

2.3.4 Modelling

Use of the different appliances is calculated similar as for the light bulbs. For each appliance the model loops though all the minutes of the day to check three criteria for a switch-on event to occur:

- The household has one or more active occupants
- The appliance is not already running
- Time since the appliance last stopped is longer than the required restart delay (for those appliances which have this)

If all these criteria are met the probability for a switch-on event for that time step is calculated and compared to a random number to decide if a switch-on event occurs. The probability is given as the appliance specific calibration factor (f_c) multiplied with the activity probability.

For a switch-on event the power rating is found using a normal distribution with a standard deviation of 10% of the mean value. This is done for all appliances except the washing machine for which a specific cycle energy demand profile is applied making it the only appliance with a variable cycle power rating.

The cycle length is constant for all appliances except for TV and the electric space heating appliances. The duration of a TV switch-on event is determined with the distribution in Equation (2.6) with x being a random number between zero and one. A and B determines the curvature of the distribution and is set to 70 and 1.1 respectively to best match the records in the TUD.

$$t_{TVon}(x) = A(-\log(1-x))^B \tag{2.6}$$

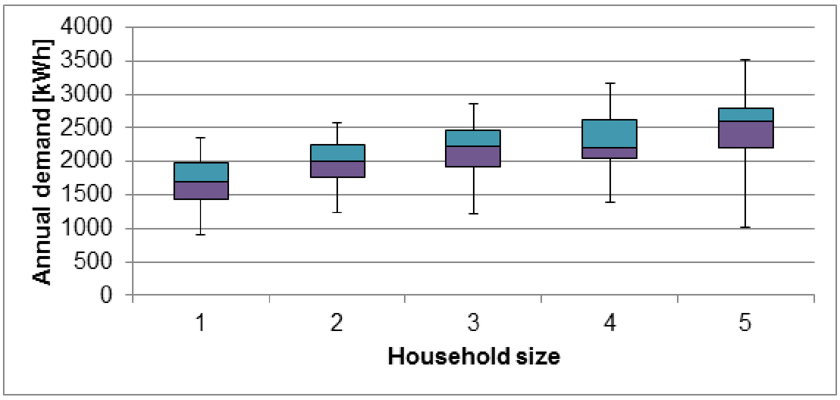
For the electric space heating appliances the cycle length is found the same way as the rating using a normal distribution.

Appliances will be switched off or "paused" if the number of active occupants becomes zero, and run the remaining cycle time when the dwelling is occupied again. This does not apply for laundry and cold appliances.

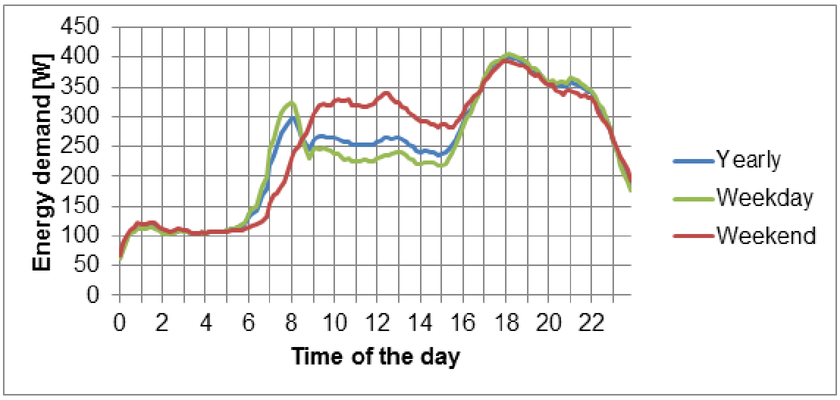
As mentioned the model takes the month of the year as an input. This is only used for the electric space heating appliances to get a higher switch-on probability in the heating season and lower in the summer.

2.3.5 Simulation output

The results of a simulation of 250 households for one year are shown in Figure 2.4. It shows the annual energy demand for electrical appliances and average daily profile. The daily profile shows a small peak in the morning and a bigger peak in the evening. An unexpected result is the energy demand for 2, 3 and 4-resident households. For 3-resident households the median is a little higher than for 2-residents as is shown in the box plot, but the arithmetic mean is slightly lower. For the 4-resident household the mean is higher than for 3-residents but the median is lower.



(a) Annual energy demand for each household size.



(b) Daily energy demand profile.

Figure 2.4: Simulation output for Richardson's appliance model. 250 units for one year.

2.4 Domestic hot water

Of the five models considered only Armstrong et al. does not include DHW simulations in any way. There are two ways of describing the energy demand for DHW: The direct hot water draw-off events and the electrical energy demand profile for electric hot water tanks or other hot-water installations. Widén et al., Yao and Steemers [33] and Jordan and Vajen [9] consider the first description while Richardson models the other one.

2.4.1 Richardson et al.

Three DHW-installations are included in Richardson's appliance model: Electric instantaneous water heaters (E-INST), domestic electric storage water heater

(DESWH) and electric shower. Use of the electric shower is linked to the “wash and dress”-activity while the two others only depend on active occupancy. Otherwise they are simulated as other electrical appliances described in the last section.

2.4.2 Widén and Lundh et al.

For Widén’s DHW-model 25 hot water consuming activities are defined with different demand profiles [29]. For showering the energy demand is assumed to be constant during the activity while for taking a bath the demand is constant with a time constraint because the bath tub will be filled up. An assumption is made that cooking and baking requires on average two hand washes or rinsing of household goods every 15 minutes.

The probability profiles for the activities is derived from the Swedish TUD which has a resolution of 5 minutes.

2.4.3 Yao and Steemers

The model of Yao and Steemers generates load profiles that can be varied from 1 minute to half an hour [33]. No statistical TUD have been used. Instead data on when the first person gets up in the morning, when the last person goes to bed in the evening and when the house is unoccupied during the day is taken as input values.

Four DHW-load categories are used: bath/shower, wash hand basin, dish washing (by hand and by machine) and clothes washing (washing machine). For each activity litres per capita and day and water temperature is used to find the daily DHW load per capita. The DHW draw-off events will occur randomly with similar probability for every minute inside the given user interval.

2.4.4 Jordan and Vajen

The model of Jordan and Vajen generates DHW load profiles with a resolution of 1 min, 6 min or 1 hour [9]. DHW draw-off events are divided into four categories; “small”, “medium”, “shower” and “bath”. For each category different values are assumed for mean flow rate, duration and incidents per day. The actual flow rate for each incident is assigned randomly from a Gauss-Distribution.

No statistical TUD is used, but a daily probability distribution for draw off events, shown in Figure 2.5 is assumed. In addition to this the probability for the bath-activity is increased for the weekend including Friday.

Seasonal variations are included by varying the total daily DHW-volume with a sinus-function with an amplitude of 10%, with the top and bottom vertices at the beginning of February and September respectively.

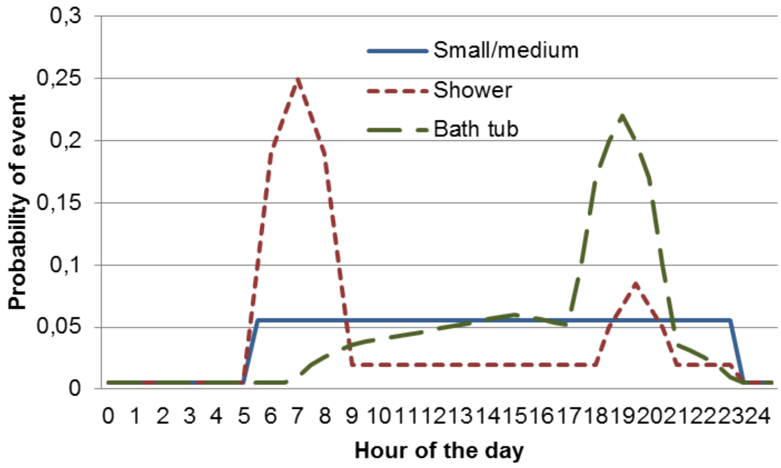


Figure 2.5: Probability distribution for DHW loads by Jordan and Vajen [9].

Chapter 3

Main data sources

In the project report several data sources is presented and proposed used in the different parts of the model [11]. A summary of the most important sources are re-presented here together with new data that can be used as input to the model or for validation of the output.

3.1 Time of Use Data (TUD)

The most extensive Norwegian TUD is the results of the national "Tidsbrukundersøkelsen" by Statistics Norway (SSB). It has been conducted once every decade from 1971. The latest survey was in 2010-2011 and had nearly 4000 respondents.

3.1.1 Survey records

In the survey each respondent make records of their time of use for two consecutive days. The respondent writes the activities he or she is doing in words with no guide lines for which activity categories to be used. SSB have then put each activity in a specific category and the final data only contain a code for each activity. In addition to writing the activities the respondents are also asked to specify if PC is used. For each time step the following values is given in the revised TUD received from SSB [23]:

- Household size [1 to 5]
- Weekday number
- Primary activity code
- Eventual secondary activity code
- PC specification for both primary and secondary activity
- Mode of travel or whereabouts

- Who the respondent is together with

For the last point it is done specification for friends, relatives, own or partner's children under 18 who do not live permanently in the residence and for each of the other household residents.

3.1.2 Discrepancy from UK TUD

Eurostat is the statistical office of the European Union established to provide the European Union with statistics at European level that enable comparisons between countries and regions [1]. For national time of use surveys Eurostat recommends household selection and that each respondent reports their time use for one weekday and one weekend day [8]. This is the case in the British and Swedish time use survey. Household selection means that all the residents in the participating households make records of their time of use, not just one from each household.

To maintain the comparability with older Norwegian TUD and with hope to get a higher response rate SSB decided to use person selection and let every respondent report for two consecutive days. This last difference only gives the Norwegian data higher accuracy for weekdays and lower for weekends than for the UK data and is not of much relevance to this project. The problem is the difference in the selections.

Because the UK TUD provides information on all the residents in the household the probability that at least one occupant is cooking given exactly X active occupants (AO) in the dwelling can be found.

In the Norwegian TUD only information on one of the residents in a household is recorded. It is also recorded if the person was alone or together with someone, meaning they were at the same place having a certain degree of contact. This gives the lower limit for number of active occupants, but there might be other active occupants in the dwelling. Therefore the probability can not be found for an exact number of active occupants but for a minimum of active occupants. The different expressions for the UK and Norwegian probabilities are shown in Equation (3.1) and (3.2). The difference is small but might have a large impact on the result. It affects both on the transition probability matrix for active occupancy and the activity probability profiles.

$$P_{UK}(\text{At least one engaging in activity A}|AO = X) \tag{3.1}$$

$$P_{NOR}(\text{At least one engaging in activity A}|AO \geq X) \tag{3.2}$$

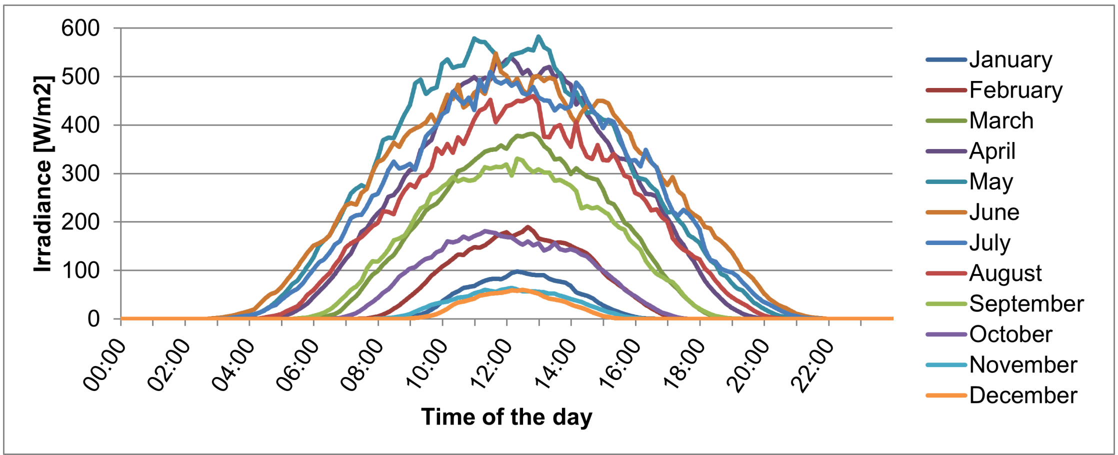


Figure 3.1: Average measured daily irradiance for each month for Ås in 2011.

3.2 Outdoor irradiance data

Several irradiance data sets are evaluated in the project report. The one proposed used is from Norwegian University of Life Sciences (UMB) [27]. This data have been chosen because it is measured data and has a high time resolution. It also gives data for every day of the year not just for one day every month or a monthly average. The measurements are done at Ås, 30 km south of Oslo, with 10 min resolution. Figure 3.1 shows the calculated average daily irradiance for each month from the measurements. For whole-year-simulations the 365 different profiles will be used instead of the monthly mean.

The chosen irradiance data will not be representative for the north of Norway but when only using one set of irradiance data it will be natural to pick the capital as the location.

3.3 Swedish Energy Agency

In order to investigate why the electricity demand is increasing in households the Swedish Energy Agency (SEA) has done measurements of electrical equipment in 400 households [26]. The measurements were done from 2005 to 2008 and included both appliances and lighting. In 40 of the households the measurements were done for a whole year while for the rest one month data was collected. Most of the participating households were located around the area of Mälardalen, near Stockholm. Data from this measurement campaign have been used by Widén for validating his lighting model.

At the moment, analyses are being carried out of the results of the measurements and when the analyses are ready, the results will be presented on the SEA website. Some of the data is available in a report by Jean Paul Zimmerman [34].

3.4 REMODECE

In the REMODECE project (Residential Monitoring to Decrease Energy Use and Carbon Emissions in Europe) measurements were performed in 105 Norwegian households for two weeks each in 2007 [6]. A total of 470 electrical appliances in 25 different categories were measured and analysed, and ownership levels were found. Annual values have been estimated for each appliance from the two-weeks measurements and are weighted according to national distribution of the three household categories; one or two person household, three or more, or retired person(s).

The REMODECE-NO-report by Grinden and Feilberg gives a lot of parameters needed in the model [6]. The most relevant is:

- Number of uses per year
- Energy per single use [kWh]
- Maximum power demand [W]
- Standby power [W]
- Total annual consumption [kWh]
- Annual standby consumption [kWh]

3.4.1 Lighting

Also lighting was measured in the project. In the report of Grinden and Feilberg a total of 74 units have been analysed and the average yearly consumption for lighting is calculated to 1000 kWh per household.

In addition to the measurements a questioning survey was conducted. The objective was to collect data on the type of lighting and appliances people have and to understand their behaviour concerning the electricity use and their choices when buying new equipment [12]. From this data power rating and holdings were obtained for five different bulb types. The survey results is available at the REMODECE homepage [13].

One of the questions in the survey was if the respondent left the lights on in unoccupied rooms. Of the 244 respondents 25% answered “never”, 72% “sometimes” and only 3% “always”.

3.5 NVE/Xrgia

Xrgia Analysis and Consulting AS conducted a survey on Norwegian households electricity use for NVE in 2011 [10]. Both lighting and non-HVAC electrical appliances were analysed, but not DESWH. The data is based on a questioning survey of 2000 people regarding the households holdings and use of different electrical appliances. The report "Main survey of electricity use in households" contains a lot of data relevant for this model like appliance ownership and energy use for different household sizes. An overall distribution of energy use for the different appliance categories is also given.

3.6 ElDeK

"Electricity Demand Knowledge" (ElDeK) is a SINTEF project started in 2009 to increase the knowledge concerning electricity demand for different types of customers [22]. This includes knowledge on electrical energy and power consumption for every costumer and different end-use demands. In the 75 participating households two types of measurements have been done [2]:

- Total electrical energy demand for one year with a resolution of one hour.
- End-use for 5-10 appliances for four weeks with a resolution of one minute.

The total energy demand measurements include electric space and domestic hot water heaters. The specific measurements have been done on the major household appliances shown in Table 3.1 together with the number of units measured for the different categories [21]. The only measurement of lighting is the lighting in kitchen and living room.

Table 3.1: Overview of appliances analysed and number of units in the ElDeK project [21].

Category	#	Category	#
Freezer	50	Desktop PC	27
Fridge	27	Laptop	10
Cooker	25	CRT TV	41
Kettle	2	LCD TV	20
Dishwasher	41	Plasma TV	6
Washing machine	48	Light kitchen	13
Dryer	28	Light living room	48
DESWH	42		

3.7 Domestic hot water measurements

PhD-student at HiB (Bergen University College) Magnar Berge is in his work doing measurements on DHW use in passive houses and low-energy houses in Bergen, Norway. Measuring instruments was installed in one apartment in October 2012 and data from 5-6 more apartments will be available during 2013. The measurements gives the total DHW volume and demand for space heating. Measurements are also done for a detached house in Hardanger, Norway. For this the load on each electric circuit is also measured [3].

Widén presents two data sets on DHW measurements done in Sweden between 2005 and 2007 in 60 and 24 households [29]. The biggest data set includes measurements down to the different taps in the household.

3.8 Household distribution

When finding values that are representative for all households in Norway based on values for the different household sizes the distribution of household sizes is needed. This is to get a weighted average value that will be more representative for all Norwegian households than the arithmetic average. Table 3.2 shows the distribution used in this project. The data is from 2011 found from SSB [24].

Table 3.2: Number of household members distribution in Norwegian households.

Household members	1	2	3	4	5 and more
Portion of all households	39,7%	27,8%	12,6%	12,7%	7,1%

Part II

Adjusting the models

Chapter 4

Methodology

The proposal for energy demand models for Norwegian household in the project report include lighting, non-HVAC electrical appliances and domestic hot water. In the following chapters the models for each energy category in addition to the occupancy model is presented.

For each model the proposed changes and adjustments from the project report are described [11]. The different aspects of the models with associated problems and possible solutions are presented separately before one or more combinations of solutions are simulated and the output evaluated.

4.1 General procedure

The general procedure for the work done with each model is shown in Figure 4.1. First the input data to the models have been replaced with Norwegian data and reasonable assumptions made when the format of the available data did not match the requested input, like the TUD. Secondly the model code might have to be adjusted to use the new data or new features is included. At last the model output is analysed and compared to available measured data. If discrepancies are detected the model or the input data have to be re-evaluated and the output analysed again. If there are no severe discrepancies more data could be found to give a more extensive validation or the model output could be stated as sufficiently representative and be used further in building simulations.

4.2 Input data

Most of the needed input data exists or can be calculated from the measurements done in different projects and surveys presented in Chapter 3: *Main data sources*. The problem is that without direct access to their data bases all queries have to go

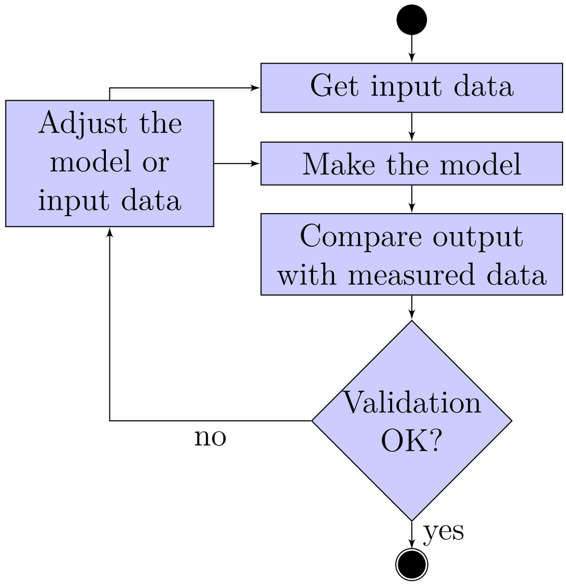


Figure 4.1: General methodology for making the Norwegian models.

through the researchers. This is often time consuming for both the one requesting the data and the “middle man” doing the queries. One of the reasons is that the quality and quantity of needed data is discovered during the whole project period requiring a lot of back and forth through the middle man.

Fortunately a lot of data from the different projects is available in published materials which most of the input data for the models is derived from. Inputs for which the available data is not sufficient it is described where data can be obtained and how it can be calculated. In these cases Richardson’s original data have been used in the simulations.

When choosing input to the models from the different data sources they are compared with regard to how representative they are for all of Norway. It has been a target to keep the models as simple as possible keeping the changes at a minimum while still getting a representative output. Therefore the input with the major impact have been changed first and the minor ones have been changed if needed after comparing with measured data.

4.3 Modelling

The original models are obtained from Loughborough University Institutional Repository online [15] [16] [14]. They are all implemented in Microsoft Excel using Visual Basic for the simulations giving as output 24 hours load profiles.

In this project all the models have been adjusted to give a yearly output with the same one minute resolution but with less interaction with the Excel sheets to reduce runtime. The general methodology is preserved but with different input data some of the code had to be adjusted. The simulations are still done for 24 hours but are repeated 365 times with a continuously 5 weekdays and 2 weekend-days pattern. Each day is independent of the others. If an appliance is running when the day ends it will not continue the next day.

4.4 Validation

The validation is the most important mean to evaluate the quality of the input data and the methodology of the models. The most logical input data for each step does not necessary give the most logical output and many small assumptions can give a big error in the end. This is or should be revealed when comparing to measured data.

The validation of the models are in some cases very limited. As mentioned previously a lot of useful data exists but the problem is the availability of data with the required resolution. Nevertheless a comparison have been done for all the models and some conclusion can be draw from this. As for the input data a proposal of how to use other data for validation is given for some of the models.

To describe the correlation between the model output and the measured data the R^2-value is used. The R^2-value is a number between zero and one describing the correlation between two data sets, R^2=1 meaning perfect correlation. It is calculated using the RSQ-function in Excel defined in Equation (4.1) [7].

$$R^2 = \frac{\left(\sum (x-\bar{x})(y-\bar{y})\right)^2}{\sum (x-\bar{x})^2 \sum (y-\bar{y})^2} \tag{4.1}$$

Chapter 5

Occupancy

The proposal for the occupancy model is not very detailed beyond stating that Richardson's method should be used together with the Norwegian TUD from SSB. Because of the discrepancy between the Norwegian and British TUD the generation of the transition probability matrices as defined by Richardson is not straight forward. Some solutions for this have been evaluated in the next sections and the output for three combinations of solutions have been analysed.

5.1 Discrepancy in TUD

Richardson's method requires information on the exact number of active occupants for each time step. Whereas the Norwegian data only gives the minimum number of active occupants as discussed in Section 3.1. To solve this problem some assumptions have to be made.

It could be assumed that the respondent and the number of people together with him is the only active occupants in the household. This will give an underestimation of the active occupancy because a person is not always together with all the people in the house and even if *he* is not at home other household members might be.

Another solution is to manipulate the output data by increasing the number of active occupants with one or more for some of the time steps. No data exists on how many time steps the number of active occupants should increase and with how many, so a lot of assumption will have to be made for this alternative.

It could also be a solution to assume that the occupancy for Norway and UK is the same and use the UK transition probability matrices. Or use the Swedish TUD that is also household specific. The UK time of use survey had over ten times as many participants compared to Sweden with only 431 persons in 169 households [29]. On the other hand it is assumed that Swedes have a more similar schedule and habits as Norwegians.

5.2 Defining active occupancy

To calculate the probability matrices the state “being at home and active” must be defined. One way is to use the record of whereabouts for which there is a separate code for “being at home”. Another way is to include all occurrences of activities usually done *at* home or *in a* home from the activity codes. Even if the activity is not done in the home of the respondent it could be included assuming that other people besides the household residents might perform the same activities in the respondents home at one time.

Another problem is who of the people being together with the respondent to include as active occupants in addition to the other household residents. In the TUD it is done specification for friends, relatives, own or partner’s children under 18 who do not live permanently in the residence and for each of the other household residents.

Visitor like friends and relatives might not use as many appliances in the household and the probability for using high energy demanding appliances like cooking and washing appliances might even be smaller when having visitors. For the cooking appliances is could be assumed that the probability of use is higher *before* having visitors. A lot of similar assumptions can be made, but without any good way of validating it the these assumptions is tried kept at a minimum.

5.3 Data sets

Three different combinations of assumptions have been evaluated and the assumptions made for each alternative is described below. The first alternative have been proposed by PhD.-student at NTNU Usman Ijaz Dar while the other two is made by the author using Dar’s VBA-script to generate the matrices.

5.3.1 Activity specific

PhD.-student at NTNU Usman Ijaz Dar have also been working with Richardson’s model. He has used three states when interpreting the TUD; *absent*, *inactive* and *active*. Each state span over a set of activity codes, the location parameter is not taken into account. If the respondent is absent he is doing an activity that is assumed to take place away from the dwelling. Inactive means he is at home and sleeping while the rest is defined as active. In the calculations Dar have disregarded respondents who are absent. The calculation of the transition probability for one step is shown in Equation (5.1). Probability of transition from one to zero active occupants (AO) is defined as the number of inactive (n_{inact}) in the next time step divided by the sum of inactive and active (n_{act}) for that time step, household size and weekday.

$$P(AO(t+1) = 0|AO(t) = 1) = \frac{n_{inact}(t+1|AO(t) = 1)}{n_{inact}(t+1|AO(t) = 1) + n_{act}(t+1|AO(t) = 1)} \tag{5.1}$$

The number of active occupants is defined as the respondent and the other household members he is with. Friends and relatives are not taken into account.

5.3.2 Location specific

For the location specific alternative the respondents must have recorded that they are "at home" to be defined as active occupants. As it turns out some of these have recorded an activity that per definition is not very compatible with being at home like "515 - Skiing" and "660-665 - Different types of travelling". Despite this they are included as active occupants assuming the activity code have a wider definition than the short description in given in [8]. From simulations of 100 households for one year the difference in the daily profile and the active occupancy distribution is small when excluding the apparently incompatible activity codes.

In the calculation of the transition probability the respondents that are absent (i.e. away from home) is taken into account. The difference can be seen if comparing Equation (5.2) and (5.1). The only change made from Dar's definition is that the number of "absent" respondents n_{abs} is added to the numerator for transition to zero AO and to the denominator for all transitions. This difference is marked green.

$$P(AO(t+1) = 0|AO(t) = 1) = \frac{n_{inact}(t+1|AO(t) = 1) + n_{abs}(t+1|AO(t) = 1)}{n_{inact} + n_{act} + n_{abs}} \tag{5.2}$$

In words Equation (5.2) shows the probability that one active occupant that is alone goes to sleep or leaves the dwelling. Dar's definition gives the probability that one active occupant that is alone goes to sleep if he stays at home.

The number of active occupants is as for Dar's alternative defined as only the respondent and the other household members he is with. Number of active occupants are not allowed higher than the household size.

5.3.3 Location specific with increased occupancy

For this alternative the only difference is the calculation of the transition probability. The number of active occupants is manipulated using the respondent and the other household members he is with as a starting point. If the number of active occupants is less than the household size the number can increase with one with a probability of 12% and with two with a 6% probability. Increase from zero is also allowed to increase the average probability for occupancy. If this was not included the occupancy would be the same as for the previous method only decreasing the share of the time when there are only one active occupant.

5.4 Simulation output analysis

Simulations have been done for each alternative for 100 households for one year. Two types of diagrams shown in Appendix B have been selected to best show the difference of the alternative.

Figure B.1 shows the daily profile, the probability that the household has one or more active occupants (AO) during the day for weekday, weekends and for the whole year. The profile is corrected for household strata according to Table 3.2. The active occupancy distribution is shown in Figure B.2. It gives the distribution of the number of active occupants and the total average occupancy for each household size.

No Norwegian data have been obtained to validate the output but it have been compared to the simulations with the UK TUD shown in Figure 2.1. In the next sections the different alternatives are denoted equally as the figures: (a) *Activity specific*, (b) *Location specific* and (c) *Location specific with increased occupancy.*

5.4.1 Daily profile

The daily profile is very different for the three alternatives. For (a) the profile is nearly binary. The probability is zero in the night and one during the day. The reason is that this is the probability that a person is not asleep if he is at home. As expected the weekend profile increases later in the morning than for weekday. In the evening the profile decreases at the same time both weekdays and weekend. It could be expected that people stayed up longer in weekends but the same can be seen in the original UK profile. If *weekend* were defined as the time interval between 5 pm Friday to 5 pm Sunday the profile for weekend might be different. It would probably give a later decrease in occupancy in the evening for weekdays.

The profile for (b) is the most similar to the UK profile. It has the narrow morning peak for the weekdays and a later and wider peak for the weekend mornings. The weekday peak is clearer for bigger households. For 1- and 2-resident households the peak is a little later, lower and longer. The evening peak is also clear but it is not as flat as for UK. Overall the occupancy is lower for this method than both the UK data and the two other methods.

For (c) the probability is too high in the night because the manipulation of the data allows increase from zero and not just from one active occupant. Other than that the morning peak for both weekdays and weekend can be recognized in addition to the evening peak.

5.4.2 Active occupancy distribution

Unlike the UK data the average occupancy probability for all alternatives is not increasing significantly with the number of residents. For (a) the occupancy is approximately 0.592 for all household sizes, about 29% higher than for the weighted UK occupancy. The active occupant distribution is similar as for the UK but the probability for 5 AO is nearly zero.

This also applies to (b). Here the average occupancy is much lower, only 0.296, 35% lower than the UK value. The occupancy increases from 1- to 2-resident household but then decreases for every household size. The lowest occupancy is unexpectedly for the 5-resident household for both weekdays and weekend.

Of all the alternatives the occupancy for (c) is the highest of 0.644, 40% higher than the UK data. As for (a) the variation is very small, less than 3% of the average for all households.

5.4.3 Comparison

Without the necessary data it is hard to say how the output should be for Norway. It could be that British people are more often at home and active than Norwegians as alternative (b) implies. Also the occupancy might not increase with the household size for Norwegian households. Families might be more active in Norway and single people more home-loving. Nevertheless it assumed that the trends in the UK data is representative for Norway as well.

Based on this (b) is considered the best to use for the Norwegian model. The occupancy is a little low especially for bigger households, but the shape of the daily profile seems the most reliable. For the energy demand models the low occupancy does not matter because they are calibrated.

More adjustments could be made to (c) but if the target is to make it more similar to the UK data than the UK data could be used as it is. That seems to be the best solution if the occupancy is to be used directly in building simulation software. Nevertheless the Norwegian data will be investigated further in the energy demand models to see if it can be used despite the obvious flaws.

Chapter 6

Lighting

For the lighting model a lot of changes on the original Richardson model is proposed. When adjusting the model some of the changes was introduced in the beginning and the model output analysed before further adjustments were made as illustrated in Figure 4.1. In the following sections solutions for the different parts of the model are discussed. At last the final model output is compared to measured data from Sweden.

6.1 Duration and relative use weighting

Because no Norwegian data have been found on duration of a switch-on event or use weighting of bulbs this have not been changed from the original data. For further work a more representative duration probability and and data on relative use weighting could be found by analysing measured data from ElDeK, REMODECE and SEA.

For the ElDeK project only lighting in the kitchen and the living room is measured [20]. The duration and use of these will probably be higher than for the rest of the rooms. But since the time resolution is as low as one minute this data might be useful.

For the REMODECE data the resolution is one or ten minutes while for the SEA data it is ten minutes [6] [34]. Despite the low time resolution the SEA data is very interesting because it includes lamps in all different room categories.

In the model all the lights are switched off if the number of active occupants turns to zero. Several data state that Norwegians do not always turn off the lights when leaving a room [13]. From a limited survey of Wilhite et al. in 1996, 10 of the 18 persons interviewed left one or more lights on when leaving the dwelling [32]. Thus it might be that the lights should be allowed to be on even if the active occupancy becomes zero in the model.

6.2 Bulb data

Data for ownership of different bulbs are more available in the reports from the three different projects mentioned in the last section. For the 100 bulb sets originally in the model the average total installed rating is 1459 W and the average number of bulbs are 23. According to the REMODECE survey data the average number of bulbs in Norway is 36 and the installed wattage is 1348 [13] [6]. The Swedish data have higher values. For detached houses and apartments the average installed power rating and number of bulbs is 1618 W and 55.2, and 829 W and 31.2 respectively. Despite the available data the bulb data have not been modified for two main reasons. First a lower number of bulbs is not necessary wrong as not all bulbs have an individual light switch. The model only handles the light switches and the bulbs connected to it not each bulb separately. The installed wattage is a little high but this will be adjusted in the calibration.

With more measured data actual switch-on power rating can be found and the bulb data adjusted accordingly.

A small bug were corrected in Richardson's original VBA code related to the selection of the bulb set. The original and the new code is shown at the end of the section. Rnd() is the random number generator in VBA generating values in the interval $[0, 1\rangle$. When deciding the bulb set number (iRandomHouse) the original code gave the values 2-100 with 1% probability for each number and the value 1 and 101 with 0.5% probability. As there is no set nr. 101, in the simulation this is handled as if the dwelling does not have any bulbs and thereby the energy demand is zero. With the adjusted code iRandomHouse is assigned a value [1,100] with uniform probability.

```
/* Choose a random house from the list of 100 provided in the bulbs sheet */
iRandomHouse = (Rnd()*100) + 1          /*Original*/
iRandomHouse = (Rnd()+0.005)*100        /*New*/
```

6.3 Daylight

The measured daily irradiance data from by Norwegian University of Life Sciences (UMB) is used in the model [27]. Originally the time resolution of the data is 10 minutes but to match the model it has been converted to 1 minute data by linear interpolation.

In the model the irradiance data is only used to decide if the available daylight is over or under the households threshold irradiance for when a switch-on event can occur. A proposed change is to make the probability for switch-on event more dependent on the irradiance as is done in the model of Widén [30]. The probability in that model decreases with increasing outdoor irradiance up to a limit for which the energy demand for lighting is constant equivalent one bulb.

6.4 Sharing of light

The method for modelling the sharing of lighting in a dwelling by using effective occupancy as defined in Equation (2.2) have been preserved. Norwegian data from Xrgia/NVE have been used in the calculation and the new values are shown in Table 6.1 [10]. The data from Xrgia is not measured but is the results of calculations based on a questioning survey. Nevertheless it is considered to be suitable for this purpose as it is the relation between the data that is used and not the values directly.

Table 6.1: Annual energy demand for lighting and effective occupancy for Norway.

Number of residents	1	2	3	4	5+
Annual energy demand for lighting [kWh/yr]	481	695	851	944	1035
Effective occupancy Norway	1	1,44	1,77	1,96	2,15

6.5 Calibration

To calibrate the model output the target energy demand used is 1000 kWh/yr. This value is obtained from the REMODECE project, the only Norwegian measured data of total lighting [6].

To get the overall calibration factor, f_c, the same procedure as Richardson have been used, simulating 100 households for one year several times. The simulations have been done until the difference in simulated and target energy demand is less than 5% adjusting the calibration factor as shown in Equation (6.1) for each 100 household simulation.

$$f_c = f_c + f_c \frac{E_{target} - E_{sim}}{E_{target}} \tag{6.1}$$

With the *location specific*-occupancy data presented in Section 5.3.2 the calibration factor was calculated to 0.02674. For the *activity specific*-occupancy data the calibration factor is 0.00946. These calibration factors applies when the model is not weighted for household strata.

6.6 Simulation output analysis

To evaluate the simulation output data for *dwellings* from the Swedish Energy Agency (SEA) measurement campaign have been used. The data is the same as used by Widén in the validation of his lighting model [30].

Most of these measurements were done in households located around the area of Mälardalen, near Stockholm, situated at approximately the same latitude as where the irradiance data is measured. This makes the data very suitable for evaluating the model output.

First the output with different occupancy data is evaluated and then the effect of minor changes. Three different data are used in the evaluation:

- Daily average profile for weekday, weekend and total
- Energy demand per month
- Annual energy demand per household size

Output both with and without weighting for household strata were compared to the measured data. The weighted data gave lower R^2-values for all the profiles for all the simulations. The household sizes for the measured data is not known only that it is for detached houses. Based on this and the R^2-values it is assumed that the household distribution in Table 3.2 does not apply. I could be assumed that there are no 1-resident households in the measured data set and use Table 3.2 for the rest. This is not done because of great uncertainties. There might be 1-resident households in the set. For further work the actual distribution should be used to weight the simulation output when comparing. For this analysis the data is not weighted, each household size has the same influence on the profiles.

6.6.1 Occupancy

To compare the output with different occupancy data 250 households for one year have been simulated with the two occupancy data: (a) *activity specific* and (b) *location specific*. These sets are described in Section 5.3. The output and measured data compared is presented in Appendix C and the R^2-values are presented in Table 6.2. The R^2-value is good for both of the occupancy data with only small differences. Because the model is calibrated for the same target annual demand the fact that the average occupancy of (a) is nearly twice as big as for (b) has no impact on the output. What causes the difference is the shape of the occupancy profiles.

Daily profile

The most apparent mismatch with the SEA data is the evening peak. For both the alternatives it is overestimated for both weekdays and weekends. The difference is bigger for (b) probably because of a greater evening peak in the occupancy data. For (a) the occupancy is higher in the evening than for (b) but it is relatively lower compared to the occupancy for the rest of the day for that alternative.

Table 6.2: R^2-values for the lighting model output for the two Norwegain occupancy data sets compared to SEA measured data.

Profile	Activity specific		Location specific	
	Figure	R^2	Figure	R^2
Daily profile WD	C.1a	0,91	C.2a	0,95
Daily profile WE	C.1b	0,97	C.2b	0,92
Daily profile AVG	C.1c	0,94	C.2c	0,95
Monthly profile	C.3	0,90	C.4	0,94

Both the alternatives underestimate the demand in the night. The demand is lower for (a) with only 6% of the occupancy before 8 am compared to 11% with (b) .

The morning peak for (a) appears 2 hours later than the SEA data in the weekdays but for weekend the match is good. For (b) it is opposite. Both the demand and the time for the weekday morning peak is equal to SEA, but for the weekend the peak for the modelled data is too distinct and approximately one hour earlier than SEA. All this corresponds with the occupancy profiles.

In the afternoon the demand has sharper curvature for (b) than for both (a) and the SEA data. For this period of the day the outdoor irradiance is above the threshold irradiance for most of the year and switch-on events can only occur in 5% of the time steps. By changing this factor the demand in this period will increase as presented later.

Monthly demand

The measured data for the monthly demand is found by for each month multiplying the average annual demand with a factor given by SEA. The difference between the months with the highest and lowest demand is 4% higher and 30% lower than the SEA data for (a) and (b) respectivly. This is caused by the share of the daily occupancy in the middle of the day. Between 10:30 am and 2:10 pm the outdoor irradiance is above the threshold value of 60 W/m^2 for 10 months. One fourth of the occupancy takes place in this interval for (a) while for (b) the value is 14%. June is the month with irradiation over the threshold for the longest period of the day in which the share of the occupancy for (a) is 83% and 72% for (b). Consequently (a) is more affected by the monthly irradiance variations than (b).

Annual demand

As for the occupancy the variations between the different household sizes are small. Because higher number of active occupants increases the probability for a switch-on event at least the annual demand for 1-resident households is the lowest for both alternatives. But compared to the Xrgia/NVE-data and the UK simulation data in Figure 2.3c the increase in demand for bigger household is underestimated. An higher increase could be forced if using separate calibration factors for each household size.

Simulation with UK occupancy data

Simulation with the UK occupancy data and Norwegian irradiance gives a better R^2-value with the SEA daily profile data than both of the other alternatives with 0.98 for weekday and 0.96 for weekend. Most of the description for (a) and (b) applies to the UK data too. Underestimation of the demand in the night and middle of the day and overestimation in the evening. The morning peak is too late in the weekdays and too early in the weekends. For the monthly demand the R^2-value was higher than for (a) but lower than for (b). The relative change in average annual demand with each household size is almost identical with the Xrgia/NVE data.

6.6.2 Duration and irradiance dependency

In addition to changing the occupancy data an analysis of adjustments with assumed less influence on the output has been carried out. The model with occupancy data (b) have been used as a reference because it had the highest average R^2-value. Each of the changes have been implemented as the only adjustments in the reference model so that the impact can be evaluated isolated. Table 6.3 gives the different adjustments and the corresponding changes in the R^2-value compared to the reference for the daily profile for weekdays and weekends and the monthly demand profile. For most of the adjustments the R^2-value is slightly reduced for all the profiles. How the adjustments are implemented and a further evaluation of how the new output match the SEA data is presented in the following sections. For all alternatives the calibration factor have been adjusted to meet the target of 1000 kWh/yr before simulating 250 households for one year.

Irradiance dependency

The easiest way of adjusting the irradiance dependency is to change the probability for switch-on events when the outdoor irradiance is above the threshold value (alt. A). As described earlier this will have greatest impact on the profile in the middle

Table 6.3: Changes in the R^2-value for the evaluated adjustments compared to the reference for the weekday, weekend and monthly profile.

Alt.	Model	WD	WE	Monthly
	Reference	0,95	0,92	0,93
A	Irradiance P_{min}=30%	1,7 %	0,1 %	-2,0 %
B	Linear irradiance dependency	-0,9 %	-1,1 %	-0,5 %
C	Leave on in 100% of the switch-on events	-20,2 %	-19,2 %	-0,5 %
D	Leave on in 20% of the switch-on events	-3,1 %	-3,6 %	0,1 %
E	Leave on 20% + P_{min}=20%	-1,1 %	-0,6 %	-1,2 %

of the day, especially for summer and shoulder months. When it was changed from 5% to 30% the demand in the midday increased causing a decrease of the evening peak and thus giving a better match with the SEA data for weekdays. For weekends the R^2-value also increased slightly for the same reasons but additionally the already overestimated morning peak also increased giving a worse fit in the morning. The monthly variation were decreased because the demand were made less irradiance dependent. As it was already underestimated the change caused the R^2-value to decrease for this profile.

An other presented way to make the model more dependent on the outdoor irradiance is to decrease the probability gradually with increasing irradiance (alt. B). To implement this Equation (6.2) taken from Widén is used [30]. Originally this is used to calculate the *ideal* power demand for lighting, but it is here used to decide the probability for a switch-on event $P_{switch-on}(t)$. P_{min} is as for Richardson's model 5% and P_{Max} 100%. I_{lim} is set to 1.5 the value of the threshold irradiance. This gives a linear decrease of the probability from zero irradiance to 1.5 of the old threshold value.

$$P_{switch-on}(t) = \begin{cases} P_{Min}\frac{I(t)}{I_{Lim}} + P_{Max}(1 - \frac{I(t)}{I_{Lim}}) & \text{for } I(t) \leq I_{Lim} \\ P_{Min} & \text{for } I(t) > I_{Lim} \end{cases} \tag{6.2}$$

No significant change on the daily profile were detected when implementing this and the R^2-value decreased for all three profiles.

Duration

Because Norwegians do not necessary turn of the lights when leaving a room or even leaving the house a simulation was done where the lights were allowed to stay turned on even if the active occupancy turned to zero. The switch-on event were calculated the same way but the bulb were not turned off before the assigned duration were over and there were active occupants in the house. The lights can not be switched off it there are no one active at home.

Two simulations were done with this feature. One where the lights were turned on for the whole assigned duration for *all* switch-on events (alt. C) and a more realistic one that this was the case in 20% of the switch-on events (alt. D).

The daily profile is straightened out with this adjustment. For C the demand in the night is overestimated and the peak in the evening is reduced to the SEA level but 2-3 hours later. The R^2-value is much lower for the daily profile but the adjustment does not affect the monthly variation.

Alternative D gives a very good match with the SEA data for the night and the match in the middle of the day is also improved from the reference. The evening peak is reduced and delayed but not as much as for C.

As a last alternative the P_{min} adjustment were implemented with alternative D allowing switch-on events in 20% of the time when the outdoor irradiance is above the threshold. This gave a better match in the early evening than for D, but the midday demand increased too much. The R^2-value was improved for the daily profiles, but like alternative A the adjustments gave a further underestimation of the monthly variations.

6.6.3 Comparison

The lighting model seems to give satisfying output with the Norwegian occupancy data. With the UK occupancy data the R^2-values are slightly higher for the daily profiles but the profile does not give as good a match with the weekday morning peak as (b). Increase in annual demand for bigger households are much better with the UK occupancy data but with separate calibration factors this increase could be forced with the Norwegian data too.

The adjustments of duration and irradiance dependency have only minor impact on the output. None of the changes have proven to give a better model output with the available measured data.

Chapter 7

Electrical appliances

The appliance model is the most complex with regard to the amount and variety of input data. Many more assumptions have to be made in making the model so the validation of the output becomes more important as the small errors can build up to great discrepancies when added together.

In the following sections the different aspects of the model are discussed and how they are or can be solved. Finally three different combinations of solutions are simulated and the output presented in the last section.

7.1 Ownership

Both the REMODECE-project and the Xrgia/NVE-survey gives data on ownership of appliances that is needed in the model [22] [10]. Because the data from the REMODECE-project is 3-5 years older and only include about 100 households versus 2000 in the Xrgia/NVE-survey the data from this latest is used. Data from REMODECE is used for fridges and TVs for which different types is not specified by Xrgia/NVE. An overview of the numbers used and what data source it is obtained from is given in Table D.2 in Appendix D.

In this model only the main electrical appliances, the ones listed in the Xrgia/NVE and REMODECE reports are included. If wanting to extend the model with more appliances ownership can be obtained from the Xrgia/NVE survey for most electrical appliances in Norwegian households.

7.2 Energy specific parameters

The required energy specific parameters are listed in Section 2.3. Obtaining correct or representative values for these parameters is challenging among other things because of the diversity of appliances in different household. Measurements could be made on one appliance for every category, but that data might not be representative for all appliances included in that category. The data from the REMODECE-project presented in Section 3.4 is very detailed and could be used to calculate all the needed input parameters listen in Section 2.3. Equations (7.1)-(7.3) shows how mean cycle length and power can be calculated with available figures from REMODECE.

$$t_{yr,on} = 525600 \text{ min/yr} - \frac{e_{yr,sb}}{p_{sb}} \tag{7.1}$$

$$t_{cyc} = \frac{t_{yr,on}}{n_{cyc}} \tag{7.2}$$

$$\bar{P}_{on} = \frac{e_{yr,tot} - e_{yr,sb}}{t_{yr,on}} \tag{7.3}$$

$$\begin{aligned}
t_{yr,on} &= \text{Minutes of the year when the appliance is on,} \\
t_{cyc} &= \text{Cycle length,} \\
n_{cyc} &= \text{Number of cycles per year,} \\
e_{yr,tot} &= \text{Total annual consumption,} \\
e_{yr,sb} &= \text{Annual standby consumption,} \\
p_{sb} &= \text{Standby power,} \\
\bar{P}_{on} &= \text{Mean cycle power,}
\end{aligned}$$

Unfortunately these values are too inaccurate and give unrealistic values. Calculated cycle time is too high; between 3 and 324 hours for all appliances. The mean cycle power is more realistic and is for most appliances lower than the maximum, but it is too low for oven and microwave oven with 53 W and 22 W respectively.

As a starting point when deciding the parameters the data given in the REMODECE report of Grinden and Feilberg was used [6]. For missing data and data that gave unrealistic values from calculations the original UK values were used. This was mainly *mean cycle time* and *delay restart after cycle*. The last one is zero for all appliances except for freezer and refrigerators.

For TV and PC the *cycle length* is derived from the TUD. Also the values for the washing appliances are calculated rather than taken directly from the reports. Both these cases are explained in the next sections.

From the chosen energy parameters the annual energy demand for each appliance were calculated and compared to values from REMODECE. Then the parameters were adjusted to best match the target demand. To the extent possible the parameters are tried kept *between* the different values given in the various sources.

For the cold appliances most of the data is taken from Richardson. By analysing the measurements of cold appliances from ElDeK or REMODECE more representative values for cycles, length and power could be obtained. This could also be done for other appliances.

7.2.1 TV and PC

The cycle time or duration for a TV switch-on event is originally as described in Section 2.3.4 determined from the probability distribution in Equation (2.6). For PC originally the duration is simply chosen as default for all appliances to be a given mean duration (300 minutes), the same for all switch-on events. As the actual diversity of duration of use of computers is as great as for TV the same approach for deciding the duration is used for the Norwegian model.

The probability distribution for duration of both watching TV and use of PC was found from the Norwegian TUD by counting the number of consecutive time steps where the activities are recorded.For TV the activity codes listed in Table D.4 are used while the separate PC specification in the TUD is used for this.

The Norwegian probability curve could have been used directly in the model, but to keep it as simple as possible without losing accuracy Equation (2.6) is used with other values for A and B. The new values are presented in Table 7.1. These values have been found using the Solver-function in Excel to get the highest R^2-value. With the new parameters for TV the R^2-value increases from very poor correlation (0.07) to fairly good (0.97) compared to the real values found from the Norwegian TUD.

Table 7.1: Parameters for the duration distribution equation, Eq. (2.6) and the R^2-value describing the correlation for TV and PC.

Appliance	A	B	R^2
TV	70	1,10	0,07
	107	0,78	0,97
PC	79	0,75	0,98

The TV duration is presented in Figure 7.1 comparing the data from the Norwegian TUD and the original distribution with and without adjusted parameters to match the Norwegian TUD. As can be seen from the figure using the UK data for TV activities the probability would be overestimated for short durations (under 30 minutes) and underestimated for longer duration.

From the distributions the mean cycle time used to calculate the annual demand is determined. This must not be changed in the calibrations to make the annual

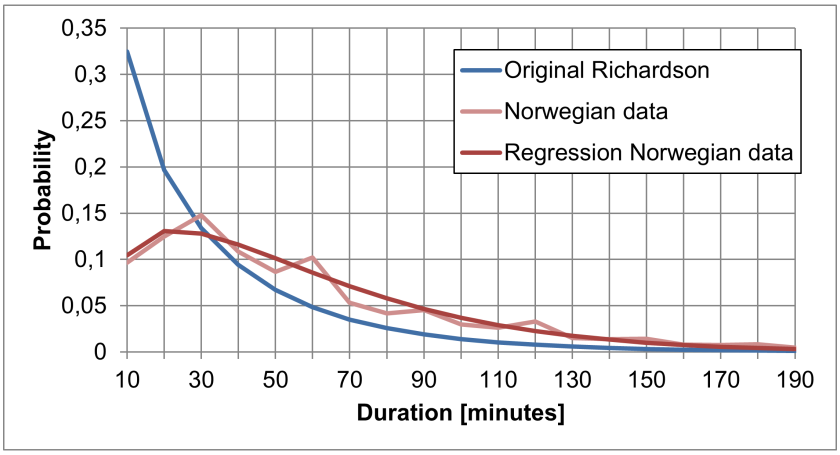


Figure 7.1: Probability distribution for how long a TV is turned on.

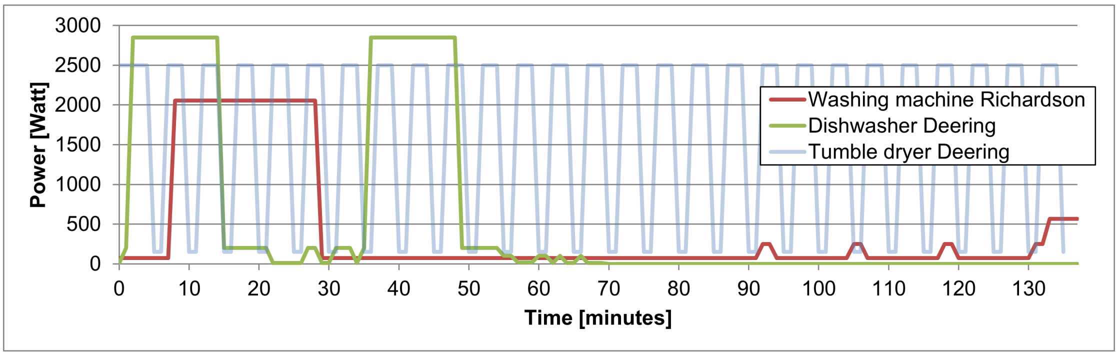


Figure 7.2: Load profile for a cycle for washing machine, dishwasher and tumble dryer.

demand meet the target as it is not used in the simulation and do not have any impact on the output. If the demand does not meet the target some of the other parameters will have to be adjusted instead like cycles per year or power rating.

7.2.2 Dishwasher, washing machine and tumble dryer

For most appliances the energy demand varies a lot during a cycle and a power profile could be included in the model to take this into account. This is most important for the main appliances with long cycle duration and high and variable power demand like dishwasher, washing machine and tumble dryer. Originally a cycle power demand profile for washing machine is included, but profiles for dishwasher and tumble dryer from Deering et al. have been added to the Norwegian model [5]. The three profiles are shown in Figure 7.2.

Similar as for TV and PC the mean cycle length and power rating is determined from these profiles and must not be changed when calibrating the annual demand. For the dishwasher and the washing machine the cycle length used in the simulation is the constant. While for tumble dryer the cycle length is calculated from a normal distribution with a standard deviation of 10% of the mean.

7.3 Annual energy calibration factor

The overall calibration factor can be used to adjust the total annual energy demand to meet a target value by increasing or decreasing the number of appliance cycles per year. The number of cycles is adjusted with the same factor for each appliance. This way the model output can represent the total demand, not only for the appliances included in the simulation. But if the total energy demand target is much higher than the sum of all appliances without calibration, the calibration factor might not be used directly. With a great increase in the number of cycles per year the yearly "on-time" can be longer than one year. If this happens base cycles per year, cycle length and power must be adjusted or additional appliances included to meet the annual target.

In the model of Widén a constant additional energy demand per household member is used to fill the gap between the simulated and target energy demand [31]. This energy demand will then represent all the other appliances in the household not specified in the model. It can be implemented as a constant load dependent or not on the number of residents or active occupants. An advantage with this method is that the simulated profile for the individual appliances will be more representative for that specific appliance category.

For the Norwegian model the target total energy demand caused a calibration factor so high that for several appliances the yearly "on-time" exceeded one year. To solve this the other parameters had to be adjusted so much that they were no longer representative for the category. Two "dummy"-appliances for inactive and active could be added with a energy demand equivalent to the gap between the other appliances and the target. But because of the uncertainties regarding the magnitude and nature of the dummy appliances they were not included in the model. The annual energy demand for them was given but no data were found to decide when the load should be added and if it should depend on household residents, active occupants or none of the two. Adding a constant load for every time step could be done but this does not require a simulation model and can be added manually if necessary for a certain usage of the output.

Additionally no measured daily profiles for the total electricity demand were obtained for use in the validation. With such data the parameters and dependency of the dummy appliances could be determined with a greater chance of being representative.

7.4 Appliance specific calibration factor

The appliance specific calibration factor defined in Equation (2.3) is used to meet the target cycles per year for each appliance. It is originally the same for all simulations and uses the average occupancy and activity probability for all households. For each household the appliances are then calibrated for the same number of cycles per year and thereby the same energy demand. Nevertheless the simulations with the UK data gives an increased demand with increasing household size shown in Figure 2.4a. The reason being that the factor is calculated using the *average* occupancy and activity probability. The active occupant distribution in Figure 2.1b shows that the occupancy for 1-resident household is below the average whereas for the 5-resident household the occupancy is above. Additionally the activity probability is usually increased with increasing number of active occupants. The 5-resident households have a higher probability for higher number of active occupants thus the average activity probability will be higher than for smaller household sizes.

Because of this the number of time steps all the criteria for a switch-on event are met is higher for higher number of residents causing increased number of cycles per year with increasing household size.

The problem with the Norwegian TUD is that the occupancy does not increase with the household size rather the opposite. On the other hand when occupied, the number of active occupants do increase with the household size and might cause an increase in total demand depending on the activity probability.

7.4.1 Differentiated calibration factor

A way to enlarge the difference in energy demand is to make the target cycles per year dependent on the number of residents. The only way the number of cycles is used in the simulation is trough the calibration factor so this will have to be calculated for each household size.

The average number of cycles per year is assumed to be weighted for household strata as shown in Equation (7.4) with the portion values from SSB given in Table 3.2. The relation between the households is calculated as in Equation (7.5) using the energy demand for different appliance groups from Xrgia/NVE. From this the individual cycle target is calculated with Equation (7.6).

$$\bar{n} = \sum_{i=1}^{5} \varphi_i n_i \tag{7.4}$$

$$n_i = \frac{e_i}{e_j} n_j \tag{7.5}$$

$$n_x = \frac{e_x \bar{n}}{\sum_{i=1}^{5} \varphi_i e_i} \tag{7.6}$$

$\bar{n}$ = Average cycles per year,
φ_i = Portion of household size i,
n_i = Cycles per year for household size i,
e_i = Energy demand for household size i for the given activity category

The activity probability have not been calculated individually. Ideally it should be calculated based on the average occupancy state distribution for each time step but for simplicity the average for all 5 states are used as in the original model.

7.5 Activity probability

Activity categories included in the Norwegian model are mainly the same as in Richardson's model. The activities *Audio* and *PC* are added, and *Iron*, *Houseclean* and *WashDress* removed. *Iron* and *Houseclean* is only linked to the two appliances *Iron* and *Vaccum cleaner* respectively which were not included because of lack of Norwegian data. The *WashDress* activity was linked to the *Electrical shower* which were also excluded. Table D.4 shows the included activities with the activity codes and code description from SSB. For the activity *PC* the separate specification in the TUD is used.

Because of the discrepancy between the TUD for UK and Norway the activity probability have to be redefined for the Norwegian model. Three different definitions have been evaluated in this process; "Modified Richardson", "Linear Multiplication" and "Effective occupancy for activity".

7.5.1 Modified Richardson

In modified Richardson the respondent and the number of people together with him is assumed to be the only active occupants in the household. The same assumption made when making the transition matrices for active occupancy. Then what the activity profile actually gives is the probability that a person is engaging in a certain activity given how many he is with. The positive with this method of defining the activity profiles is that no additional data is needed. On the other hand in several cases the results might not be very realistic. The problems are mostly related to the profiles for higher number of active occupants. For many time steps and activities there are few records of higher number of people together and they will therefore have a large impact on the probability. If there are no records with the given number of active occupants in a time step the probability is set to zero. This is the case for 3-5 active occupants for most time steps between 1:00 and 5:00 am. The result is profiles with increasing volatility with increasing number of "active occupants". For the activities *audio*, *laundry* and *dishwash* the probability is zero for more than 20 hours in the weekend and 18 hours on weekdays for the 5 active occupants profile. It is reasonable to assume that the low probability for these activities also is caused by the fact that these are less social activities than e.g. cooking or TV. Doing laundry is mainly a one-person activity. The probability that a person is together with four other persons while doing laundry will in most households be smaller than for the person to do laundry while there are four other occupants active in the household.

7.5.2 Linear multiplication

From the Norwegian TUD the unconditional probability that a person is at home and performing an activity can be found. With linear multiplication every active occupant is treated independently and the probability that someone is performing an activity is thereby multiplied with the number of active occupants. The calculated probability is not allowed to exceed one.

This is a simple method only assuming that the occupants are independent of each other, a valid assumption for some of the activities more than others. Figure 7.3 shows by which factor (later defined as effective occupancy) the average probability in the UK TUD increases with different number of active occupants compared to the probability when only one occupant is active. It is hard to argue how the probability is in reality but comparing to the UK TUD the effective occupancy is lower than the increase in household members for all activities. The probability factor for weekdays is in average 99% (between 21% and 299%) higher with linear mulitiplication compared to the UK effective occupancy.

7.5.3 Effective occupancy for activity

For this method of defining activity probability it is assumed that the probability increases for higher number of active occupants with the same ratio for Norway and the UK. As for the linear multiplication method the activity probability for higher number of active occupants is calculated based on the profile for the lower ones.

Effective occupancy factor

Effective occupancy for activity (EO) as mentioned in the previous section is defined in Equation (7.7). $\bar{P}_{act}(AO = X)$ is the average activity probability from the UK activity probability profiles for the given number of active occupants. The effective occupancy is then the average probability that at least one in the dwelling is engaging in a given activity when the number of active occupants (AO) is X compared to when only one is active. It is defined similar as the effective occupancy for sharing of light in the lighting model by Richardson [19].

$$EO(AO = X) = \frac{\bar{P}_{act}(AO = X)}{\bar{P}_{act}(AO = 1)} \tag{7.7}$$

For *audio* and *PC*, values from the NVE/Xrgia-report of annual energy use for "media players" (mediespillere) and "computer equipment" (datautstyr) for different number of residents have been used [10]. The effective occupancy is then calculated as the relation between the energy demand for household size equal to the number of active occupants and the demand for a one-resident household as shown in Equation (7.8).

$$EO(AO = X) = \frac{E_{Xres}}{E_{1res}} \tag{7.8}$$

The values for effective occupancy for weekday is shown in Figure 7.3. As Richardson does not include the activity *Dishwashing* the values for *Houseclean* have been used for this activity. The effective occupancy factor for *Houseclean* gives a big jump from 4 to 5 active occupants. For *Laundry* and *TV* EO decreases from 4 to 5. This have not been adjusted in any way as it is assumed to give a negligible error as the there are only 5 active occupants in very few of the time steps. Even in for the UK occupancy data in only 3.6% of the time steps the 5-residents households have 5 active occupants.

Base probability

To generate activity profiles with the effective occupancy at least one of the five profiles for every activity must be known. The other profiles are then calculated from this base profile and the relation between the effective occupancy factors. For linear multiplication the base is for one active occupant and it is defined as the total number of records of the activity divided by all records of being at home and not sleeping. The household size and presence of other is not taken into account. Assuming the activity probability increases with number of active occupants this will then give an overestimated probability even for the 1-AO profile used as base. Also the daily variations will be the same for all households and active occupants

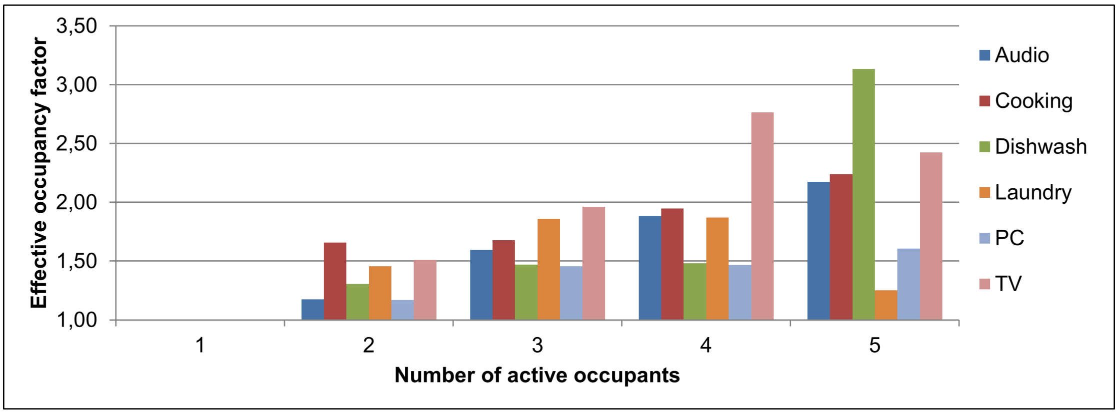


Figure 7.3: Effective occupancy factor for each activity.

although a person living alone might have a whole different schedule than a person in a 5-resident household. To make more representative base probabilities two main assumption are made:

- When being home alone people acts like they are living alone
- The activity pattern is the same for all households with two or more residents.

Based on these two, base profiles have been extracted from the TUD; one for 1 active occupant and another for the other states. The base probabilities are defined in Equations (7.9) and (7.10). For base 1 the first assumption applies and only the 1-resident households with one active occupants are taken into account. The second assumption applies for base 2 so only the 2-residents households are included regardless of number of active occupants. Both bases applies to one active occupant, the first one is used directly for one occupant and the second is multiplied with the effective occupancy for each AO-state 2-5.

$$P_{base1} = \frac{n_{1res}(AO = 1, X = act_i)}{n_{1res}(AO = 1)} \tag{7.9}$$

$$P_{base2} = \frac{n_{2res}(AO \geq 1, X = act_i)}{n_{2res}(AO \geq 1)} \tag{7.10}$$

The advantage with this method is that the profiles are relatively smooth compared to the UK and the modified Richardson profiles. They do not have the many, for most cases, unrealistic peaks or zero-values. On the other hand the need for additional data introduces an extra possible source of error that the data might not be representative for the purpose of this project.

Table 7.2: Overview of the activity probability alternatives presented.

Method		Positive	Negative
A	Modified Richardson	No extra data needed	Limited data for high AO
B	Linear multiplication	Simple	Overestimation
C	Effective occupancy	Avoids peaks	Additional data needed

7.5.4 Comparison

The three different methods of defining activity probability is summarized in Table 7.2. Four activity profiles for *Cooking* weekday is shown in Figure D.1. Figure D.1a shows the activity profile from the UK TUD and the other three shows Norwegian TUD with the different methods presented in the previous sections. To make it easier to compare, the y-axis for *Modified Richardson* and *Effective Occupancy* both goes from 0-0.5.

These profiles are only to some extent representative for the other activities, but in general method B and C have smoother profiles than A. And for A the high AO-profiles more often have the values zero and one. It is not a goal in it self to get profiles that are as smooth as possible, but very volatile profiles and the probabilities one and zero are not very realistic when representing a big population, like a nation. For example with *Modified Richardson*, if there are five people active in the household between 10 and 13 pm on weekdays none of them are cooking.

7.6 Validation data

To evaluate the output from the simulations two data sets is used. For the relation between the annual demand for each household size the data from Xrgia/NVE is used [10]. The values will not be used directly but to find the relative increase in energy demand for increased household sizes.

The other validation data is average hourly profiles for weekdays and weekends for the following appliances:

- Freezer
- Fridge
- PC desktop + laptop
- TV
- Cooker
- Dishwasher
- Dryer
- Washing machine

The data is received from Hanne Sæle working with the ElDeK-project. It gives the average for all measurements in the project. The number of appliances measured for each category is given in Table 3.1.

In the model there are two different fridges, with and without freezer, and there are three different TVs. For these the profile used in the evaluation is the average of all. There are an additional 8 appliances included in the model. These will not be evaluated as no measured data for the given appliance categories have been obtained.

For a further validation more detailed data from the ElDeK-project in addition to REMODECE and SEA data could be used.

7.7 Simulation output analysis

500 households were simulated for one year for three models with different occupancy data and calibration factor. Table 7.3 gives a brief overview of the selected combinations. (a) and (b) uses Norwegian *location specific* occupancy data while Richardson's original transition probability matrices are used in (c). Only for (b) is the appliance specific calibration factor calculated individually for each appliance *and* each household size.

Aside from this all the parameters and the methodology are the same. Only the effective occupancy have been used for the activity probability. Table D.2 shows the values used and which sources they are taken or derived from. The abbreviations for the data sources are explained in Table D.1.

Table 7.3: Overview of the three simulation specifications.

	(a)	(b)	(c)
Occupancy data	NOR	NOR	UK
Appliance specific calibration factor	1-D	2-D	1-D
Activity probability profile	EO	EO	EO

7.7.1 Daily profiles

The daily profiles for the three simulations are very similar. Figure 7.4 shows the profile for (a) with a resolution reduced from 1 minute to 10 minutes to better show the main trends of the profile. The profiles are corrected for household strata with the data form SSB. Compared to the original UK demand profile in Figure 2.4b all simulations underestimate the morning peak for the weekdays and evening peak for the weekends. Even with the UK occupancy data there are no peak in the morning for weekdays. This is a result of a low activity probability in the morning especially for the 1-AO profiles and a lower morning peak for occupancy for 1- and 2-residents households for both UK and Norwegian TUD. Without correction for household strata the morning peak is higher for all simulations.

For (c) the demand increases more rapidly in mornings for weekdays than the two others, like the original profile.

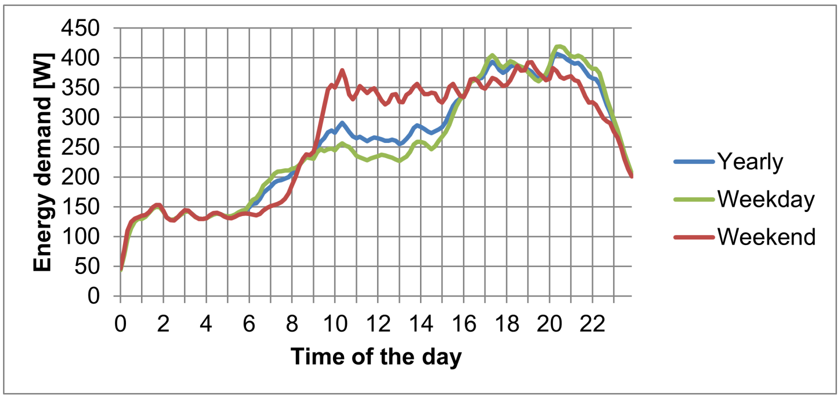


Figure 7.4: Simulated average annual daily energy profile for electrical appliances for alternative (a).

7.7.2 Annual demand

Greater variations were detected for the annual demand shown in Figure E.1. As anticipated based on the occupancy data the demand does not increase with the household size for (a). For the Xrgia/NVE data the demand have a close to linear increase from 1- to 5-resident households with the highest demand being 2.16 times the lowest. Neither (b), (c) nor the original profile increases this much. Highest increase is achieved with (b) with the 5-resident demand 1.78 times the 1-resident demand.

7.7.3 Individual appliance profiles

With the 500 households simulation, the appliance specifications in Table D.2 and the correction for household strata the match with the ElDeK appliance profiles was poor. Generally the modelled profiles were smoother and the demand significantly lower compared to the measured data. The number of units for each appliance category differed between 216 and 868 with an average of 530 whereas the highest number of measured units is 67. Also the measurements were only done for four weeks not one year as was simulated.

The energy demand for the ElDeK data is most likely higher than the average for all Norwegian households. A questioning survey including 23 of the participating households (about 35% of the total) shows they are larger than the average for Norway both in area and number of residents. Additionally 11 of the 23 households have one or more stay at home resident.

To better assess the validity of the model output it was adjusted to be more representative for the households in the measurement campaign, not the whole population. First the simulated profiles were not corrected for household strata, but is simply the average of all five household sizes. As was done for the lighting demand comparison. Secondly the simulated average demand should be based on the same amount of data as the measured. The measured profiles are in average the result of data for 42 units for 4 weeks each, i.e. 167 unit-weeks. Therefore all the appliances were simulated for only 8 months for each household i.e. 174 unit-weeks. Finally the energy specifications were gradually adjusted after multiple simulations to match the demand regardless of other data sources but tried kept within realistic boundaries.

Only model (b) with Norwegian occupancy data and the 2-D calibration factor were adjusted because this alternative gave the best match with the annual energy demand per household size from Xrgia/NVE.

Figures E.2-E.9 shows the daily profiles for all the appliances in the ElDeK data together with the simulated profiles for weekdays and weekends. The modelled data is averaged over hourly intervals to get the same resolution as the ElDeK data. The adjustments made for the appliance specifications are shown in Table D.3. Mainly the number of cycles per year and power rating were changed; increased for *Fridge*, *PC* and *TV*, and decreased for *Tumble dryer*.

The new simulation gave a much better match with the measured profiles specially for the appliances which were adjusted and for *Washing machine*. The most clear discrepancies is an underestimation of the demand in the night for most appliances and more and higher peaks for some of the measured profiles.

7.7.4 Comparison

When looking at the daily profile and the annual demand, using the UK occupancy data does not give a significantly better output. The annual demand variations are bigger without 2-D calibration but still too low compared to the available data and would therefore have to be manipulated in a way anyhow. The low increase can not be cause by the use of Norwegian activity data as the increase in probability for higher number of active occupants is the same as for the UK activity data. Simulations have not been done with the UK activity probability and Norwegian appliance data as some of the activities used are lacking in the UK data.

The individual appliance analysis shows that the methodology and use of TUD seems to give realistic output if the appliance parameters and household distribution for the modelled data is the same as for the measurements, i.e. the same boundary conditions are used.

Chapter 8

Domestic hot water

As mentioned earlier there are two ways of describing the energy demand for use of DHW: The direct hot water draw-off events from taps and showers etc. and the electricity for hot water tanks or other hot-water installations. These two energy demand profiles are linked, but are usually phase shifted with the electricity demand for the storage tank (DESWH) coming after the draw-off event. For zero emission buildings (ZEBs) the first definition is of higher interest as the water heating will be covered by other energy sources than high quality energy like electricity.

8.1 Direct hot water draw-off events

The proposal for a Norwegian model in the project report only handle the first DHW-energy load definition. It is mainly based on the model of Jordan and Vajen with the draw-off load categories implemented the same way as the electrical appliances in Richardson's model. But there is nothing in the proposal that makes this model more representative for Norway than the existing Jordan and Vajen model that is made for Germany.

Data for draw-off events for each load category like litres per minute and incidents per day could be replaced with Norwegian data.Additionally the daily and weekly probability distribution could be replaced with Norwegian data but there are several reasons why the TUD from SSB is unsuitable for this purpose.

First it is the time resolution of the data. With 10 minute time steps the most energy demanding loads like showering and bathing will be recorded but a lot of the short and medium loads like hand wash will not. “Showering” and “taking a bath” are included in activity number “411 - Personal hygiene, getting dressed or undressed” and “240 - Care and assistance to own children”. The problem is that these activity codes are too widely defined.

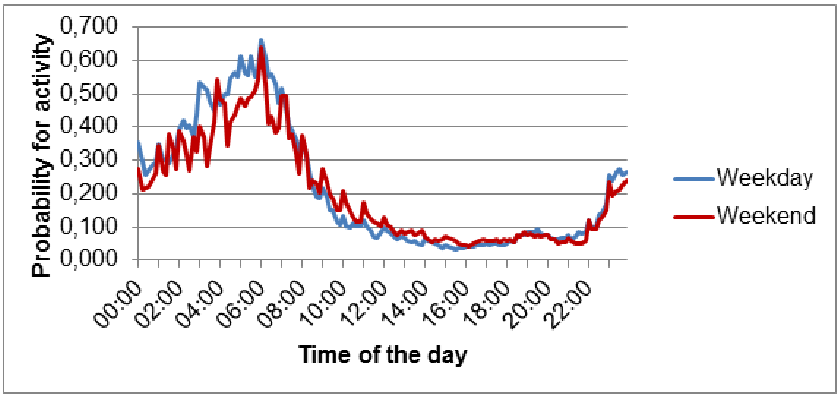


Figure 8.1: Probability for activity number 240 and 411 from SSB TUS.

This can be seen of the probability profile for these activities presented in Figure 8.1. The probability is too high in the night and compared to Jordan and Vajen's profile in Figure 2.5 it is too low in the evening. With access to the diaries written by the respondents in the Norwegian time of use survey a more specific profile could have been extracted for showering and bathing but that is an extensive job and have not been done.

Another solution for a Norwegian model is to use the German model as it is and try to validate it with Norwegian data. The problem with this is the limited Norwegian data. Berge's measured data presented in Section 3.7 for about 6 passive house apartments and one detached house is not representative for all Norwegian households. It could be assumed that Swedish data would be representative for Norway. But the number of Swedish households measured is also limited and if this assumption is made then it would be just as expedient to use the Swedish model from Widén as it is. Widén's model have been made from a more thorough analysis of the Swedish TUD as suggested for the Norwegian in the last paragraph.

8.2 Electrical hot water heater

Of the three DHW-installations included in Richardson's appliance model the domestic electric storage water heater (DESWH) is the most common in Norway. According to the REMODECE project 85 percent of the Norwegian households have this installed [6]. No data is found on the ownership of the two other installation but it is assumed to be very low.

A simulation of a DESWH for one year for each household size is done using Richardson's original data. The output is compared to data from the ElDeK and REMODECE projects. For each of the two the model have been calibrated to meet the same annual energy demand as the measured data; 2674 kWh/yr for ElDek and 3422 kWh/yr for REMODECE. The occupancy data used is the Norwegian location specific. As for the lighting and electrical appliances demand analysis the data have not been corrected for household strata. This is because of the unknown distribution of the measured data and an assumed higher share of bigger households for the measured data.

8.2.1 Comparison with ElDeK

The ElDeK data is an hourly average of 42 DESWH for weekday and weekend. The arithmetic average of the simulation is compared to this data in Figure F.1 in Appendix F.

The diagrams show the daily profile for weekdays, weekends and for one year, that is the average of 261 weekdays and 104 weekend-days. The modelled energy demand is lower in the night and higher in the evening. The best match is for the morning for both weekdays and weekends but morning peak for the weekdays is a little underestimated. For the weekend the morning peak is both higher and earlier for the model.

The R^2-value for the data sets is 0.24, 0.57 and 0.58 for weekday, weekend and the average respectively.

In the simulation the DESWH depend on active occupancy to be switched on, naturally the profiles is closely linked to the occupancy profile shown in Figure B.1b. This explains the low demand in the night and because the total demand is equal to the measured data the profile then have to be higher for other periods of the day.

8.2.2 Comparison with REMODECE

For the yearly average data from the REMODECE project is also used to evaluate the model output [13]. This data is the average of 20 DESWH.The relation between this data and the model output is almost identical as for the ElDeK comparison.The R^2-value is 0.50, slightly lower than for ElDeK.

It is evident that the demand should not only be depending on active occupancy. With more detailed TUD the profiles could be improved by better reflecting the big loads like showering and taking baths. The morning peak for all simulations are earlier in the morning than the measured data. To solve this the demand should be delayed after the DHW activity starts.

Part III

Conclusion and further work

Chapter 9

Further work

For the four presented models several proposals as given for how to improve both the models and the validations with existing data. Access to the data bases for especially the REMODECE and ElDeK projects would give more representative input data and possibilities for more thoroughly analysis of the model output.

For the lighting model data on-duration, relative use weighting and power rating of switch-on events could be derived from REMODECE, ElDeK and SEA data. Additionally a more extensive validation can be done with the measured data from the SEA campaign with the 10 minute resolution rather than the 1 hour average obtained from Widén.

A lot of the appliance specifications is assumed or taken from the original UK data. With more Norwegian data the cycles for the appliances could be analysed and adjusted. The appliance simulation output could also be compared with higher resolution profiles and other methods for evaluating the output as done by Richardson could be conducted [18]. With the data from Xrgia/NVE many more appliances could be included as they have records of both the ownership, use and energy demand for additional appliances than the ones currently included in the model.

When more data is available from the measurements by Magnar Berge these profiles could be compared to the output of the models of Jordan and Vajen and Widén et al. to assess the validity of these models for Norwegian households. Additionally the TUD could be analysed further to extract the activity profiles for DHW draw-off events isolated.

For all the models the occupancy and energy demand seems to be underestimated for the first hours of the day. The reason is probably that the output is actually just multiple 24-hour simulations not connected in any ways. Appliances and bulbs that are turned on at the end of the day does not continue to run for the next day. By connecting each day this discrepancy will most likely decrease.

Chapter 10

Conclusion

A model for generating stochastic and statistical representative user profiles for dwellings in UK by Richardson et al. have been analysed. In the model data from a national time of use survey is used to make profiles for occupancy and energy demand for lighting and electrical appliances. It have been investigated if the model can be applicable for Norway with existing data from various research projects and surveys.

The biggest problem is the discrepancy in the Norwegian and UK TUD.In the UK survey it is used household selection, meaning that all the members of a household participate. For the Norwegian survey, person selection is used. Thus necessary information on the activity and whereabouts of the other household members are limited. As a consequence the TUD have to be manipulated to be used with Richardson's method for generating representative user profiles.

The simulation output with the Norwegian models is compared with various measured data. The analysis shows that despite the discrepancies for the Norwegian TUD the models make a realistic reproduction of electricity demand for lighting and appliances. But presumably more representative profiles will be achieved if a time of use survey were conducted for Norway with a household selection. For simulations with UK occupancy data and Norwegian appliance data the output is a little better for some aspects but gives a worse match with measured data for others. With more access to measured data from REMODECE, ElDeK and SEA further and better adjustments of the models and validations of the output could be preformed.

The occupancy profiles generated with the Norwegian TUD should not be used directly in building simulations. The shape of the daily profile seems realistic compared to the UK profile but it is underestimated for the whole day. Additionally the occupancy decreases with increasing household size opposite of the UK profile and what is intuitively. The UK occupancy data would be better for direct use in building simulation software.

Both the lighting and appliance model output shows a close relation to the measured data. Because the models are calibrated to meet a target annual energy demand the low magnitude of the occupancy profile does not affect the output. The increase in demand for bigger households is underestimated but can be forced by using separate calibration factors for each household size.

No model have been made for domestic hot water draw-off events because too little data was available for both adjusting the model input and validating the output. Without more detailed TUD the existing model of Widén or Jordan and Vajen is recommended to use as is. Electrical demand for water heater have been simulated with Richardson's algorithm but the profiles does not give a good match with the measured data. This could presumably be improved with more detailed TUD.

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Appendix A

Pseudocode for Richardson's algorithm

A.1 Occupancy

```
for Every 10 minute time step 1 to 144 do
    Pcumulative = 0;
    Random = Random number [0, 1⟩;
    for Each occupancy state 0 to 6 do
        Pcumulative = Pcumulative + Probability for state;
        if Random < Pcumulative then
            Occupancy(t) = state;
            exit for;
        end
    end
end
```

Algorithm 1: Generating occupancy profile for 24 hours with 10-minutes resolution.

A.2 Energy demand for lighting

```
Run the occupancy model;
Get a random irradiance threshold from N(60,10);
Get a random set of bulbs and power rating;
Assign a random bulb use weighting to each bulb with -ln(Random number);
for Each bulb do
    while Minutes ≤ 1440 do
        if (Irradiance < Irradiance Threshold) or (Random number < 0.05) then
            Switch-on event can occur;
            Probability for switch-on = Effective occupancy * Relative use weighting * Calibration factor;
            if Random number < Probability for switch-on then
                There is a switch on-event;
                Get a random duration;
                while Minutes ≤ 1440 and Active occupants > 0 do
                    Add the bulb power rating to the total demand for that minute;
                end
            end
        end
    end
end
```

Algorithm 2: Generating energy demand profile for lighting for 24 hours with 1-minute resolution.

A.3 Energy demand for appliances

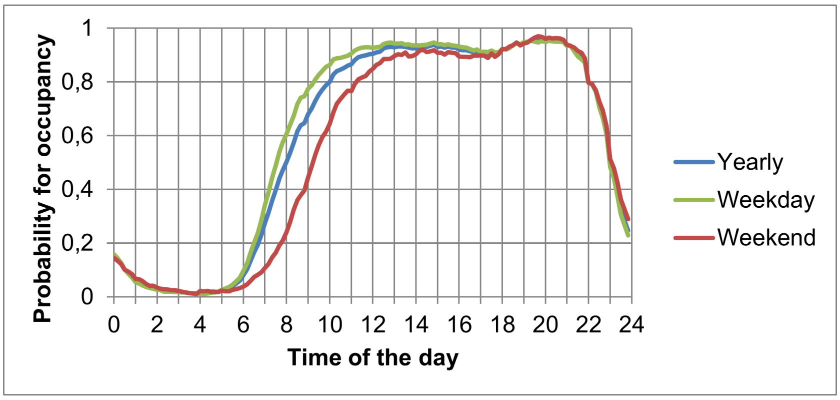
```
Run the occupancy model;
Randomly assign appliances to the household based on ownership;
for Each appliance do
    while Minutes ≤ 1440 do
        if The appliance is off then
            if There is a restart delay then
                Decrement the restart delay counter;
            else
                Probability for switch-on = Calibration factor * Activity
                probability;
                if Rand<Probability for switch-on then
                    There is a switch-on event;
                    Get the duration;
                end
            end
        else
            The appliance is running;
            if The appliance is active occupancy dependent and active
            occupants = 0 then
                Pause the appliance;
                Power demand = standby power;
            else
                Get the power demand for this time step of the cycle from
                a profile or from N(P_mean, P_mean/10);
            end
        end
        Add the power demand for the appliance to the total demand for
        that time step;
    end
end
```

Algorithm 3: Generating energy demand profile for appliances for 24 hours with 1-minute resolution.

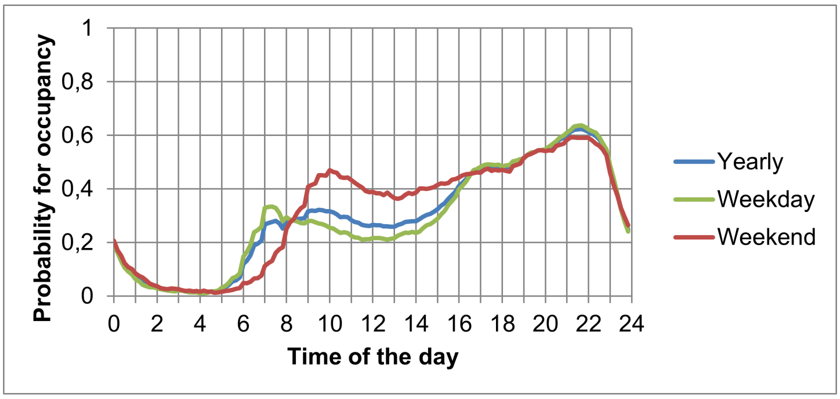
Appendix B

Occupancy simulations

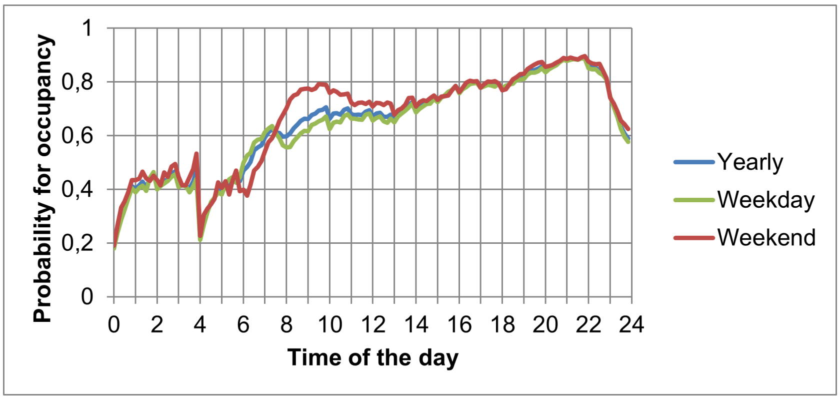
B.1 Daily profiles



(a) Activity specific



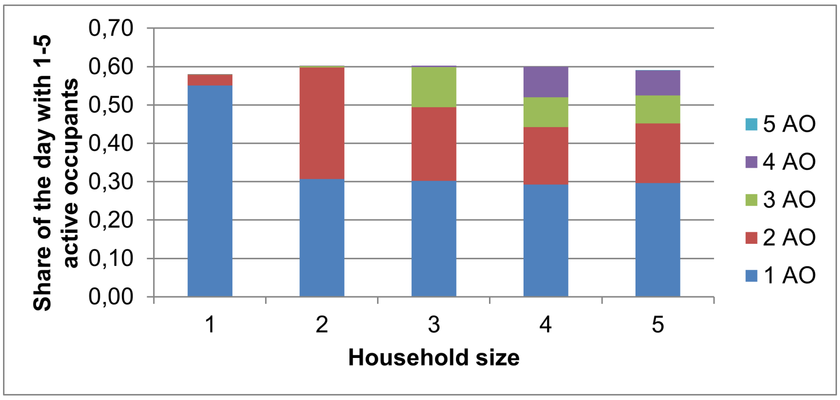
(b) Location specific



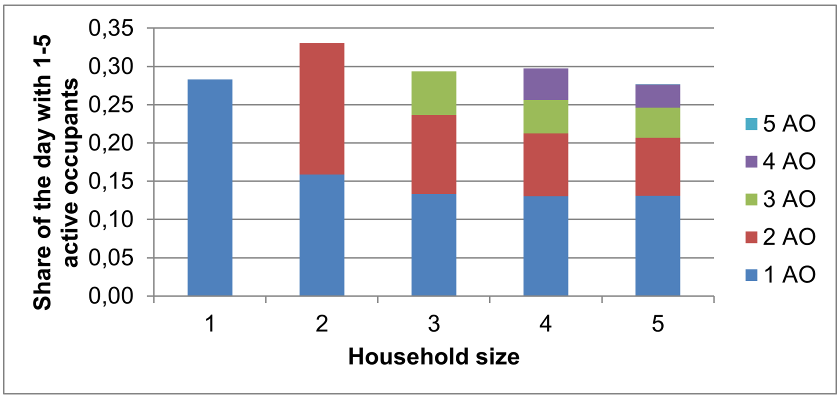
(c) Location specific with increased occupancy

Figure B.1: Daily probability that the household has one or more AO. Corrected for household strata.

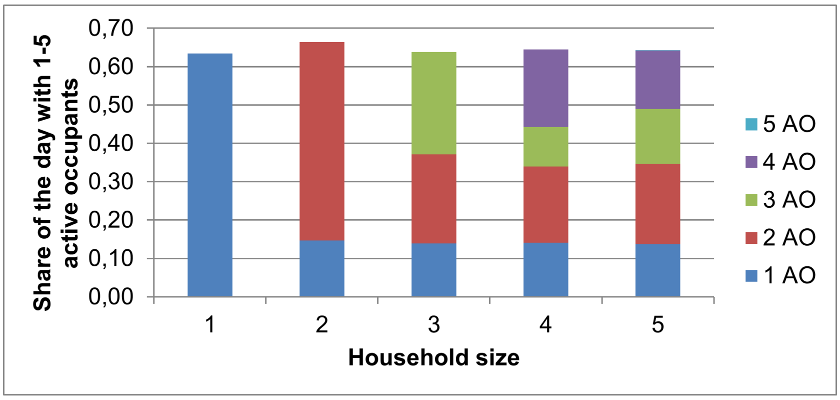
B.2 Active occupancy distribution



(a) Activity specific



(b) Location specific



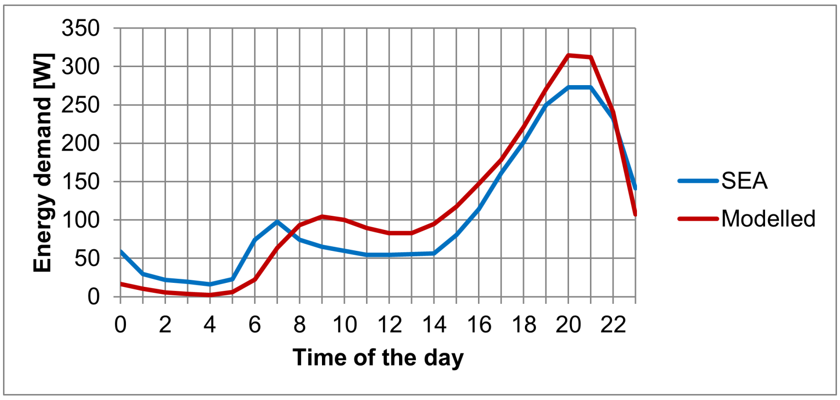
(c) Location specific with increased occupancy

Figure B.2: Active occupancy distribution for each household size for the 3 alternatives.

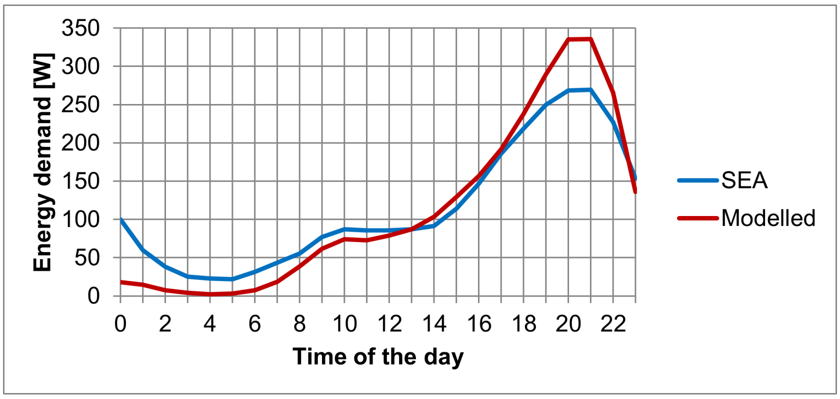
Appendix C

Lighting simulations

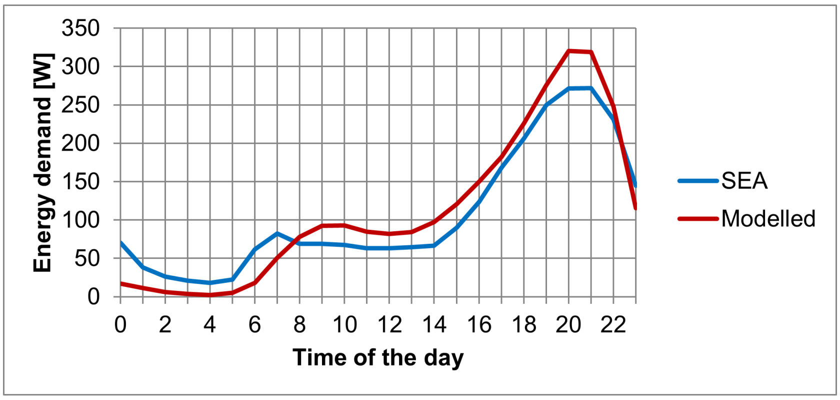
C.1 Daily profiles



(a) Weekday

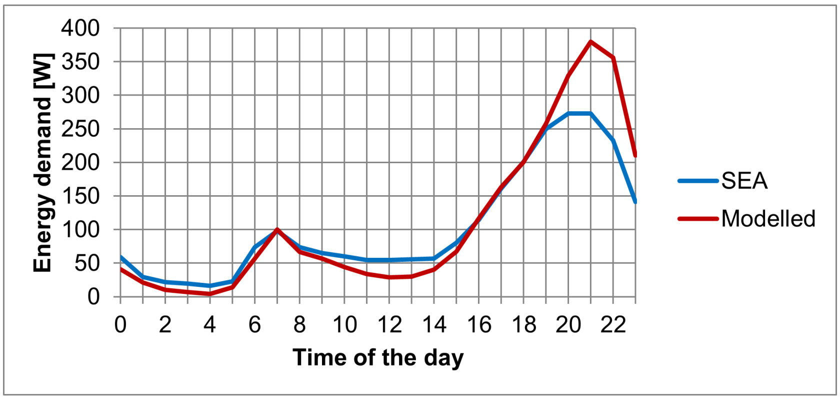


(b) Weekend

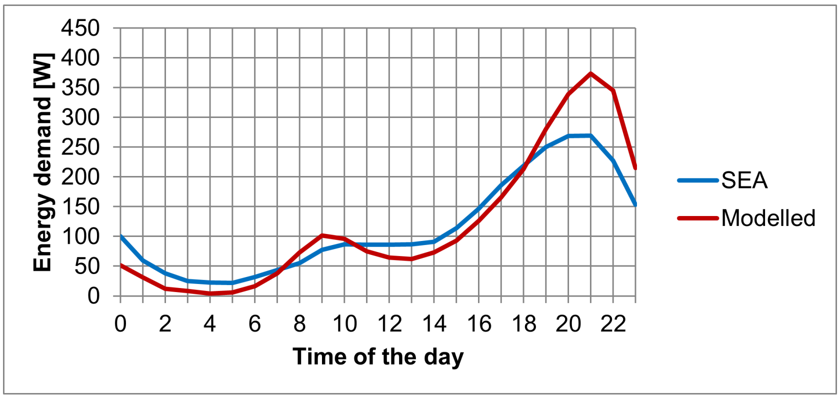


(c) Average for one year (261 weekdays and 104 weekend-days)

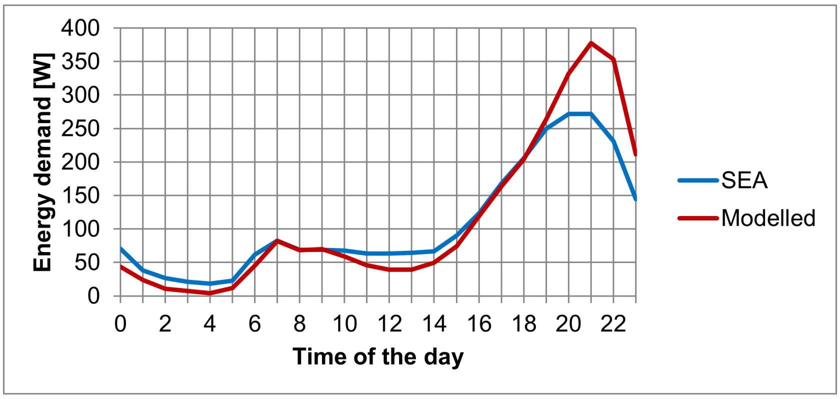
Figure C.1: Hourly average energy demand for lighting with the *activity specific*-occupancy data.



(a) Weekday



(b) Weekend



(c) Average for one year (261 weekdays and 104 weekend-days)

Figure C.2: Hourly average energy demand for lighting with the *location specific*-occupancy data.

C.2 Monthly demand

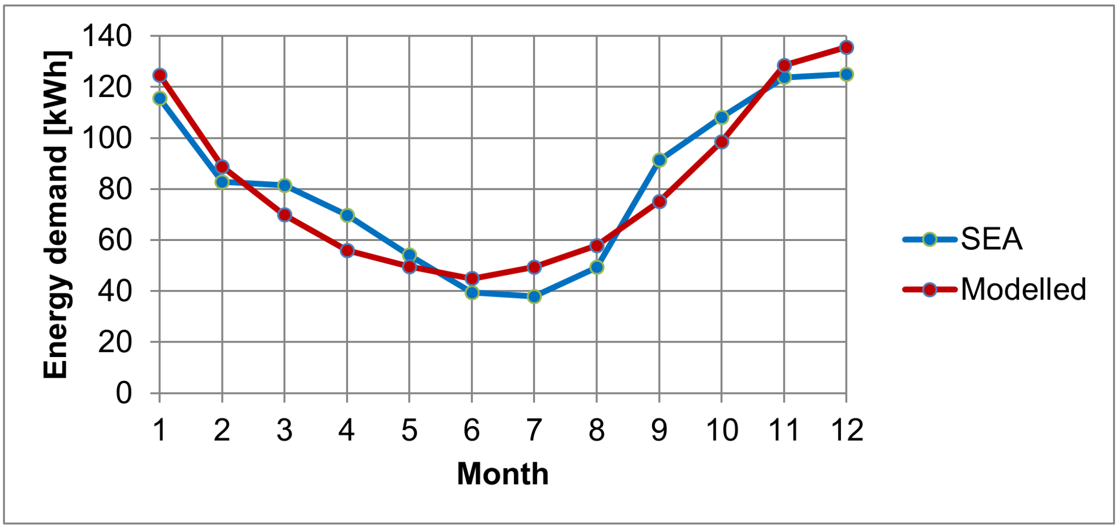


Figure C.3: Average energy demand for lighting for each month of the year with the *activity specific*-occupancy data.

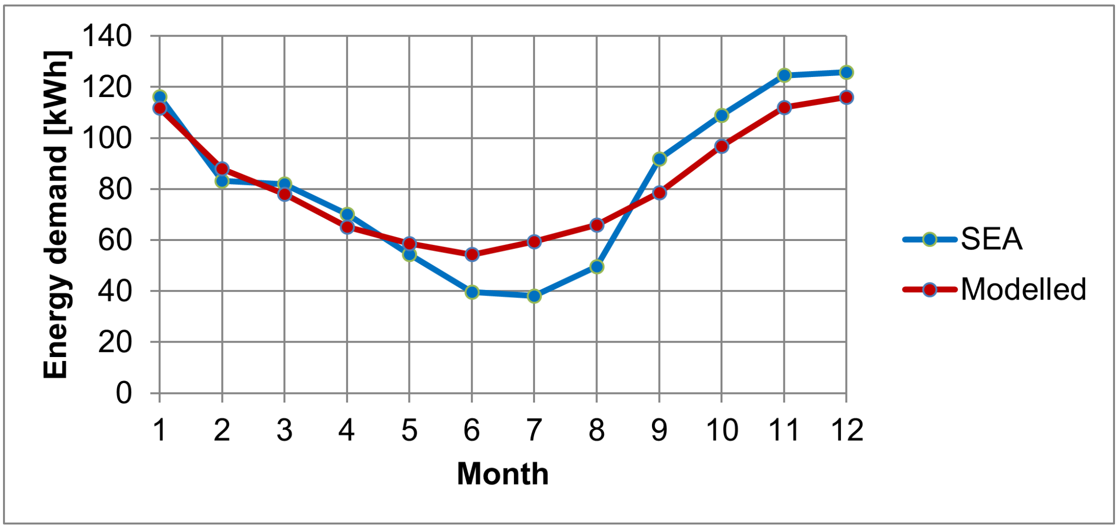


Figure C.4: Average energy demand for lighting for each month of the year with the *location specific*-occupancy data.

C.3 Annual demand

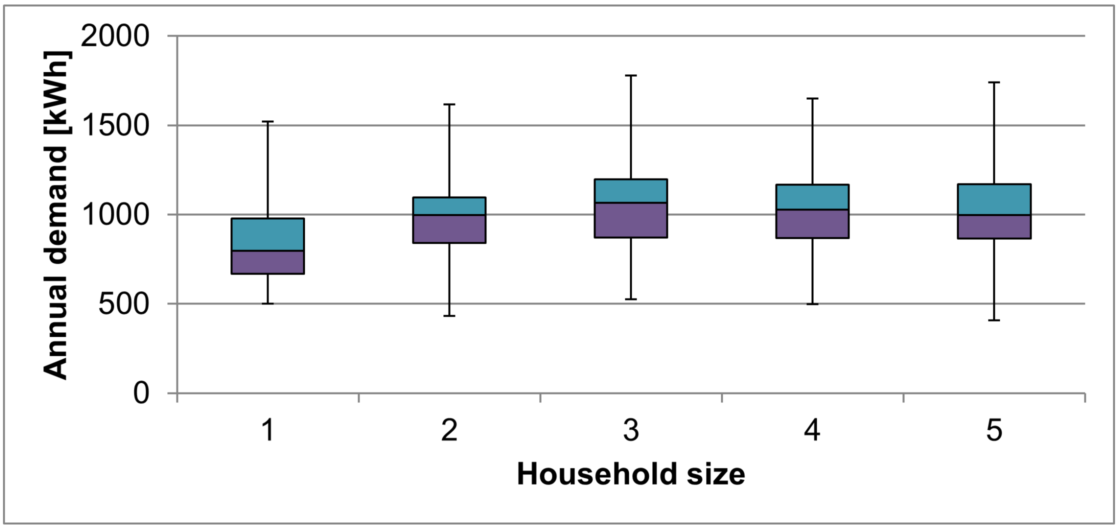


Figure C.5: Annual energy demand for lighting for each household size with the *activity specific*-occupancy data.

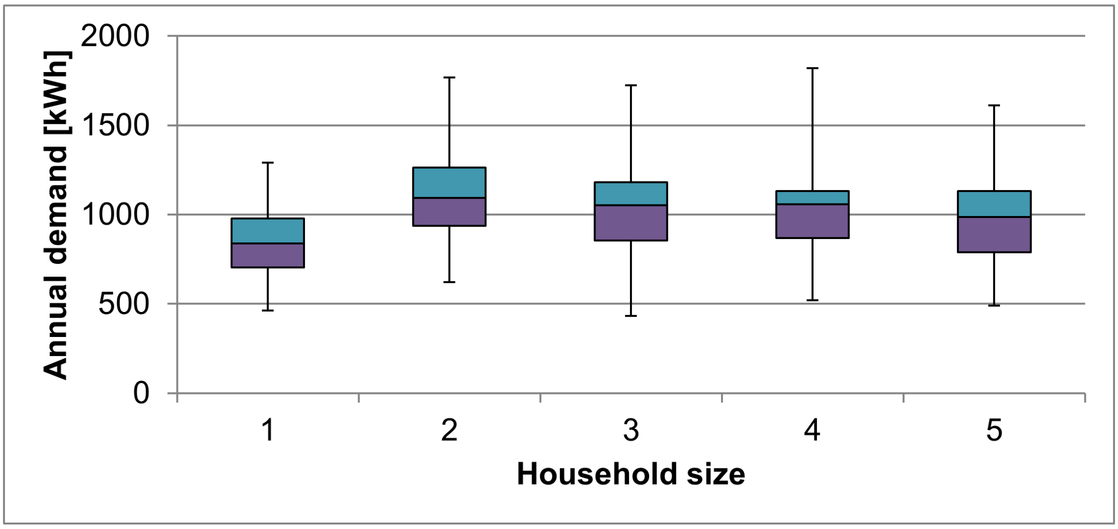


Figure C.6: Annual energy demand for lighting for each household size with the *location specific*-occupancy data.

Appendix D

Appliances

D.1 Data used and sources

Table D.1: Codes used in Table D.2 for the data source for each parameter.

Code	Source
X	Xrgia/NVE [10]
R	REMODECE [6]
UK	Richardsons original data [18]
TUD	Time of use data from SSB [23]
E	Eldek [21]
D	Deering et al. [5]
A	Assumed value

Table D.2: Ownership and energy specific parameters used in the electrical appliance simulations and the sources used for each value.

Appliance type	Ownership		Cycles/yr [-]		Mean cycle length [min]		Mean cycle power [W]		Standby power [W]		Delay restart after cycle [min]		Target annual energy demand kWh		Actual energy demand kWh	
Chest freezer	0,78	X	6116	UK	14	UK	350	A	0	UK	56	UK	631	R	499	-21 %
Fridge w/feezer	0,66	R	6116	UK	22	UK	190	UK	0	UK	44	UK	374	R	426	14 %
Fridge wo/feezer	0,52	R	6116	UK	18	UK	167	A	0	UK	36	UK	307	R	306	0 %
Wireless access point	0,75	X	1000	A	80	A	8	A/R	4	A/R	0	UK	74	R	40	-45 %
Router for Internet	0,79	X	1000	A	80	A	8	A/R	4	A/R	0	UK	51	R	40	-21 %
Hi-Fi	0,60	X	122	R	70	A/UK	42	R	11	R	0	UK	103	R	101	-2 %
Laptop	0,90	X	440	R	41	TUD	141	UK	2	R	0	UK	87	R	59	-32 %
Desktop PC	0,62	X	440	R	41	TUD	141	UK	3	R	0	UK	220	R	68	-69 %
Printer	0,23	X	26	R	4	UK	335	UK	4	UK	0	UK	26	R	36	37 %
TV 1 (CRT)	0,70	R	854	R	57	TUD	124	UK	1	R	0	UK	172	R	109	-37 %
TV 2 (LCD)	0,50	R	854	R	57	TUD	154	R	3	R	0	UK	223	R	149	-33 %
TV 3 (Plasma)	0,50	R	854	R	57	TUD	280	R	2	R	0	UK	325	R	243	-25 %
DVD	0,76	X	31	R	90	A	34	UK	3	R	0	UK	21	R	28	32 %
TV Receiver box	0,79	X	800	A	100	A	30	UK	7	R	0	UK	84	R	92	10 %
Cooker	0,98	X	473	R	27	UK	1400	A	1	R	0	UK	280	R	307	9 %
Microwave	0,77	X	95	UK	7	A	1324	R	2	R	0	UK	30	R	32	9 %
Kettle	0,82	X	343	R	3	A	1857	R	0	R	0	UK	24	R	32	31 %
Dish washer	0,86	X	174	R	60	D	1131	D	1	R	0	UK	206	R	205	0 %
Tumble dryer	0,45	X	174	R	70	D	1200	D	3	A/E	0	UK	267	R	269	1 %
Washing machine	0,97	X	270	R	138	UK	406	UK	1	R	0	UK	207	R	260	26 %

Table D.3: Adjustments of the appliances specifications to increase the match with the ElDeK data. Difference in percentage of the original value.

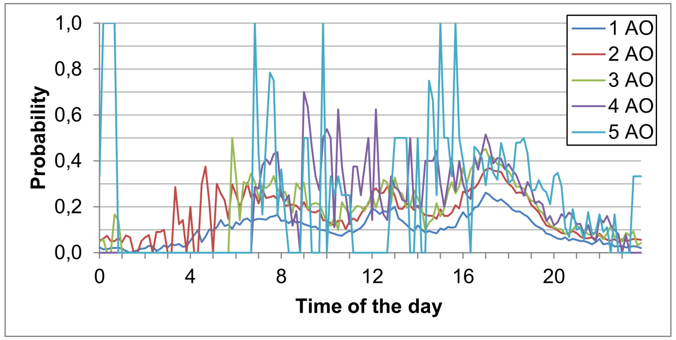
Appliance type	Cycles/yr	Cycle length	Cycle power
Fridge w/feezer	-	-	5 %
Fridge wo/feezer	40 %	-	8 %
Laptop	170 %	-	100 %
Desktop PC	170 %	-	100 %
TV 1 (CRT)	50 %	-	70 %
TV 2 (LCD)	50 %	-	70 %
TV 3 (Plasma)	50 %	-	70 %
Tumble dryer	-50 %	-25 %	-

D.2 Activities and activity codes

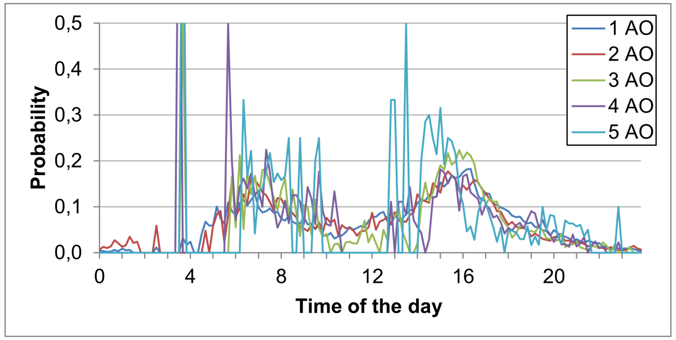
Table D.4: Activity categories and the included activity codes from SSB [8].

Activity category	Code	Description
Audio	566	Listening to radio
	567	Listening to records/CD
Cooking	211	Cooking, making the table, serving food
	212	Baking
	219	House production of berries, fruits and vegetables
Dishwashing	213	Dishwashing, cleaning of tables
Laundry	215	Doing laundry
TV	568	Watching television
	569	Watching video, DVD or recorded material

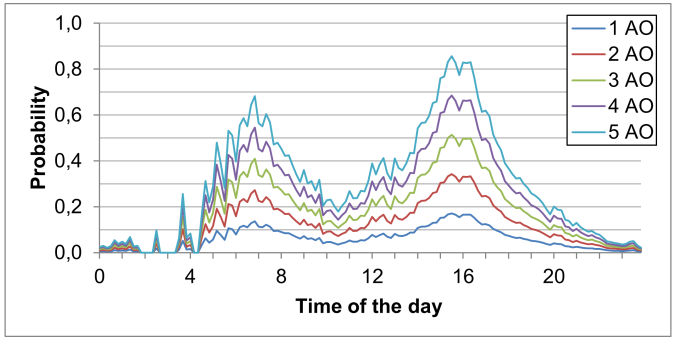
D.3 Activity probability profiles



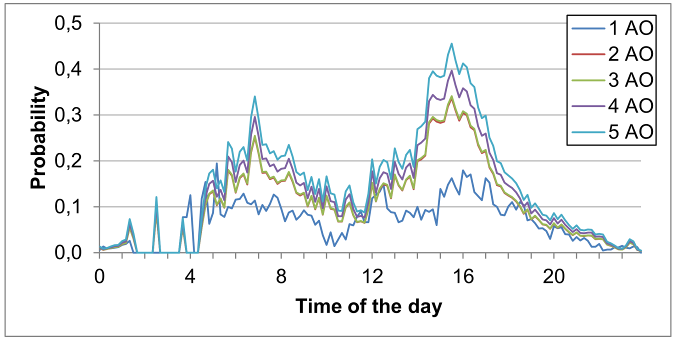
(a) UK TUD



(b) Modified Richardson



(c) Linear multiplication



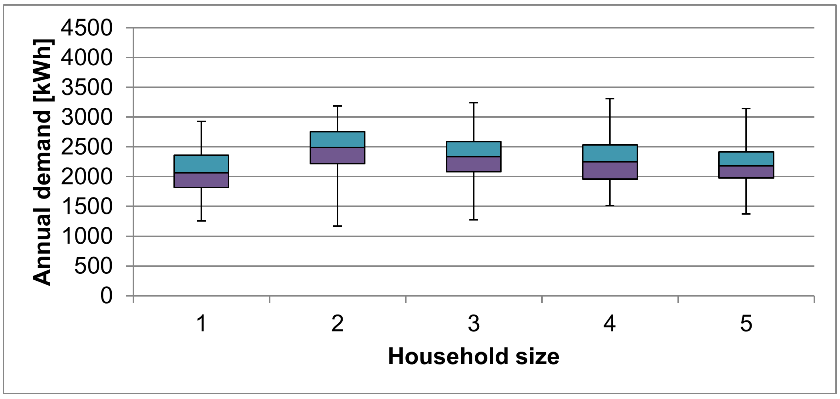
(d) Effective occupancy

Figure D.1: Activity probability profiles for *Cooking* for weekdays for different sources and methods.

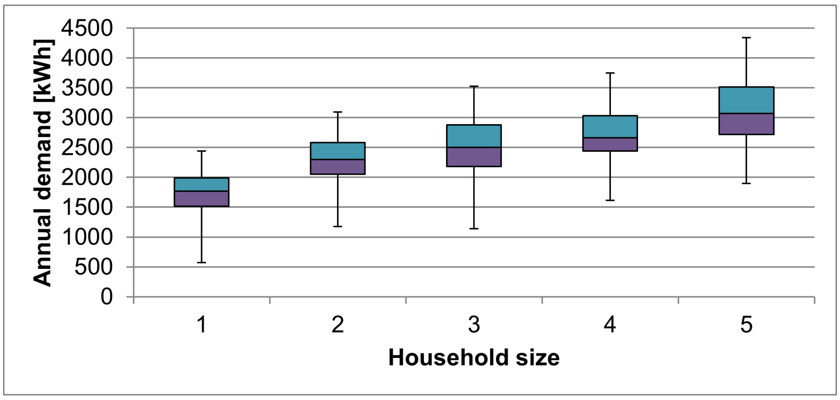
Appendix E

Appliances simulations

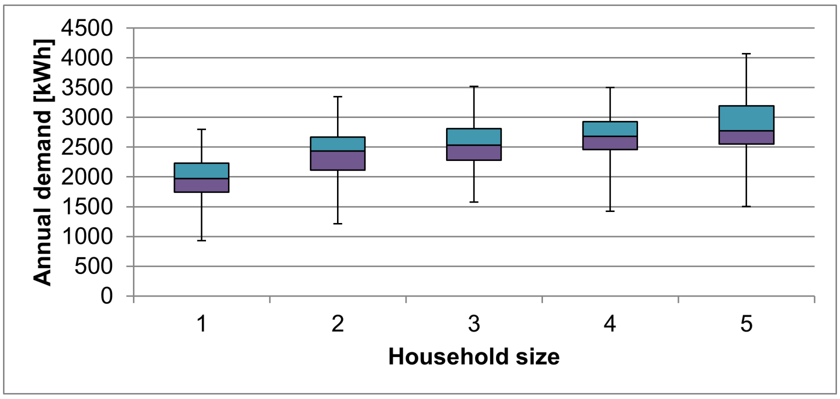
E.1 Annual demand



(a) Norwegian occupancy data and 1D-calibration factor



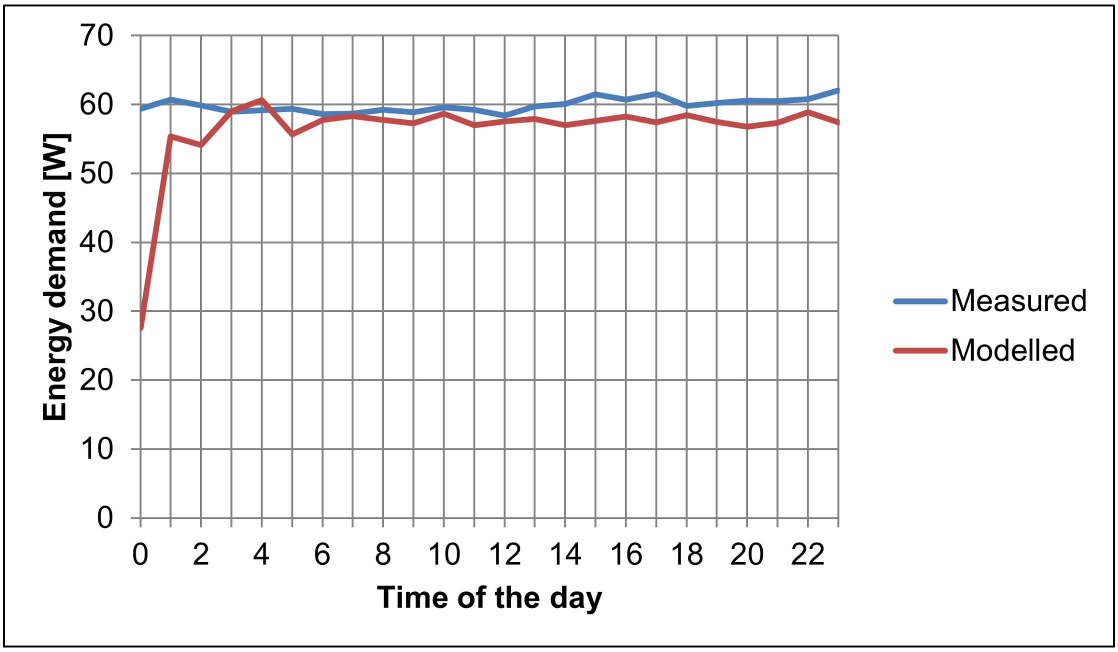
(b) Norwegian occupancy data and 2D-calibration factor



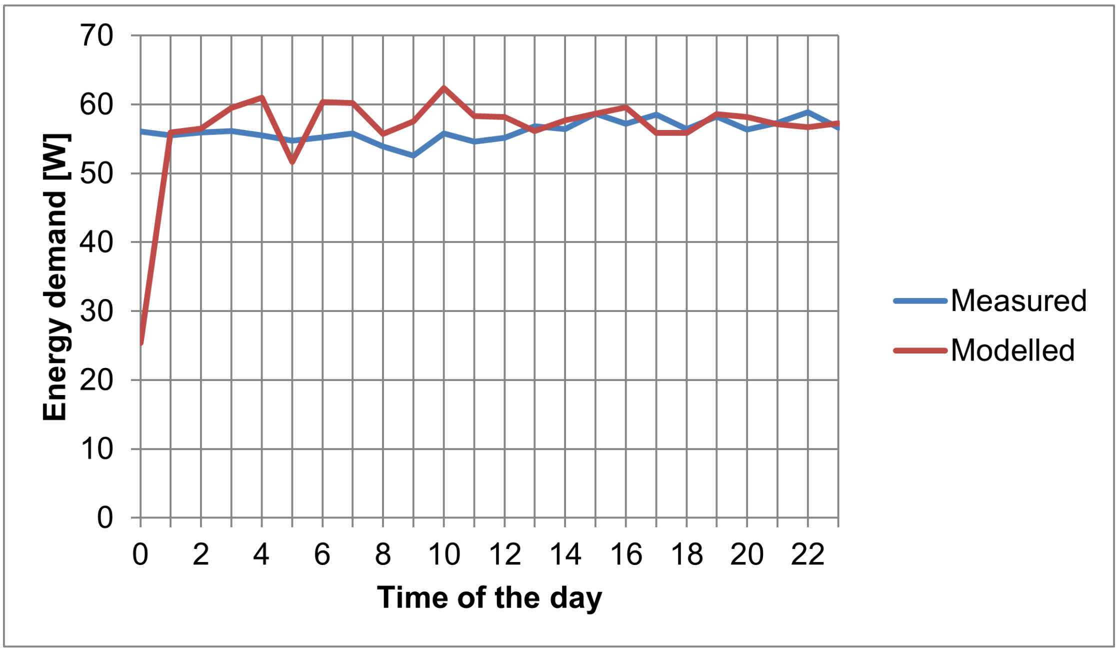
(c) UK occupancy data and 1D-calibration factor

Figure E.1: Simulated annual energy demand for appliances for each household size.

E.2 Daily profiles for individual appliances

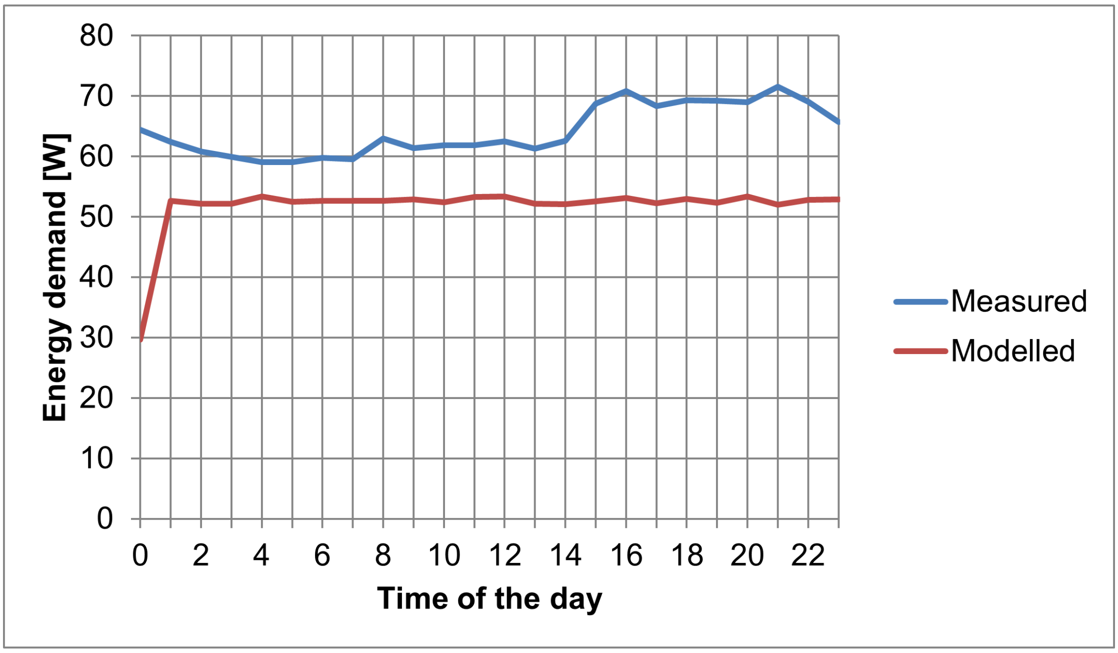


(a) Weekday

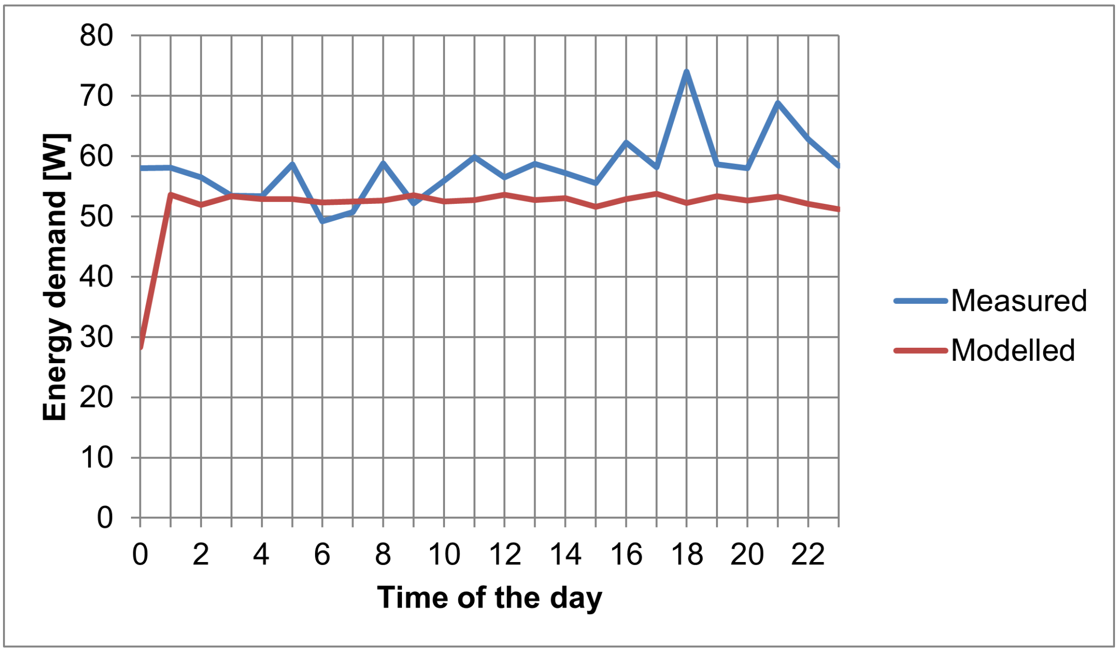


(b) Weekend

Figure E.2: Average daily profile for freezer. Comparison of model output and measured data from ElDeK.

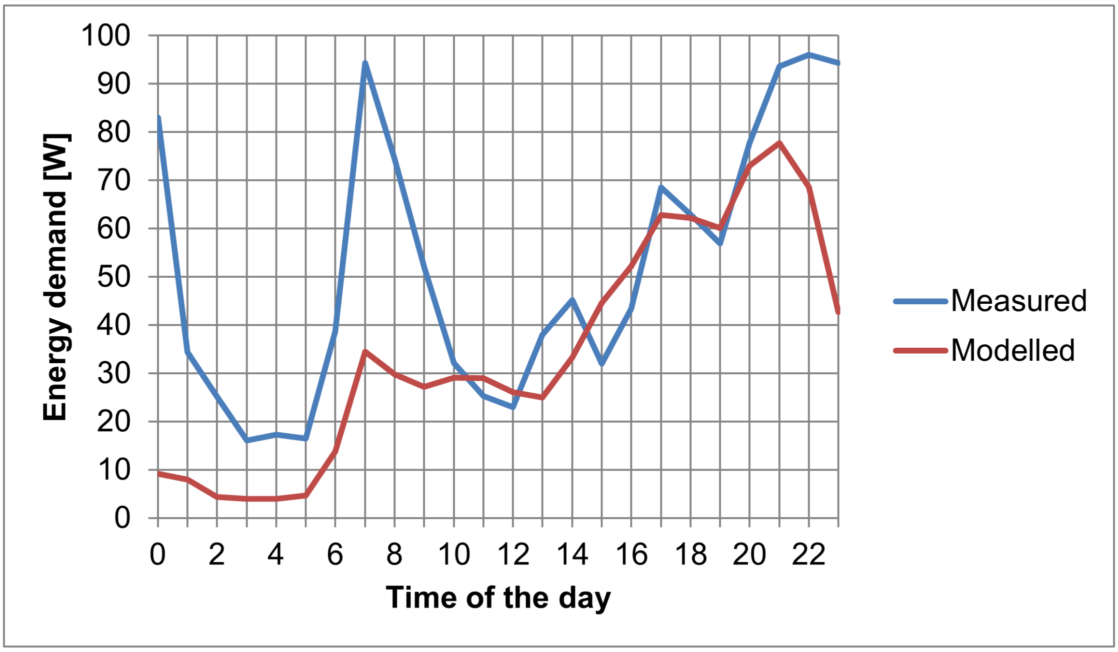


(a) Weekday

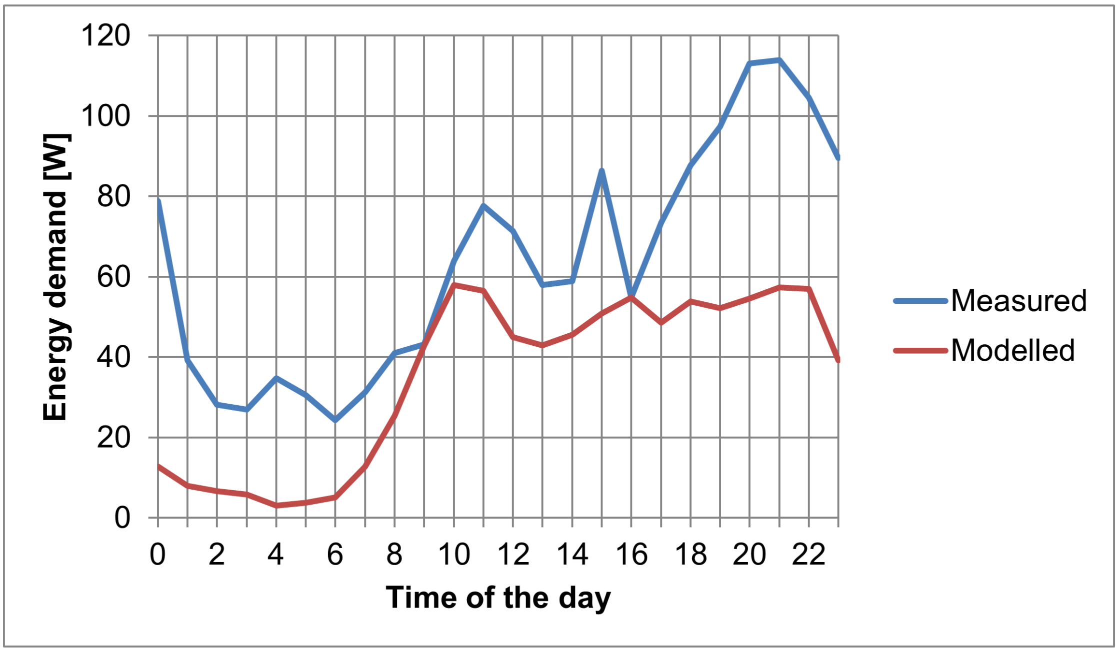


(b) Weekend

Figure E.3: Average daily profile for fridge. Comparison of model output and measured data from ElDeK.

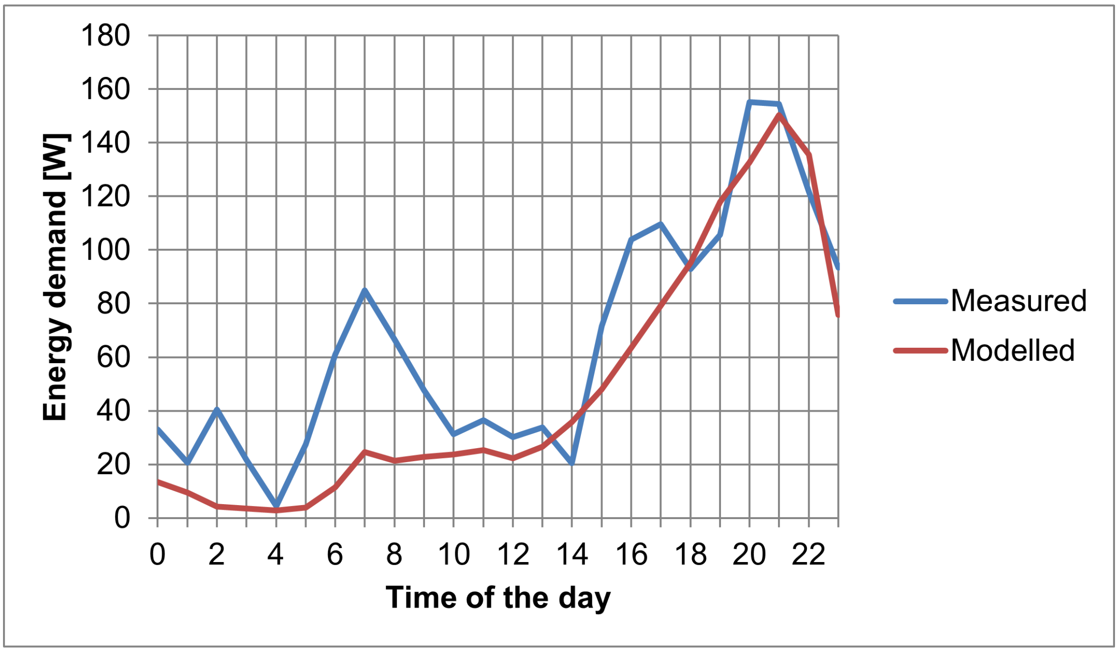


(a) Weekday

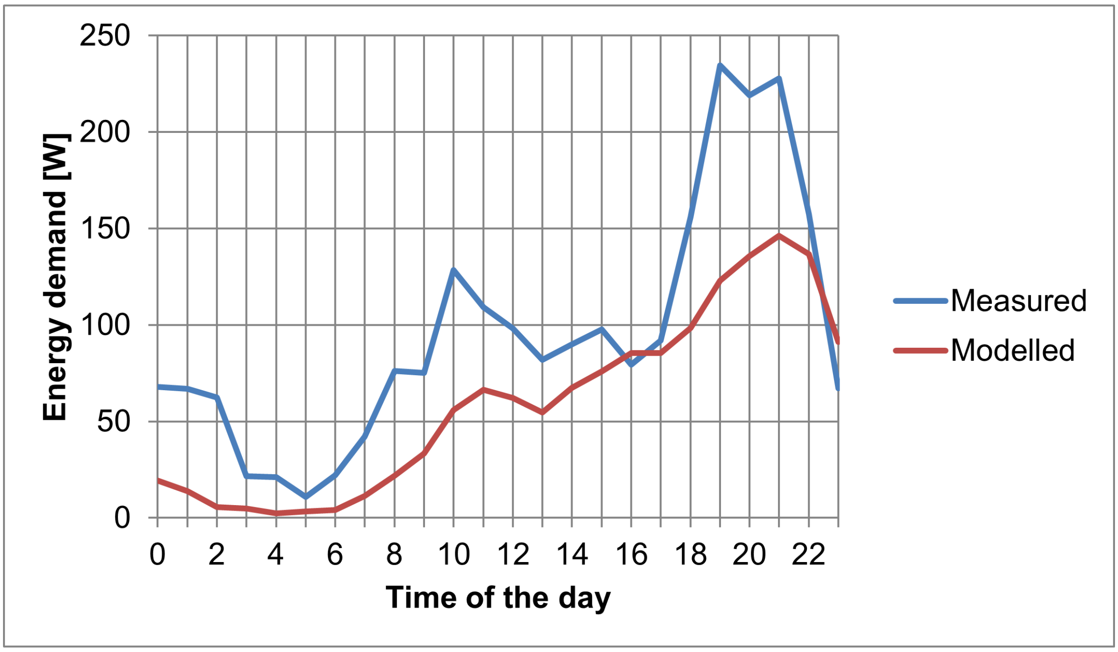


(b) Weekend

Figure E.4: Average daily profile for PC. Comparison of model output and measured data from ElDeK.

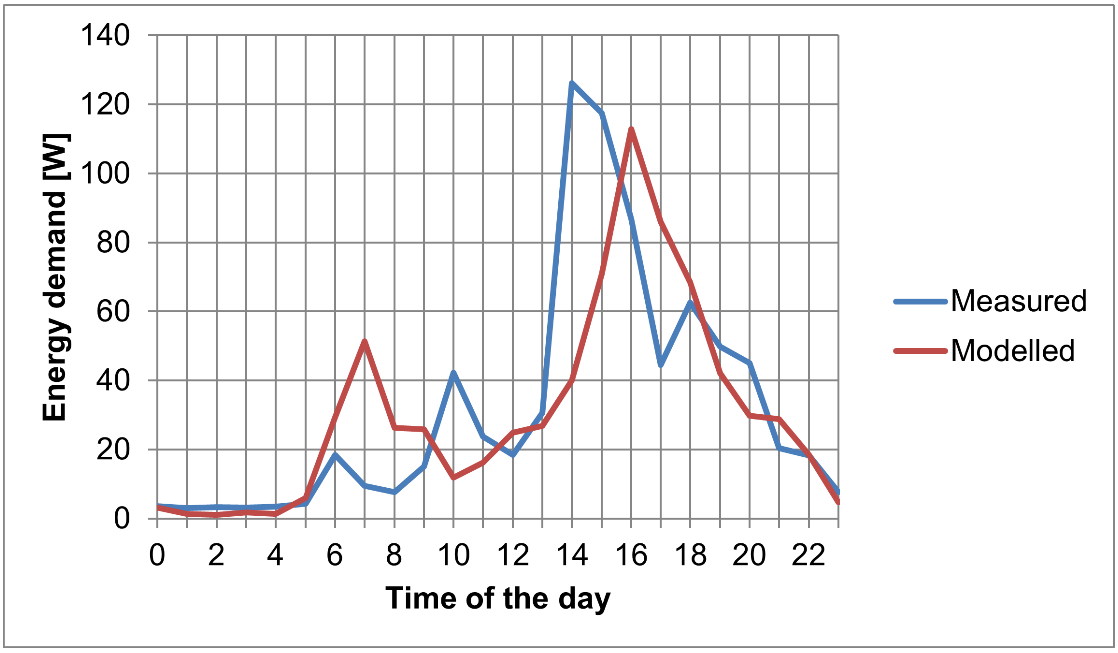


(a) Weekday

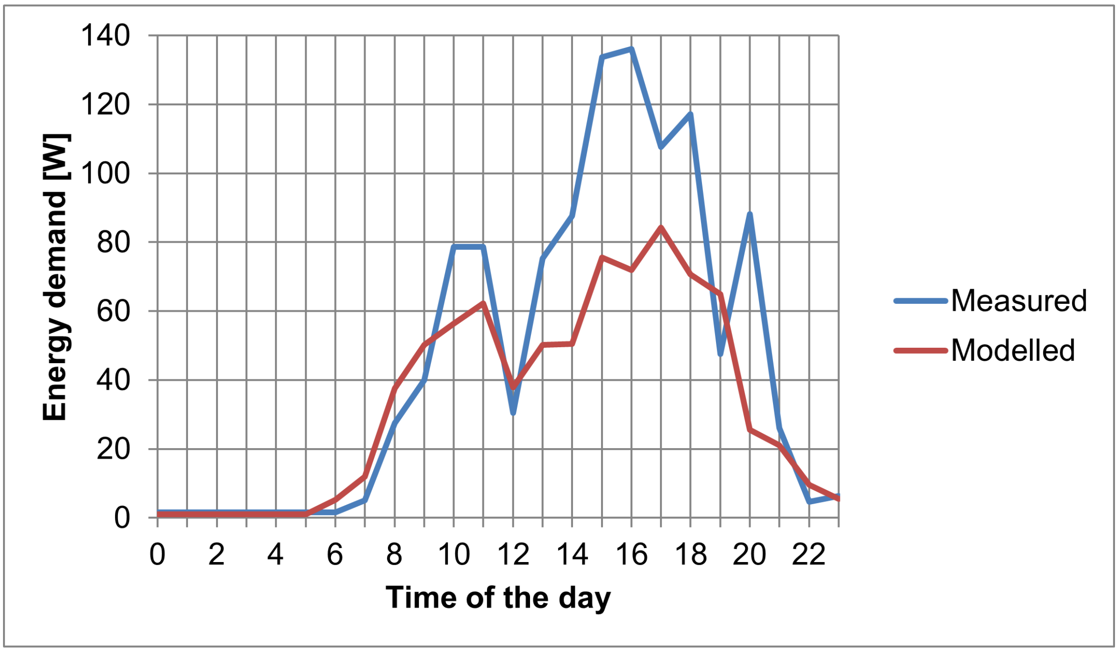


(b) Weekend

Figure E.5: Average daily profile for TV. Comparison of model output and measured data from ElDeK.

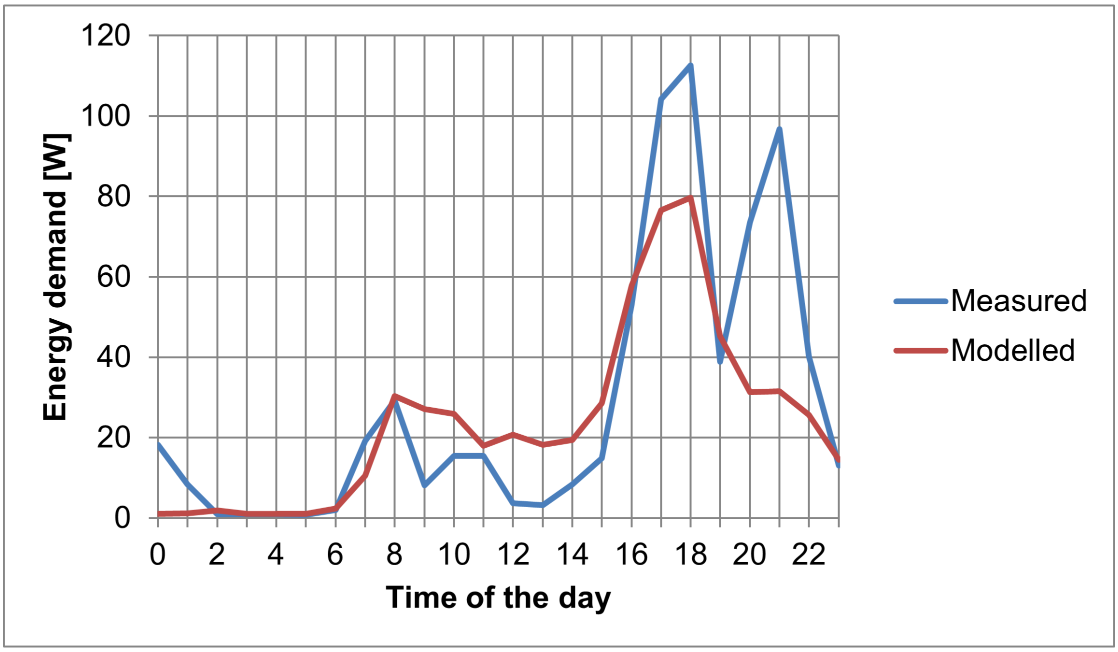


(a) Weekday

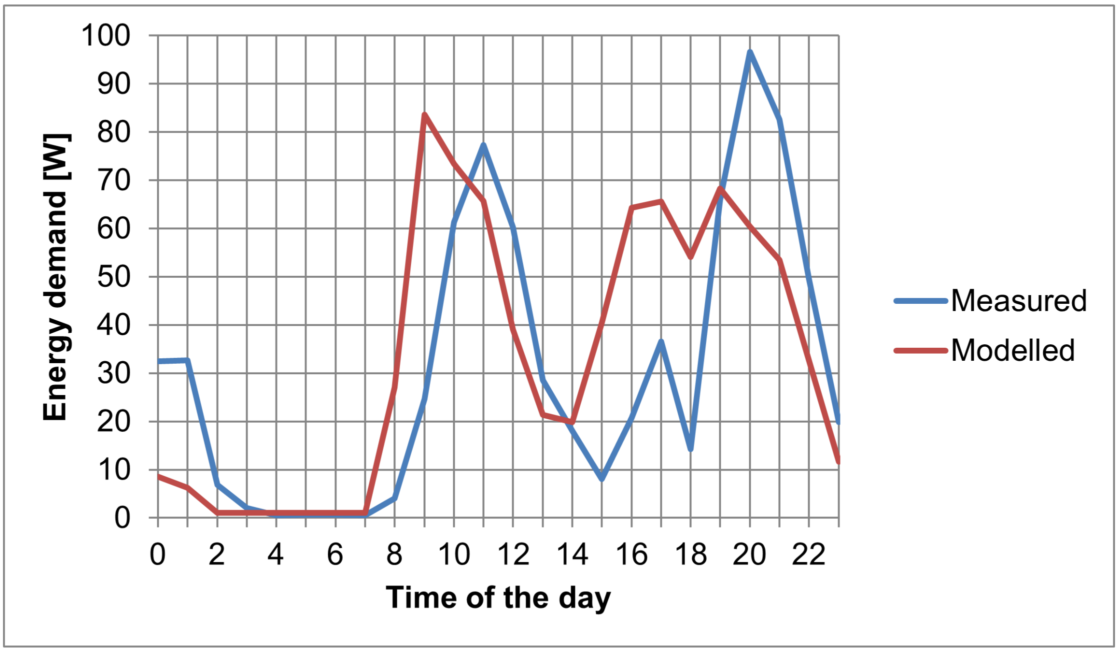


(b) Weekend

Figure E.6: Average daily profile for cooker. Comparison of model output and measured data from ElDeK.

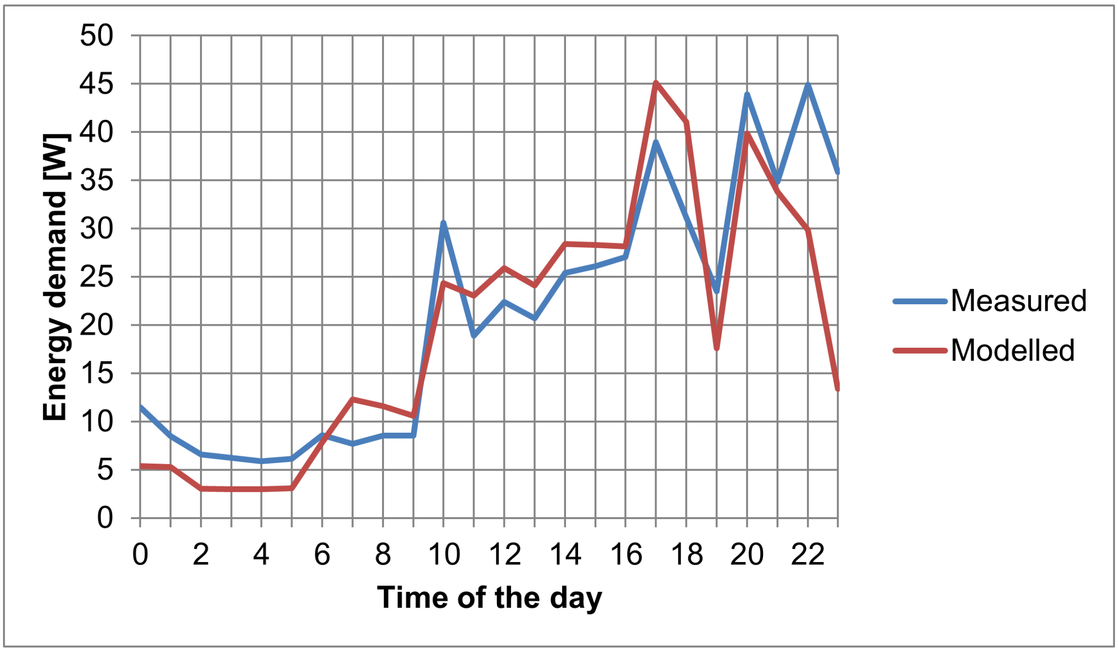


(a) Weekday

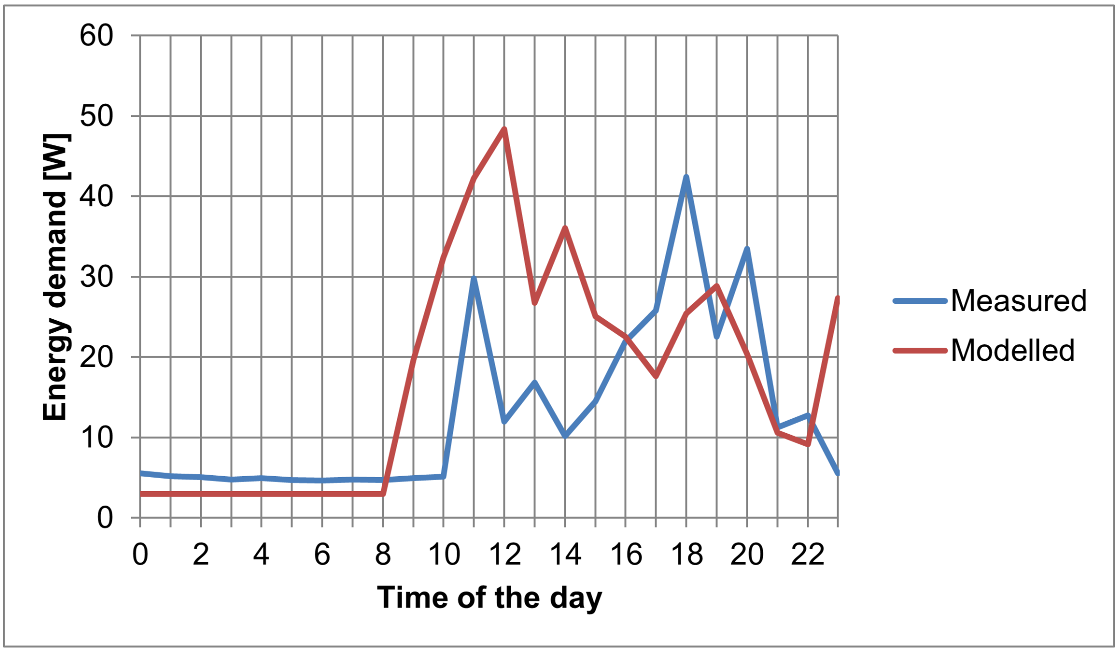


(b) Weekend

Figure E.7: Average daily profile for dishwasher. Comparison of model output and measured data from ElDeK.

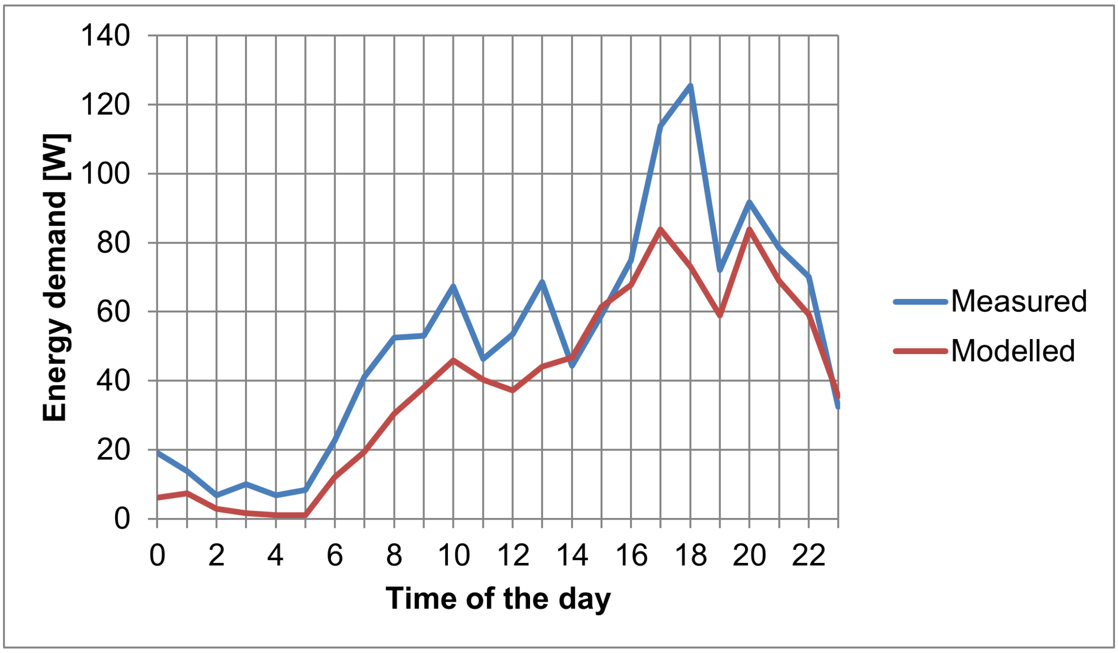


(a) Weekday

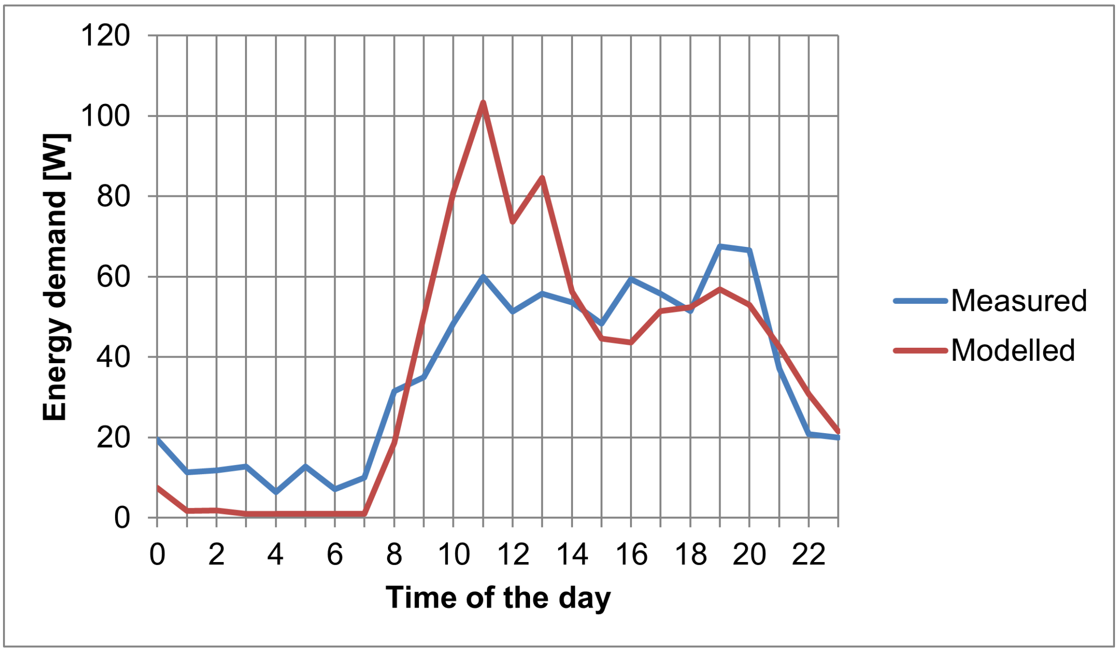


(b) Weekend

Figure E.8: Average daily profile for dryer. Comparison of model output and measured data from ElDeK.



(a) Weekday



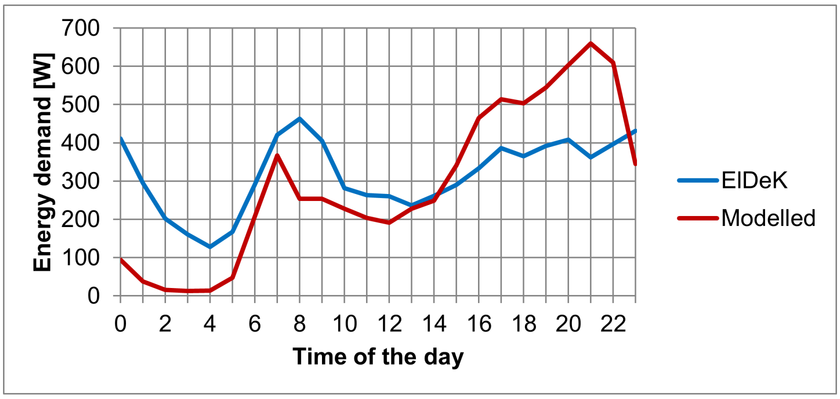
(b) Weekend

Figure E.9: Average daily profile for washing machine. Comparison of model output and measured data from ElDeK.

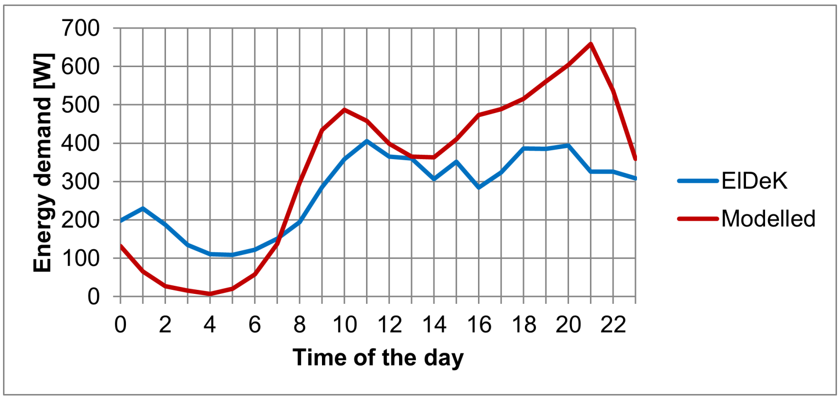
Appendix F

DHW simulations

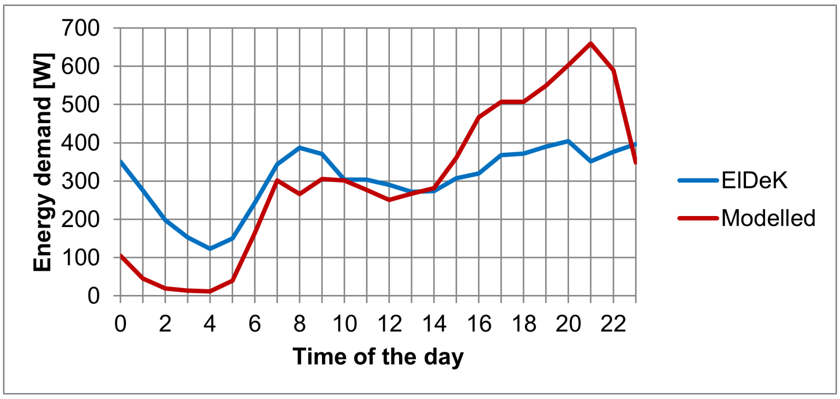
F.1 Daily profiles



(a) Weekday



(b) Weekend



(c) Average for one year (261 weekdays and 104 weekend-days)

Figure F.1: Hourly average energy demand for electrical hot water tank.