Czech Technical University in Prague
Faculty of Electrical Engineering

BACHELOR THESIS

Design of Algorithms for Electric Water Heater State Estimation

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Czech Technical University in Prague
Faculty of Electrical Engineering

Department of Cybernetics

BACHELOR PROJECT ASSIGNMENT

Student: Martin H u b í k

Study programme: Cybernetics and Robotics

Specialisation: Robotics

Title of Bachelor Project: Design of Algorithms for Electric Water Heater State Estimation

Guidelines:

1. Study principle of operation of electric water heater (EWH).
2. Design and implement model of EWH in Simulink environment.
3. Design and test algorithm for EWH state (amount of warm water) estimation based on power consumption measuring.
4. Test impact of measuring granularity on estimation quality.
5. Propose methods for algorithm recovery after loss of measured data.

Bibliography/Sources: Will be provided by the supervisor.

Bachelor Project Supervisor: Ing. Ondřej Novák

Valid until: the end of the winter semester of academic year 2013/2014

prof. Ing. Vladimír Mařík, DrSc.
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L.S.

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Dean

Prague, January 10, 2013

České vysoké učení technické v Praze
Fakulta elektrotechnická

Katedra kybernetiky

ZADÁNÍ BAKALÁŘSKÉ PRÁCE

Student: Martin Hubík

Studijní program: Kybernetika a robotika (bakalářský)

Obor: Robotika

Název tématu: Návrh algoritmů pro odhad stavu zásobníkových ohřívačů vody

Pokyny pro vypracování:

1. Seznamte se s principem funkce elektrického zásobníkového ohřívače vody (bojler).
2. Navrhněte a implementujte model elektrického bojleru v prostředí Simulink.
3. Navrhněte a otestujte algoritmus pro odhad stavu (množství teplé vody) bojleru na základě měření příkonu.
4. Otestujte vliv granularity měření příkonu na kvalitu odhadu.
5. Navrhněte způsob zotavení algoritmu po výpadku měření.

Seznam odborné literatury: Dodá vedoucí práce.

Vedoucí bakalářské práce: Ing. Ondřej Novák

Platnost zadání: do konce zimního semestru 2013/2014

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děkan

V Praze dne 10. 1. 2013

Prohlášení autora práce

Prohlašuji, že jsem předloženou práci vypracoval samostatně a že jsem uvedl veškeré použité informační zdroje v souladu s Metodickým pokynem o dodržování etických principů při přípravě vysokoškolských závěrečných prací.

V Praze dne

19.5.2013

Podpis autora práce

Declaration of Authorship

I declare that I worked out the presented thesis independently and I quoted all used sources of information in accord with Methodical instructions about ethical principles for writing academic thesis.

Location, Date

Prague, 19.5.2013

Signature

Acknowledgement

This bachelor thesis was made under the sincere guidance of Ing. Ondřej Malík and Ing. Ondřej Novák. I would like to thank them, my parents and my cousin Sandra for helping me in this project. Without their help I wouldn't be able to make it. Thank you once again.

Abstract

The main goal of this thesis is to present a method of approximation of the amount of hot water stored in domestic water storage heaters based on analyzing information from electricity meters. Only the heaters that are powered electrically and are controlled by remote control signal provided by electricity distributor are considered. Results from simulations show that the value of the real amount of hot water lies within the interval (-72, 72) [l] around the current estimate with the probability 0.95. This result was obtained from empirical distribution of an error of the estimate. Deviations from the actual value are predominantly due to the stochastic nature of hot water consumption in dwellings. The process used to develop the estimate incorporates following steps. We need to find out at which phase the heater is connected and what nominal power input it has. We need to detect periods when the heater is on. By knowing the above information, we can approximate the average hot water consumption over a desired period. We then take typical daily hot water consumption as a function of time and adjust it with respect to approximated overall consumption. By knowing at which period the heater is on and how much hot water is being used at a particular time, we can approximate how much water is left in the tank, which is the desired result.

Abstrakt

Cílem této práce je navrhnout algoritmy pro odhad množství teplé vody uložené v zásobnících bojleru na základě analyzování informací z elektroměru. V úvahu se berou pouze ty bojlery, které jsou řízeny signálem hromadného dálkového ovládání. Výsledky simulací ukazují, že hodnota skutečného množství teplé vody leží v interevalu (-72, 72) [l] okolo okamžitého odhadu s pravděpodobností 0.95. Tento výsledek byl obdržen z empirického rozdělení chyby odhadu. Odchylky od skutečné hodnoty jsou převážně způsobeny stochastickým charakterem spotřeby teplé vody v domácnostech. Vytvoření odhadu množství teplé vody v zásobníku lze rozdělit do následujících úkolů. Potřebujeme zjistit, na jaké fázi je bojler připojen a jaký je jeho nominální příkon. Identifikujeme intervaly, v kterých je bojler zapnutý. S touto znalostí můžeme aproximovat průměrnou spotřebu teplé vody za požadované období. Následně naškálujeme typický denní průběh spotřeby teplé vody s ohledem na celkovou denní spotřebu. Se znalostí, v kterých okamžicích je bojler zapnutý a kolik vody se ze zásobníku odebírá v daný čas, můžem aproximovat, kolik vody v zásobníku zbývá.

Contents

Introduction

In order to maintain balance between supply and load, which is necessary for stability of the electrical grid, several approaches have been developed to control the load. This paper focuses on domestic power demand control and the use of water storage heaters in particular. Domestic demand was responsible for 20% [1] of total electricity demand in the Czech republic in 2011, therefore plays an important role in consideration of power plant economic efficiency, sizing of the electrical grid and stability of supply. One of the aims of load management is to reduce the peak of the loading curve which varies substantially over each day.

With the increasing number of renewable energy sources, new challenges arise. The electrical grid was designed for decades to distribute power from large power plants through a hierarchically built network to the end-users. However, photovoltaic sources and wind generators can be placed at lower levels of the electrical grid.. Transformers which step down a transmission level voltage to a distribution level voltage are designed to operate in one way mode. The energy can be transfered in the opposite direction only with large heat losses. For that reason, the requirement for energy to be used in near surroundings of these producers exists.

At present the most common method of demand side management is ripple control. Certain appliances such as water storage heaters can be partially controlled by remote control signal (RCS) which is superimposed onto the standard 50 Hz of the main power signal. The receiver in a dwelling triggers a switch that enables power to flow into the appliance. In the case of a heater, the RCS enables the thermostat to take charge of the decision, whether to switch the heater on. If the RCS is at logic level "0", the heater is always off. Distribution companies transmit codes relevant to certain group of appliances. Each group has its own subset of codes but the receiver is programmed to respond to only one of them. Distribution of receivers among customers is done according to the distribution company's needs. The advantage for end-users is that it generates savings because the consumed energy is billed differently. By this process, electricity distributors can balance the consumption thus to optimize power generation, reduce the need to invest in infrastructure and as a result cut down expenses.

A new possibility of demand side management arises from the planned massive spread of intelligent electric meters (smart meters). These devices can communicate with the the central node in a two way fashion using radio frequency or powerline communication based systems. The algorithm in the smart meter can reveal the patterns of use and current state of certain appliances. This information together with weather forecast, requirements from the industrial sector, temporary shutdowns of power plants, etc. can

then be gathered at central node of the communication network. Appropriate actions can be taken by means of optimization algorithms. Simple example is demand response, which encourages customers to change "their normal consumption patterns in response to changes in the price of electricity" [2].

Demand response can take advantage of any electrical appliance that is able to store the electrical energy (battery operated cars) or irreversibly convert it into different types of energy (thermal, chemical, mechanical) and then store it [3]. Common appliances that can be used in this way are: air-conditioners, space heaters and water storage heaters. The operation of these appliances results in an increase of thermal energy of certain medium. In case of water heaters it is obviously water in the tank. For the air-conditioner and space heater the medium is the air and walls of a building. With knowledge of the amount of energy stored in these mediums and sufficiently reliable prediction of its future demand, various planing strategies can be taken.

This thesis focuses solely on the approximation of the amount of hot water stored in the tank and the future prediction of its demand. The reliability of the estimate is indicated by an interval estimate of the error.

For the sake of completeness, there exists another group of appliances, whose functioning patterns can be affected. The operation of these appliances can be postponed under certain circumstances. Such devices include washing machines, dishwashers or clothes dryers. These devices could be programmed to turn on when the period of cheap energy occurs. In case of dryers, the operation could be even interrupted during peak period. A manual mode for these devices should always be implemented. Another rather sever possibility is to dim the lighting in a building during critical peak periods.

Chapter 1

Algorithms for estimation of the amount of hot water stored in the tank

In this chapter I propose a method of approximation of the amount of hot water stored in the tank based on available data from electricity meters. The scheme is able to deal with situations when electricity meter stops providing data. It is captured in figure 1.1. Block HWC represents hot water consumption. If the meter functions properly, the switch is in the upward position. The algorithms process the available information and detect when the heater is on. The output is than fed into the model of the heater together with the estimate of hot water consumption (block HWC) yielding the amount of hot water stored in the tank.

The aquaterm block simulates the function of the thermostat based on estimate of the amount of hot water in the tank. If the meter stops providing data the status signal goes to logic level "0" and the switch connects the aquaterm block to the heater. It then becomes the imaginary source of power for the model of heater. The RCS is either still received, if this functionality is available, or retrieved from the memory of previous days. As soon as the error in measuring disappears, the switch goes back into the upper position.

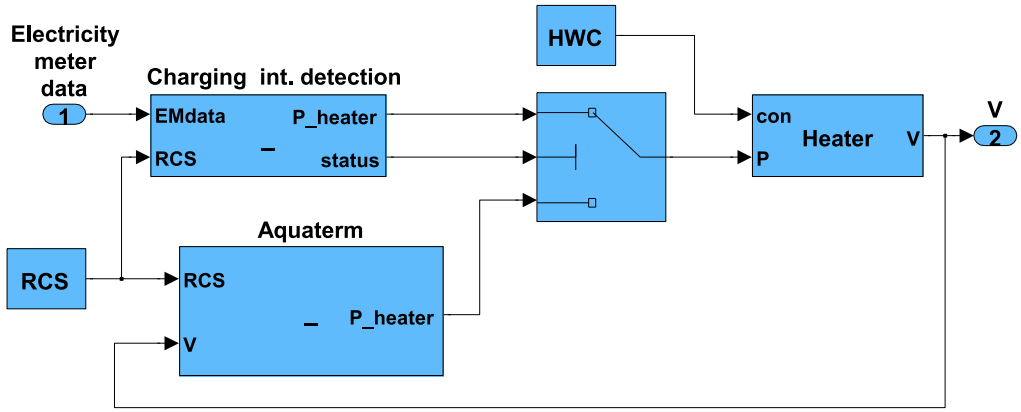

Figure 1.1: Block diagram of the estimation of the amount of stored hot water

1.1 Available data

Data was obtained in project BIOZE performed by ČVUT. The measurements were taken from ten households in a village of Horušany for a period longer than one year. I will work with three types of data sets. Let's call them A, B and C. Algorithms developed for each one of them need to be treated separately.

All sets contain the following quantities

- time when the reading was taken
- time when the record was added to the database
- status providing information whether the energy meter is working properly
- remote control signal (further referred to as RCS)

Data set A - 1 minute sampling period

- power of each phase

Data set B - 15 minute sampling period

- electrical energy consumed over 15 minute periods for each phase separately

Data set C - 15 minute sampling period

- overall electrical energy consumed over 15 minute periods from all three phases

Data set B and C is addressed because most smart meters provide energy consumption measurements for billing purposes rather than power itself.

In figure 1.2 we can see example of data set A. Power is normalized in the sense that nominal power of the heater is equal to one. When RCS goes to logical one, power immediately rises. This is clearly due to the heater. When the data from the electricity meter is not available, the status goes to zero.

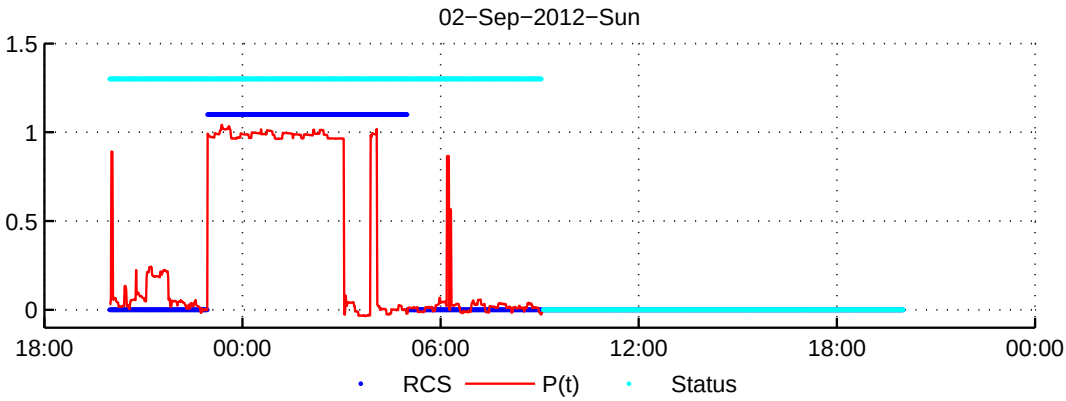

Figure 1.2: Example of data

1.2 Detection of heater operation

In this section I will discuss the methods to obtain the nominal power input of the heater from measurements of electricity consumption and to identify phase the heater is connected to. This information is then used to detect times when the heater is on.

1.2.1 Approximation of nominal power input of heater and phase at which it is connected

It is very likely that the heater will turn on and stay on for a few minutes after the RCS turns on. This conclusion follows from observation of measurements and from an assumption that even though no hot water has been consumed since the last RCS active period, there is always some heat loss that need to be compensated for.

Algorithm which works with data set A can be described as follows

1. Choose a sufficiently long period of time to provide for irregular events.
2. Find rising edges of RCS over this period.
3. Calculate consumed energy over the whole period but only for the first few minutes after each off-on transition of RCS. The consumed energy is calculated for each phase separately so we obtain E1, E2, E3.
4. The heater is connected to the phase with the maximum value of E.
5. The nominal power input of the heater is the mode of power over periods specified above.

The examined period needs to be long enough to provide for irregular events such as absence of occupants in the household due to holidays. The argument for item 4 is that there are very few electrical appliances with nominal power input comparable to that of a heater. More importantly running periods of these other appliances, that are not controlled by RCS, are not correlated with rising edges of RCS. I used mode for obtaining the nominal power input because it is more robust than average or median for this type of data. The other reason is that it agrees with the actual nominal power input of heaters that were known for the observed dwellings.

In order to integrate the power when working with data set A, the discrete signal is reconstructed using zero order hold method. That simply means we sum the samples of power and multiply it by the sampling period. For calculating E1, E2, E3 the length of period after rising edge of RCS was chosen to be 5 minutes long.

In case we work with data set B, we do not need to obtain the energy by integrating power as the data set B already contains consumed energy. Only one sample after rising edge of RCS is taken into account. All of those samples are then summed to form E1, E2, E3. The problem is that the heater can turn on at any time between detected rising edge of RCS and the previous sample. This is because RCS is also a measured quantity with sampling period of 15 minutes. This actually lowers the observed energy consumption so to avoid it I use the sample following rising edge of RCS, assuming the heater is usually turned on for at least 30 minutes. The phase with the heater connected to it is again chosen according to the maximum value of E. The nominal power input is obtained by dividing the the value of E by the length of the corresponding period of time.

When working with data set C we use the same algorithm as for data set B. As it only contains the consumption from all phases together we cannot find out which phase the heater is connected to. However, the information about the nominal power input of the heater can still be found with only a negligible error.

1.2.2 Determination of charging intervals of the heater

The output of this section is variable state, which tells us when the heater is on. Time difference between samples of state vector depends on which data set is used to determine it. It is 1 minute for data set A and 15 minutes for data sets B and C. Firstly, we start with data set A which is power with sampling period of one minute. The algorithm is based on finite state machine with memory. The two states are simply ON and OFF. It is difficult to distinguish between electrical appliances which have similar nominal power input to the heater. RCS offers a clear hint. There are two possible ways to follow

- Comparing the measured power to the nominal power input of the heater.
- Detecting rising and falling edges of the size of nominal power input of the heater.

The second approach has several advantages. It recognizes superposition of medium powered (less than nominal power input of the heater) appliances in case they do not switch on in-between the interval of one minute. Care must be taken in detecting the ON-OFF transition. We need to count the number of consequent rising edges of the amplitude of the nominal power input of the heater and change the state from ON to OFF only when the corresponding falling edge occurs. This way for example, we avoid a superimposed water kettle consumption to cause the ON-OFF transition. If the rising edge is twice as high as it would correspond to the heater itself, it is probable that the heater and some other high power appliance turned on inbetween two measurements. In this case two rising edges are counted. This approach has proven to be an effective way of detection on measured data as far as human can recognize when the heater is on.

There is a possibility that the heater switching on or off will not be detected. Suppose another appliance switches off and the heater switches on. If these events happen between two measurements one minute apart, the rising edge of the heater will be smaller and thus avoids detection (similarly for the ON-OFF transition). However, this was not observed on measured data.

In the figure 1.3 the three topmost transition from ON to OFF state have not been discussed yet. When the RCS is at logic level "0" or the power is significantly below the nominal power input of the heater, we can be certain that the heater is off. This can partially help to solve the problems with detection discussed above. When the status is at logic level "0", which means the measurement device is not working properly, we have no information to help us make the decision. In this case the finite state machine sets the state to OFF.

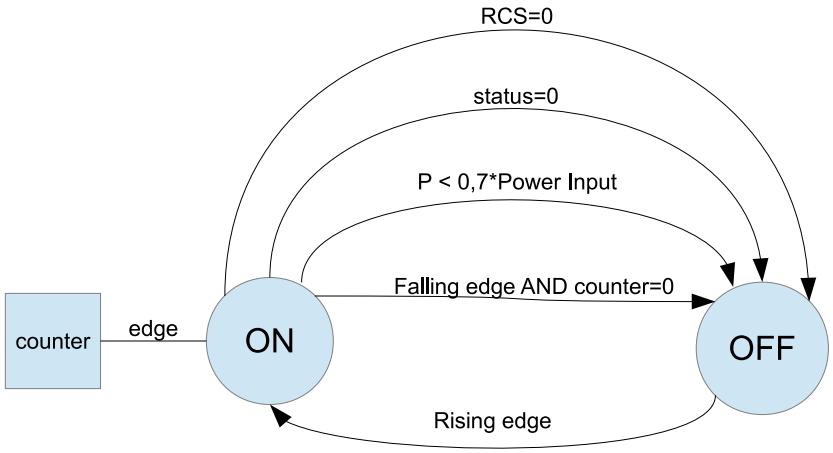

Figure 1.3: Finite state machine diagram - data set A

When working with data set B or C, which contain energy consumed over 15 minutes, the algorithm becomes much simpler. Figure 1.4 shows the principle. The heater is supposed to be at ON state, when the consumed energy exceeds half of that which would be consumed, if the heater was on for the whole 15 minutes. The RCS and status conditions remain the same. This algorithm can randomly add up to ± 7.5 minutes every time the heater switches on or off. 14 minutes-long water heating can go completely unnoticed and on the other hand, 16 minutes-long water heating can be detected as 30 minutes-long. This can be partially solved in special cases with the knowledge of RCS. For example if the heater is detected to turn on at the second sample after the rising edge of RCS it is very likely it actually had turned on exactly when RCS was activated (similarly for falling edge of RCS). Compared to detection using data set A, there is no immunity against superposition of medium powered appliances.

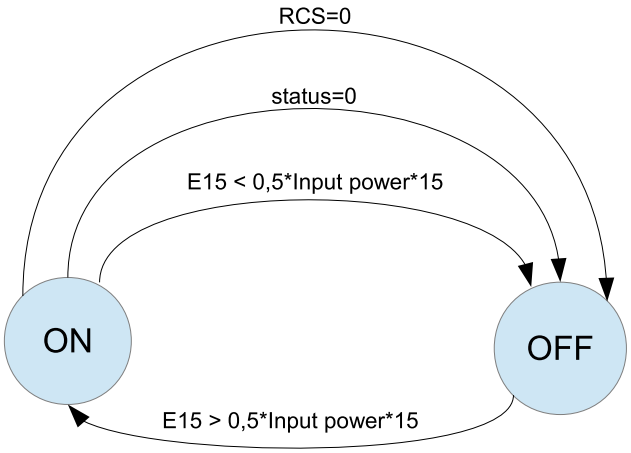

Figure 1.4: Finite state machine diagram - data set B and C

Figure 1.5 demonstrates the function of algorithms. The variable P(t) is normalized in the sense that nominal power of the heater is equal to one. The power variable P(t) comes from data set A and therefore has a one minute sampling period. Only the power of phase, to which the heater is connected, is shown. Variable heater is the binary output of detection. We can see a close match between P(t) and variable heater.

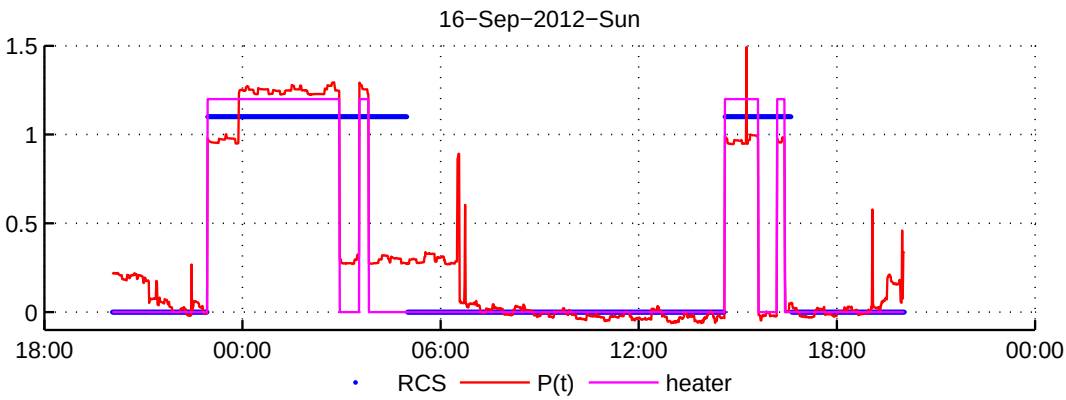

Figure 1.5: Detection from minute samples of power

When using data set B, the output of algorithm is delayed as can be seen in figure 1.6. Variable E15 is the normalized input from data set B which is energy consumed over 15 minutes. It can be easily seen, why the algorithm decided as it did by observing variable E15. When the green star exceeds the value of 0.5, the heater is supposed to be on. The last pulse on September 16 passed undetected unlike in figure 1.5 because it is placed almost exactly inbetween two measurements. We can see two stars close to the value of 0.5.

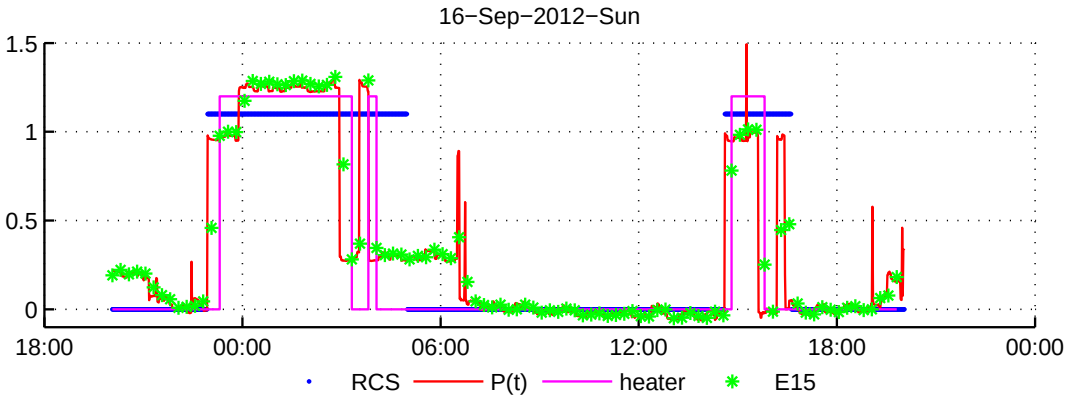

Figure 1.6: Detection from 15-minute samples of energy - data set B

Output for data set C is similar to the previous one. Variable P3(t) is the sum of power from all phases. We can see an earlier start of the first pulse of variable heater which is due to added consumption from other phases.

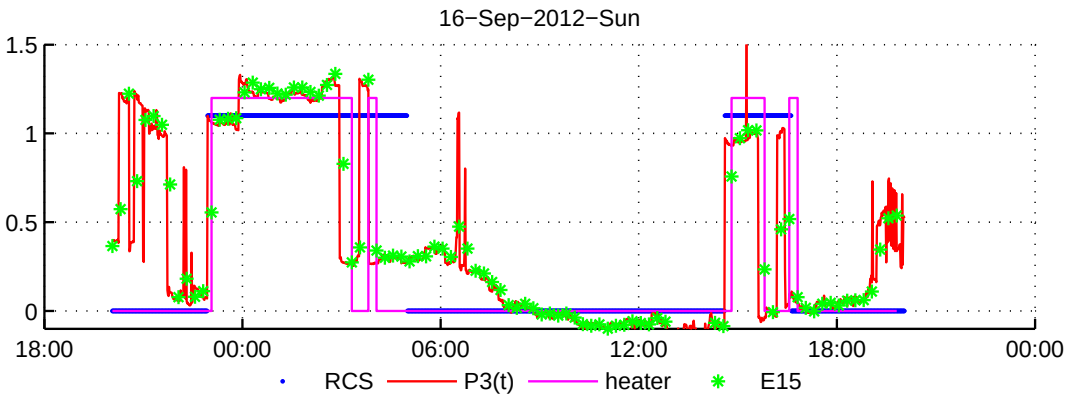

Figure 1.7: Detection from 15-minute samples of energy - data set C

1.3 Approximation of hot water consumption

This section presents a simple method of approximation of hot water consumption (block HWC in figure 1.1) based on scaling a typical hourly histogram of consumption by the estimate of average daily consumption. A more advanced method is proposed in chapter 2.

1.3.1 Approximation of hot water consumption over given period of time

With the knowledge of intervals at which the heater is on and with the known nominal power input, we can calculate the integral of power over time, yielding energy consumption of the heater

$$E = \int_{t_0}^{\tau} p(t)\,\mathrm{d}t\,[\mathrm{J}]. \tag{1.1}$$

Using the equation for specific heat capacity we can obtain the volume of hot water

$$V = \frac{E}{\mathrm{c}\rho\Delta\mathrm{T}}\,[\mathrm{m}^3], \tag{1.2}$$

where $\mathrm{c} = 4186\,[\mathrm{J\,kg^{-1}\,K^{-1}}]$ is specific heat capacity of water, $\rho = 1000\,[\mathrm{kg\,m^{-3}}]$ is density of water and $\Delta\mathrm{T}\,[\mathrm{K}]$ is the temperature difference of water coming into the heater and the temperature to which it is heated. $\Delta\mathrm{T}$ was chosen to be 40 K as the typical temperature of water inlet is 15 °C and the boiler heats the water to approximately 55 °C.

We would like to know the average daily hot water consumption. The integration bounds for every day could be simply placed for example at midnight of current and following day. This would not be a problem, if we suppose that the consumption is a periodic function with a period of one day as the integral over a period is the same, no matter where the bounds are. However, the result show that the consumption varies from day to day based on people's habits. The most significant difference is between workdays and weekends.

Water heating that occurs from 0 AM to 6 AM usually refers to consumption from the previous day. The RSC is often active at this time, which results in long period of heating. Also very little water is being used during this time, which helps to separate the consumptions from different days. The integration bound is sought in this interval. The algorithm tries to find a moment during this period, when the heater switches off spontaneously without RCS forcing it to do so, which means the tank is full of hot water. If that happens we put the integration bound at this point. If this moment is not found, the right integration bound is placed at 6 AM. The right bound is also the left bound for the next day.

To explain the spontaneous switching off of the heater we need to discuss the function of thermostat first. I modelled it using finite state machine shown in figure 1.8. If the RCS is at logic level "0", the heater is always off. If the RCS is at logic level "1" and the amount of hot water in the storage tank is below 90 % of its maximum volume, the thermostat turns the heater

on. If the heater is fully filled with hot water, the thermostat turns the heater off.

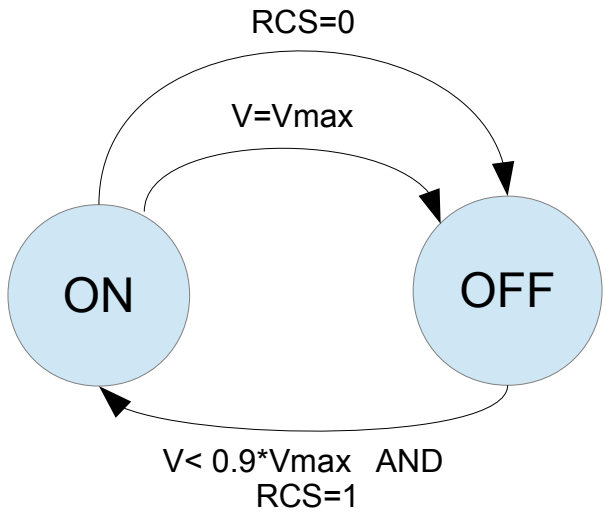

Figure 1.8: Finite state machine - thermostat

Water consumption varies from day to day according to people's habits. The daily hot water consumptions from individual days were therefore averaged for each day of the week separately and then for all working days together. Because the results are determined more precisely with data set A we can use it as a reference. Working with data set B yields similar results to data set A. Data set C results in sometimes very different outputs. The average daily hot water consumptions for five households can be found in figure 2.21 in appendix.

In section 1.2.2, we discussed the error when using data set B and C, which is a consequence of long sampling period. It can be as high as 7.5 minutes every time the heater switches on or off, which corresponds to approximately 5.4 liters for a heater with the nominal power input of 2000 W and temperature difference ΔT = 40 K. The error can be thought as a random variable with uniform distribution on the interval (-5.4 5.4). It's variance is defined by

$$\sigma^2 = \frac{1}{12}(\mathrm{b} - \mathrm{a})^2, \tag{1.3}$$

where a and b are left and right bound of the interval respectively.

By observing the measured data, I found that the heater switches on seven times a day on average, which makes 14 transitions. The variance of sum of uniformly distributed variables increase linearly with the number of variables being summed. Variance of the sum is

$$\sigma^2 = 14 \cdot \frac{1}{12}(\mathrm{b} - \mathrm{a})^2, \tag{1.4}$$

and standard deviation is then

$$\sigma \doteq 11.7\,[\mathrm{l}]. \tag{1.5}$$

The mean is equal to zero, because the interval is symmetrical. In the worst but unlikely case that the error at each transition add 5.4 liters, the total maximum daily error can raise up to 76 liters.

The error discussed above applies to the method I am using to detect interval from discrete data set B and C. It does not take into account the possibility that

- the heater switching on or off will not be detected by error
- another appliance will be mistakenly detected as a heater

The first event was very rare on measured data. The second can happen more regularly and always increases the approximated hot water consumption. The most important result from this error discussion is, that because the error has zero mean, we can avoid its effect on the estimate of an average daily hot water consumption by integrating for a long period of time.

1.3.2 Hot water consumption as a discrete function of time

Now that we know how much hot water is being used during the day, we try to determine how consumption depends on time. Consumption of hot water is partially random on a short time-scale. However, it follows certain patterns on a long time-scale. Factors that might affect consumption are

- number of residents in the household
- hygienic habits
- time of year
- time of week
- holidays
- weather

I will use the median of consumption obtained from hot water monitoring report [4]. In figure 1.9 there is a histogram normalised in the sense that sum of all hourly consumptions equals to one.

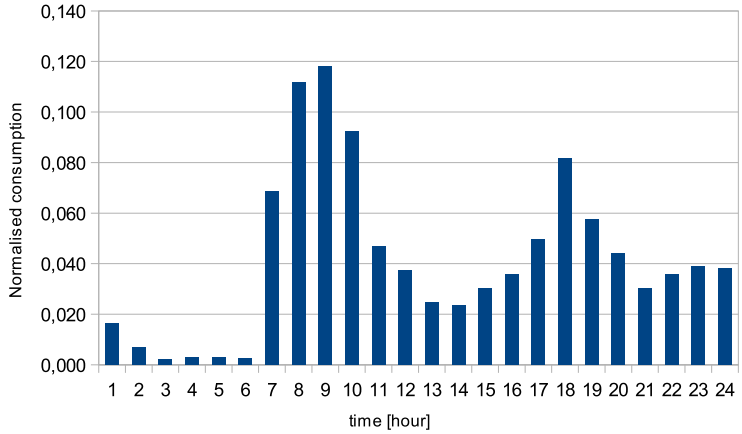

Figure 1.9: Histogram of hourly hot water consumption

Because we know the approximated hot water consumption over the whole day, we can simply multiply the histogram by that number. For future use, I will suppose that during the particular hour, consumption is constant.

1.4 Model of a storage heater

I developed a model that is simple but still models the behavior of the storage heater accurately enough. Figure 1.10 shows the block diagram of the system. The storage heater is modelled as an energy storage with two inputs. The input electric power is represented by letter P [W] and it increases the amount of stored energy. On the other hand, the input of hot water consumption Q [l/s] decreases the amount of stored energy. The closed loop modells the heat losses of the tank. According to heater manufacturer Tatramat [5], heat losses are approximately $8\,\mathrm{Wh\,day^{-1}\,l^{-1}}$, which means they are proportional to the amount of hot water stored in the tank.

The amount of energy which can be stored in the tank is bounded on each side. The lower limit is 0 J which corresponds to the tank full of only cold water. The upper limit is reached when the tank is full of hot water. This boundary depends on the volume of the tank, which is another unknown parameter. The value of the volume is usually between 120 and 200 liters. These limits are implemented in the integrator block. The relationship be-

tween P and Q can be obtained as a time derivative of equation 1.2,

$$\frac{\mathrm{d}V}{\mathrm{dt}} = \frac{1}{\mathrm{c}\rho\Delta\mathrm{T}}\frac{\mathrm{d}E}{\mathrm{dt}} \tag{1.6}$$

$$Q' = \frac{1}{\mathrm{c}\rho\Delta\mathrm{T}}P\left[\frac{\mathrm{m}^3}{\mathrm{s}}\right] \tag{1.7}$$

$$Q = \frac{1000}{\mathrm{c}\rho\Delta\mathrm{T}}P = \frac{1}{K_1}P\left[\frac{\mathrm{l}}{\mathrm{s}}\right]. \tag{1.8}$$

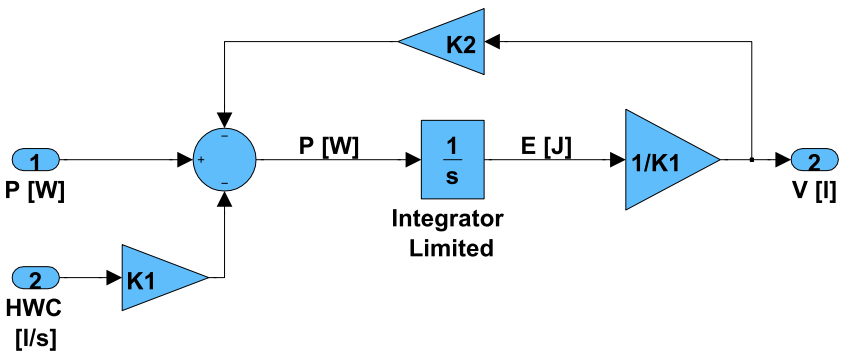

Figure 1.10: Model of storage heater

We can write the differential equation of the system and transfer it into discrete counterpart.

$$\begin{aligned}
\dot{E}(t) &= P(t) - K1 \cdot H(t) - \frac{\mathrm{K}_2}{\mathrm{K}_1}\mathrm{E(t)} \\
\frac{E(t+h) - E(t)}{h} &= P(t) - K1 \cdot H(t) - \frac{\mathrm{K}_2}{\mathrm{K}_1}\mathrm{E(t)} \\
E(t+h) &= h\left(P(t) - K1 \cdot H(t) + E(t)\left(\frac{1}{\mathrm{h}} - \frac{\mathrm{K}_2}{\mathrm{K}_1}\right)\right),
\end{aligned}$$

where $E(t)$ [J] is stored energy, $P(t)$ [W] is electric input power, $H(t)$ [l/s] is the hot water consumption and h is the differential step, which is chosen to be as long as the sampling period.

1.5 Approximation of the amount of hot water in the tank

Now, we can feed the information about charging intervals from section 1.2 and the approximated hot water consumption from section 1.3 into the model of the heater from section 1.4. The situation is captured in figure 1.11.

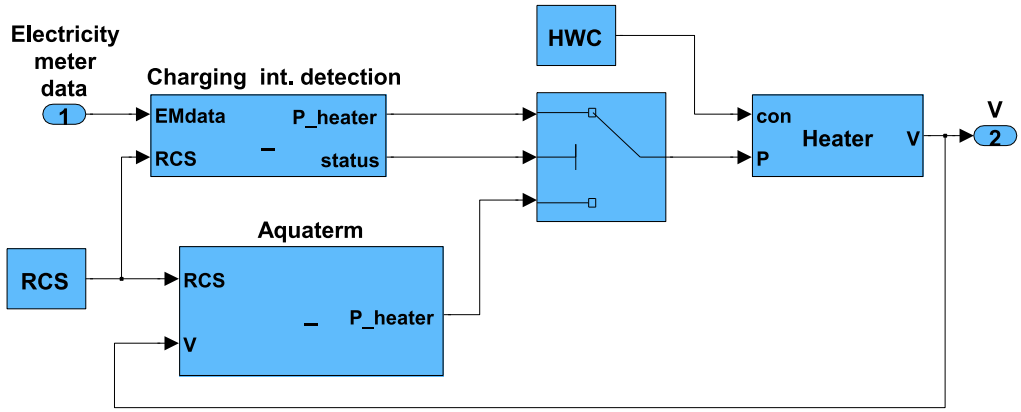

Figure 1.11: Block diagram of the estimation of the amount of stored hot water

This paragraph refers to standard operational mode of the electricity meter when the switch is in the upward position. As described in section 1.3.1, every time the heater switches off and the RCS is at logic level "1", we can be certain that the storage tank is fully charged. This information is used to synchronize the value of the volume $V(t)$ to V_{max}. Figure 1.12 shows the approximation of accumulated energy in the form of hot water. The variable hot water is normalized in the sense that the amount of hot water corresponding to the maximum volume of the tank equals to one. Variable heater is the output of charging intervals detection block. It is normalized in the sense that nominal power of the heater is equal to one. When the heater switches off without RCS forcing it, we can see jumps to the value one. When the energy rises above one, it means it is charging over the expected volume of storage the tank. Both of these events can help us alter parameters of the model to better reflect reality. First we can change the histogram of daily hot water consumption. Another possibility is to change the maximum volume of the tank, the temperature difference ΔT or the settings of the thermostat. Altering those parameters and their effect is described in chapter 2.

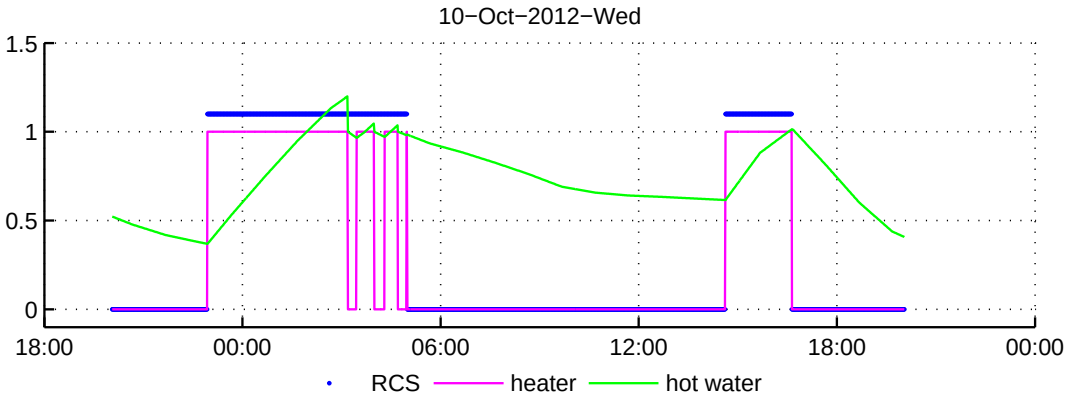

Figure 1.12: Approximation of accumulated energy

Figure 1.13 shows the behavior of the algorithm in the case of error in electricity meter measurements and continuous transition to standard operational mode. We can see that the amount of hot water starts rising at midnight, even though no data is coming from the electric meter. This is due to aquaterm block which evaluates the estimate of the stored amount of hot water and switches the model of the heater on. At approximately 2 AM the electricity meter starts providing data, which means that aquaterm is no longer needed. The RCS was retrieved from the memory of previous days. At the time of synchronization at the end of the first pulse the error is 20% of the total volume of tank.

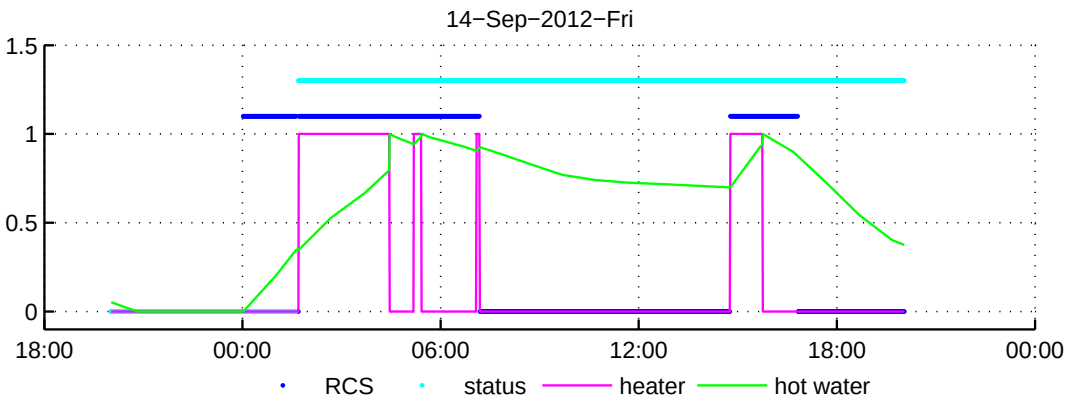

Figure 1.13: Approximation of accumulated energy - error state

Chapter 2

Validation

In order to demonstrate the capability of developed algorithm for approximation of stored energy in water tanks two approaches can be adopted. Experimental validation could be performed if additional sensors were to be used in the dwellings involved. Information from the flow meter installed on a hot water outlet of the heater together with the knowledge of the volume of the tank could be used to calculate the stored energy. The unknown initial condition would be resolved at the first occurrence of synchronization as discussed in the previous chapter. The result could then be compared to estimated amount of stored energy. However, this approach would have to be performed on a large number of dwellings to yield satisfactory statistical outputs. It would be very costly and therefore another method was used.

Different and less expensive approach would be to make the temperature measured by thermostat of a heater available for analysis. This would also provide valuable information about the volume of hot water stored in the tank.

I built a simulation environment which is able to model a long-term load profile based on stochastic approach. The load profile substitutes a measured data of electricity consumption and works as an input to the developed algorithm. Because the hot water consumption is used to obtain the loading curve of the heater, which is part of the aggregated loading curve, we can evaluate the ability of the algorithm to approximate stored energy in the same way as described in the experimental validation. The results obtained here can be used to improve real-life application.

2.1 Validation with simulated data

The validation process is shown in figure 2.1. Part of system to the left of the red line is responsible for synthesizing domestic load profile. Part of system on the right side estimates the amount of hot water in the tank from

the synthetic load profile. In future it will be referred to as Estimator. No information except the volume of the tank and RCS are provided from the left part to the right part. All parameters that are used for its function are approximated or it is shown that they are not significant.

If you look closely, you will see resemblance to figure 1.11. On the right there is the setup with the switch in an upward position which refers to the standard operational mode of electricity meter. On the left there is the setup with the switch in an downward position, which was used in error conditions when measurement data was not available. Block Pag represent agregated instantaneous consumption from all electrical appliances except the water heater. Even though in apartments and houses, which have water heater, it is common to have three-phase connection, in this paper it is assumed that only the sum of consumptions from all phases is available. A method for approximation of the hot water consumption, which is used to generate the load profile of the heater, is proposed. Great emphasis is put on this estimate, because it has a major effect on the final estimate of stored hot water. Two blocks representing heaters are not exactly the same because we have no exact information on temperature difference between cold and hot water and the settings of the thermostat in real dwellings. The effect of these parameters is discussed in sections 2.3.3. The algorithm for approximating the nominal power input of the heater is examined in section 2.3.1. The remote control signal was chosen to be one of broadcasted RCS of Czech electricity supplier ČEZ. The signal is the same for all days and is active from 0:01 AM to 4 AM and from 0:01 PM to 5 PM. The error variable shows how successful the approximation is.

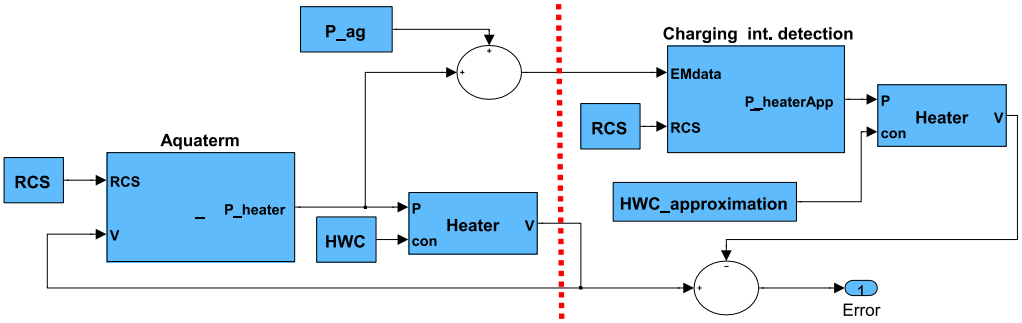

Figure 2.1:

2.2 Domestic load model

There are several possible approaches to develop a load model of domestic demand. One of the most common is the constructive and deductive

method [3].

- "Constructive option describes all sources of external influences on the process (such as human behavior, weather etc.) and then synthesizes the probability from this."
- "The deductive option uses data gained from observations and maps it to the probability function."

Here, the first option is used. I will use the load profile as an input to the algorithm approximating stored hot water. For this purpose, the constructive (bottom-up) method is more suitable, because it not only produces valid aggregated loading curve for a number of dwellings but unlike the deductive method it produces accurate results on the level of individual dwelling and captures the diverse nature of electrical consumption due to behavioral factors. A loading curve is developed for a standard set of electrical appliances present in dwellings. The heater is treated separately because it also uses the physical model of the heater and is therefore more complex.

2.2.1 Description of model

Because of the probabilistic nature of electric consumption, random variables will be used to describe it. The aim is to obtain probability mass functions (PMF) of the time of activation for each type of appliance from the common set of appliances present in a dwelling. The disadvantage of the bottom-up approach is the amount of necessary input information. Domestic demand is highly dependent on a number of factors that are not easily predictable. The model was based on the article [6]. It breaks down the input data into these classes. Because my model is a simplified version of [6] I only include the input data relevant for my purpose.

- "Data concerning the lifestyle of the person concerned and their electricity-usage habits."
- "Engineering data on operation of the relevant household appliances."

Customer's lifestyle and habits

One way to obtain this information is direct measurements of the energy use in households on the level of single appliances. Because of economic reasons these studies tend to be very costly and are rarely performed. The Swedish Energy Agency obtained this data from 400 households [7]. According to the authors, it is the biggest measurement campaign ever made in the world. The output of this study used in this thesis are hourly load profiles for each

type of appliance for each type of inhabitants living in either apartments or houses. Similar but less comprehensive studies have also been performed across Europe [8].

An alternative approach is proposed in [9] where a method to map time-use data to load profiles for household electricity and domestic hot water is created. "Time-use data is collected with time diaries where household members write down their daily activity sequences" [9]. Advantage of this approach is that it is less costly and also enables determination of the contribution of each household member to the total energy use of the household.

The resulting load profile is relevant to a dwelling with certain type of inhabitants who share the same consumption habits. Nine types of dwellings were chosen to represent the diversity of domestic consumption. The number was based on available data from the Swedish measuring campaign. Categorization of habitants is important for two reasons.

- The effectivity of the algorithm for charging intervals detection decreases when the total electrical consumption increases. This is because the consumption from other appliances is basically noise to the algorithm.

- To demonstrate various demand response strategies a large geographical area could be modeled. To achieve satisfactory precision a model should distinguish between different consumers. These types of inhabitants could then be mapped on the area population with information from data obtained in census and similar studies.

For demonstration of the proposed algorithm I chose the type of inhabitants with medium consumption - couples without children, 26-64 years old living in an apartment.

Moreover, the consumption habits are relevant to a certain geographical area. Heating and lighting are most dependent on different climate and geographical locations. No electrical heaters were included in the simulations because their saturation is low. In the Czech republic for example, saturation is below 9% in cities with population over 2000 people and falls with the increasing size of the city [10].

Engineering data of appliances

This data comprises of the nominal power input of each appliance and their consumption pattern during their operation (for example during a washing cycle of a washing machine). The biggest emphasis is put on modelling appliances that have comparable nominal power input to the heater. These can potentially confuse the algorithm for charging intervals detection. They are: washing machines, clothes-dryers, dishwashers, ovens, kitchen stoves,

microwaves and water kettles. Air conditioners were not included because they are not present in samples of the Swedish measuring campaign and their saturation in the Czech republic is below 0.3% according to [11]. Each household has one of each high-power appliance. The kitchen stove, which is comprised of 4 hot plates, is modelled as 4 independent appliances. There are certainly more high-power appliances but they are usually not used that regularly and therefore they are neglected. The rest of the modelled devices present in dwellings are: fridge-freezers, lighting, audiovisual site and computer site. A table of the nominal power input of each appliance is given in table 2.2.

	Input power [W]
Oven	3300
Stove	1200
Microwave	1000
Water kettle	2000
Washing machine	2000
Clothes dryer	2000
Dishwasher	2000
Computer Site	100
Audio Visual Site	150
Fridge-freezer	100
Lighting	100

Figure 2.2: Nominal power input of domestic appliances

All electrical devices are modeled to consume either zero or their nominal power input for an uninterrupted period of time. In the case of the washing machine this is satisfactory to a certain point. The consumption pattern of the washing machine can be seen in figure 2.3. We can see three phases: water heating, laundry agitation and spin-drying. Only the first pulse is modelled as it is the most significant. The width of pulse increases dramatically with the increasing temperature settings. The same approximation is used for dishwashers.

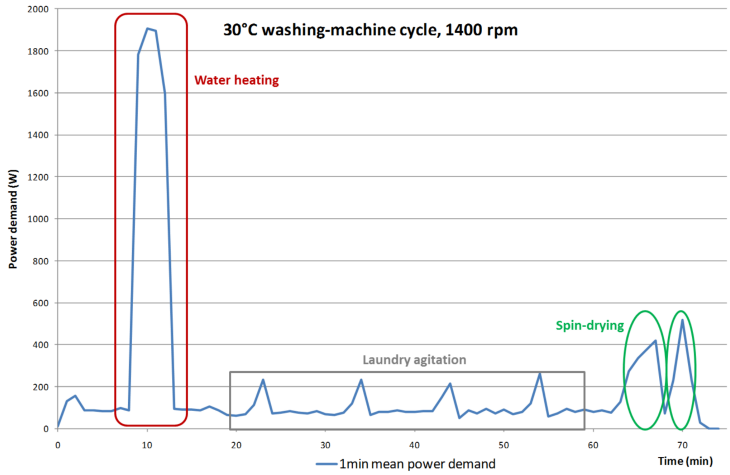

Figure 2.3: Consumption pattern of a washing machine [12]

Operation of older fridges is also cyclic. Newer fridges with automatic defrost operate almost all the time. Because the power drawn from it is not significant it is modelled as constant power of approximately 30 watts and therefore is not referred to any further.

2.2.2 Load profile of common appliances

This section describes the derivation of stochastic relations for each appliance and its use for synthesizing an agreagated load profile. The output of of this section is the block P_{ag} in figure 2.1.

Probability mass function of the time of activation

This function is obtained with the help of an hourly load profile for appliance related to a certain type of dwelling. An example is shown in figure 2.4.

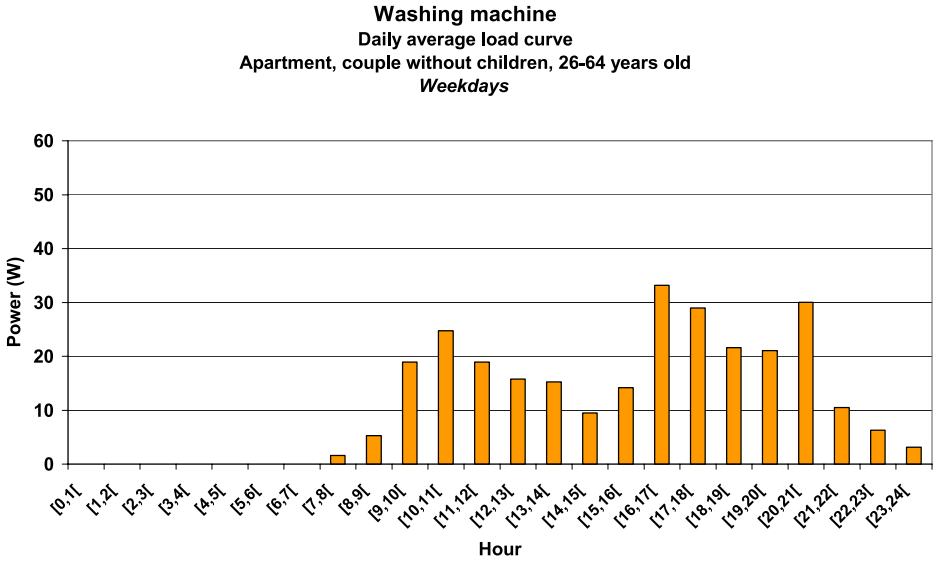

Figure 2.4: Load profile of washing machine [7]

Because we need higher time-resolution, we sample the profile with 1 minute sampling period. The profile is then normalized in a sense

$$\sum_{k=1}^{24\cdot 60} = f_k(x) = 1.$$

This is already the desired PMF. Justification for this approach can be obtained using the Monte Carlo method. If we knew

- the PMF,
- duration of operation of the appliance,
- the average number of activation per day,
- probability that the appliance will be used at all in that day,

we can run the simulation for many days and compare the average load profile to the one in figure 2.4. The PMF obtained above generates an average hourly load profile that match closely the shape of 2.4. Duration of operation is then tuned in order to match the amplitude. Figure 2.5 shows the result of two simulations running for 1000 days or alternatively for one day for 1000 dwellings of the same type.

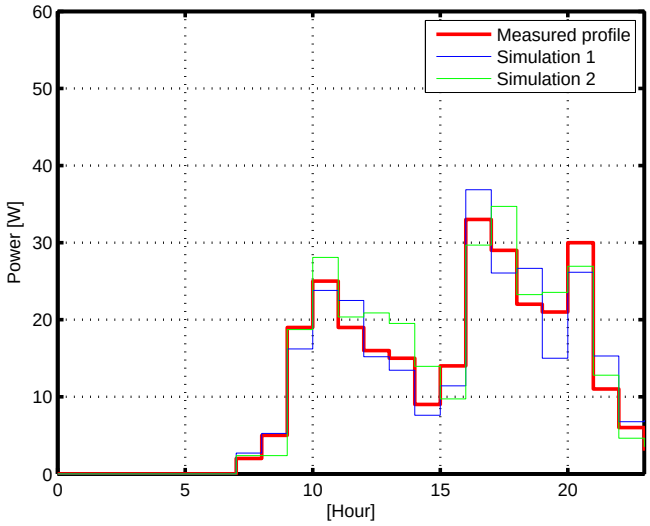

Figure 2.5: Comparison between measured and simulated load profile of washing machine

The average number of activations per day for each appliance was based on personal experience. If there is more than one activation per day, the ones following the first one cannot occur while the appliance is still running. This does not apply to the kitchen stove as there are 4 hot plates and the consumption from each one of them can be added. Lighting is treated in exactly the same way. Because the number of activations is higher for a stove it is actually very common that the consumption from individual lights add together.

The probability that a washing machine, a clothes dryer and a dishwasher will be used in a given day was calculated from average number of cycles per year [7]. Probability for an oven and stove was chosen based on personal experience. For the rest of the appliances the probability was chosen to be one, which means they are used everyday. All parameters of simulation for each appliance including experimentally observed duration of operation are summarized in table 2.6.

	Probability of usage	Number of activaitions	Duration of Operation [min]
Oven	0,25	1	42
Stove	0,5	2	32
Microwave	1	2	2
Water kettle	1	2	1
Washing machine	0,41	1	21
Clothes dryer	0,64	1	21
Dishwasher	0,36	1	48
Computer Site	1	3	105
Audio Visual Site	1	3	170
Lighting	1	10	75

Figure 2.6: Parameters of simulation

The example of one day loading curve can bee seen in figure 2.7.

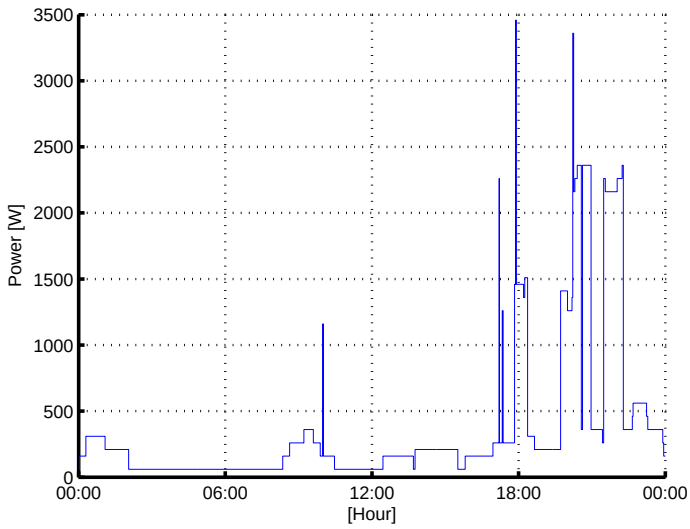

Figure 2.7: Synthetic loading curve

2.2.3 Load profile of water heater

The output of this section is the variable P_{heater} in figure 2.1. The function of the related blocks was described in section 1.5 while discussing the error operation mode when no data from the electric meter is available. The main difference is in hot water consumption block. This time it will be described

using PMF which is generated in the same way as in previous sections. Hot water consumption will be formed by daily household activities, which involve consuming hot water. The start of these activities will be described with the PMF. The PMF is obtained from the typical hourly profile of normalized hot water consumption shown in figure 1.9.

Parameters of the heater, the tank and the Aquaterm block are shown in figure 2.8.

Input power	2000 [W]
Max. volume	200 [l]
ΔT	40 [K]
Hysteresis of thermostat	0.9 V_{max}

Figure 2.8: Parameters of simulation

Hysteresis of thermostat is the maximum volume of hot water in the tank which allows the heater to turn on. See model of the thermostat in figure 1.8.

Parameters of simulation are in figure 2.9. The power drawn from the storage tank is calculated as

$$P = \frac{\mathrm{Qc\Delta T}}{60}\ [\mathrm{W}],$$

where Q = 3 [l/min] is the typical volumetric flow rate of hot water during showering. The number was based on home experimentation, in which the flow of water and temperature for a typical shower or bath was measured. Duration of operation is not tuned this time but calculated from the total daily hot water consumption $\mathrm{Q_{total}}$ [l] according to

$$\mathrm{T} = \frac{\mathrm{Q_{total}}}{\mathrm{QN}}\ [\mathrm{min}],$$

where N is the number of activations per day. The total daily hot water consumption was chosen at 200 litres.

	Probability of usage	Number of activations per day	Total daily HWC [l]	Duration of operation [min]	Power [W]
Heater	1	5	200	13,3	8372

Figure 2.9: Parameters of simulation of heater

2.2.4 Total load profile

Variables P_{ag} and P_{heater} are summed to form the total power. This output is similar to data set A from the previous chapter except it comprises all three phases. If we integrate the total synthetic load profile in 15 minute intervals using zero order hold method we obtain an analogy of data set C. These sets will be further referred to as A and C, even though they are slightly different from measured data sets from chapter 1.

2.3 Estimator

In this section we discuss the results of detection of charging intervals for both data sets A and C and finally the difference between actual and approximated stored hot water.

2.3.1 Detection of nominal power input of the heater

For both data sets A and C it only takes a few days to determine the nominal power input with the algorithm described in section 1.2.1. The only thing that we have to be careful about is that the occupants might not be present in the household when the observation is made. However, in this case the heat losses still force the heater to turn on, even though no water is being consumed. This was also tested with satisfactory results. For the sake of certainty, the observation of nominal power of the heater can be repeated in predefined intervals.

2.3.2 Detection of charging intervals

In section 1.2.2 two sources of error were described for the algorithm for data set A.

- To mistake the heater for another high power appliance.
- The heater was not detected because the rising or falling edges of the heater were smaller due to another (not necessarily high power) appliance turning on or off inbetween two measurements.

Both of these events were observed. The simulation ran for one day for 1000 dwellings of the same type. In figure 2.10 we can see a histogram of the daily difference between the estimate of the daily time of charging and the actual time of charging $T_{estimate} - T_{real}$. Algorithm for data set A shows very good results.

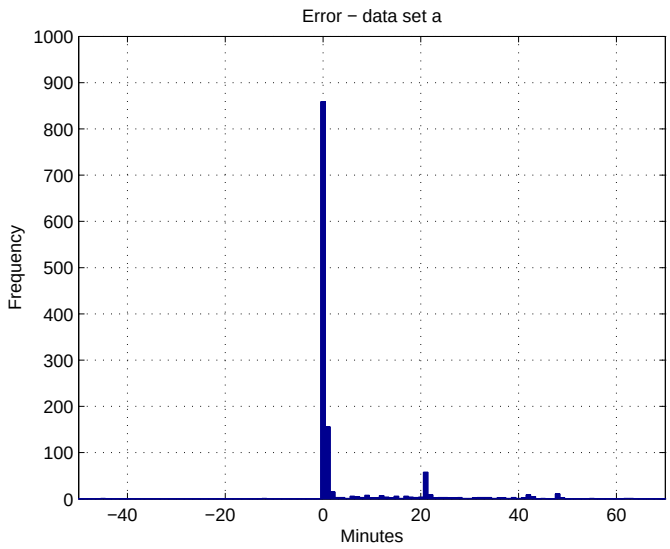

Figure 2.10: Histogram of daily error of the time of charging - data set A

When working with data set C, the sources of error are the following.

- To mistake the heater for another high power appliance.
- The sampling period of 15 minutes and the nature of decision making, which determines the heater operation, causes an error from the interval (-5.4 5.4) [l] every time the heater switches on or off. The error is uniformly distributed.

These will be further referred to as error of the first and second type. Because we know the actual load profile of the heater, we can use it as an input to the Charging interval detection block without the added load profile from other appliances, which are the sources of the error of the first type. This will allow us to selectively show the effect of the the second source of error on a time scale of a single day. In section 1.3.1 it was shown that the error of the second type during the whole day is the sum of 14 uniformly distributed variables as the heater switches on 7 times a day on average. Each random variable refers to the heater switching on or off. According to the central limit theorem this sum of errors should be approximately normally distributed. In the bottom graph in figure 2.11 we can see it occurs.

Upper graph in figure 2.11 shows the total daily error of the algorithm for data set C. By comparing the upper and bottom graph we can see that the error caused by mistaking the heater for some other high power appliance is less significant. However, we can see that the error of the first type always increases the estimate, whereas the error of the second type has zero mean.

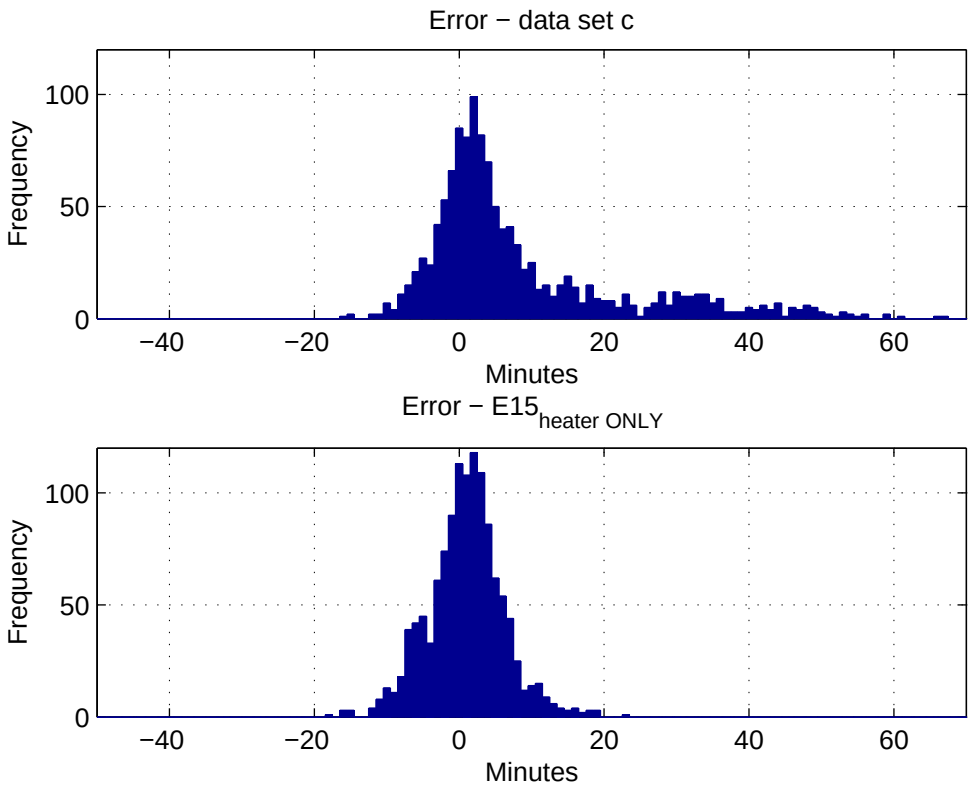

Figure 2.11: Histogram of daily error of the time of charging - data set C

Statistical parameters of daily error of time of charging calculated in liters are in the figure 2.12. STD stands for standard deviation.

	mean [l]	STD [l]	max [l]	min [l]
Data set a	2,9	7,4	45,2	-32,3
Data set c	6,2	10,4	65,2	-11,5

Figure 2.12: Parameters of error

2.3.3 Approximation of hot water consumption

We now have the output of the block of charging interval detection. However, the heater also needs an approximation of hot water consumption (HWC approximation block) to produce the estimate of stored hot water. We could use the typical consumption as described in section 1.3.2 but the simulation environment allows us to create a more sophisticated and more precise estimate. Results of this method can also be used in real dwellings.

The estimate is acquired during a learning phase which needs to be approximately 30 days long. Firstly, the synthetic load profile is obtained in a similar way as described in previous chapters. The only difference is that the RCS is always on, which means that only the thermostat decides whether to switch the heater on. The load profile in the form of data set A or data set C is then fed into the Charging intervals detection block and then the average daily load profile for the whole period of learning phase is calculated. When the RCS is always active, the average load profile reveals valuable information about the hot water consumption.

In the figure 2.13 we can see results of a simulation which ran for 1000 days in the observed dwelling. Variable Q represents the power drawn from the storage tank in the form of hot water. The load profile was obtained from data set A and then integrated in 15 minute intervals using the zero order hold method. This was done to smooth the curve of variable Q. It was necessary because the pulses are very short and the power is very large (see figure 2.9) and even 1000 days were not enough to average out the peaks. The most important observation is that variable P_{heater} copies the shape of Q, but lags behind. This is because water heating is much slower than the the hot water consumption. The other reason is that the heater does not switch on immediately after the water is consumed because of the hysteresis of the thermostat.

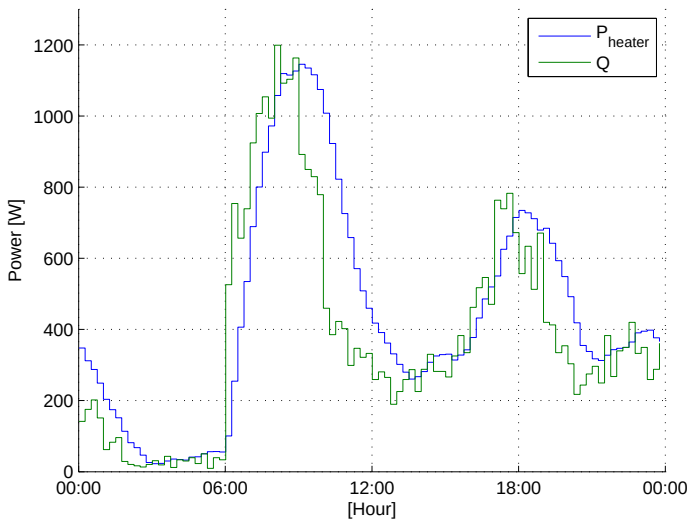

Figure 2.13: Daily average load profile of the heater and the water consumption

The value of the lag can be found using cross-correlation. The maximum

of this function determines the lag which is 41 minutes.

$$(P_{heater} \star Q)[n] = \sum_{m=-\infty}^{\infty} P_{heater}[m]\, Q[n+m].$$

In real life it is not feasible for the learning phase to be 1000 days long. However, even after 30 days the average load profile looks similar to the one in figure 2.13. The comparison can be seen in figure 2.14.

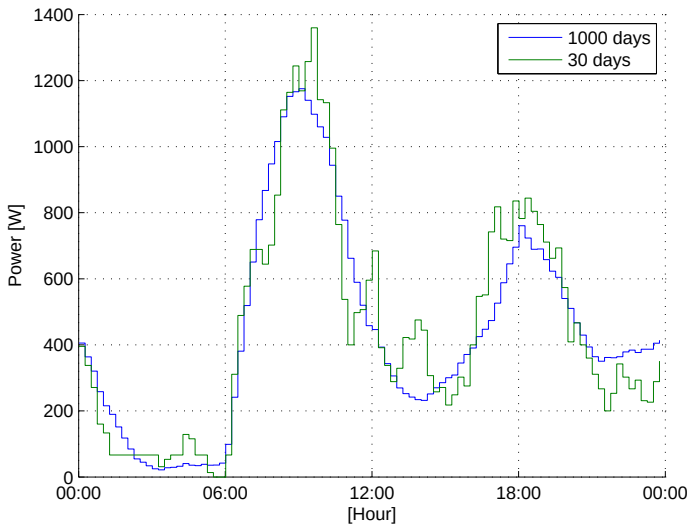

Figure 2.14: Daily average load profile of the heater

The average daily load profile of the heater obtained from a 30 day long simulation is then lagged for 41 minutes and used instead of typical hourly hot water consumption histogram from figure 1.9. The advantage is obvious because the obtained profile reflects the real hot water consumption better than typical profile. Each dwelling has specific pattern of consumption and this method is able to approximate it with high precision.The implementation in real dwellings could be obtained in the same way.

We now discuss the effect of parameters of the heater and the thermostat on the average load profile. In figure 2.15 we see the results of simulation for storage tanks with different volumes. We see that tanks with higher volume have slightly higher consumption, even though the consumption of hot water is the same. This can be explained by the heat losses that are linearly dependent on the volume of the hot water stored in the tank. Bigger tanks tend to store more hot water thus have higher heat losses.

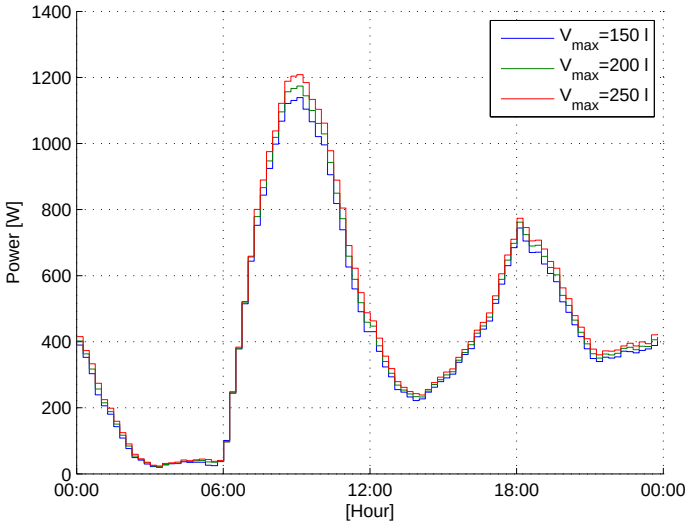

Figure 2.15: Effect of the volume of the storage tank on the load profile of the heater

Figure 2.16 shows the dependence of the hysteresis of thermostat on the load profile of the heater. We can see there is a big difference between the curve for hysteresis of $0.7V_{max}$ and $0.8V_{max}$. It would be very beneficial to conduct a measurement on real storage heaters to find out which value best reflects reality. For further usesage the value was set on $0.8V_{max}$.

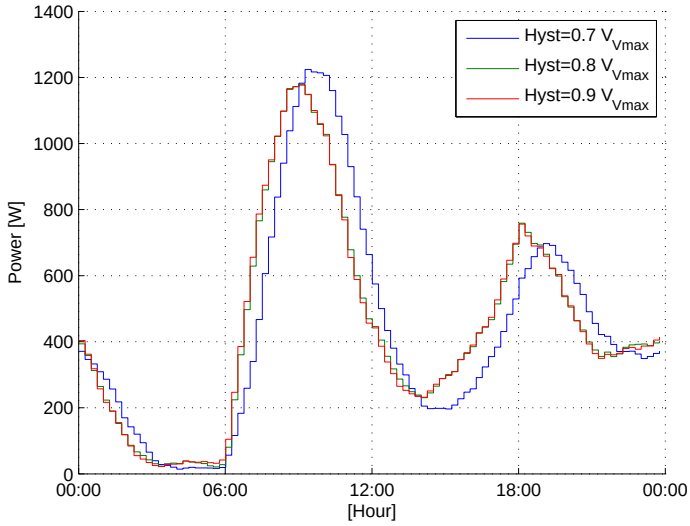

Figure 2.16: Effect of parameters of thermostat on load profile of the heater

A similar graph was plotted for temperature differences $\Delta T = 40$, 50 and 60 K. However, no significant differences were found.

2.3.4 Comparison between actual and approximated volume of stored hot water

This section uses the output of Charging intervals detection and information about RCS and produces an estimate of hot water stored in the heater. In order to express the error in liters the maximum volume of the tank V_{max} must be known. From simulations it was observed that this unknown parameter introduces additive error to the estimate which is similar in size to the difference between real maximum volume and the volume used in the model. The parameter could be obtained the first time the heater is used supposing all water in the tank is initially cold and no water is consumed until it is fully charged.

$$V_{max} = \frac{P\tau}{c\Delta T}\,[l],$$

where P [W] is the nominal power input of the heater and τ [s] is the time of charging. However, this method relies on the Charging interval detection algorithm, which cannot guarantee accurate output. As this parameter is crucial it is recommended that the electricity distributor obtains this information from its customers. In the model of the heater the same value of V_{max} as the one used for synthesizing the load profile is used. V_{max} is therefore a known parameter.

The simulation ran again for 1000 days in the observed dwelling. The result for two days can be seen in figure 2.17. We can see abrupt changes in real volume of hot water, which is caused by sudden consumption. The approximated volume descends in a more gradual way as it based on mean

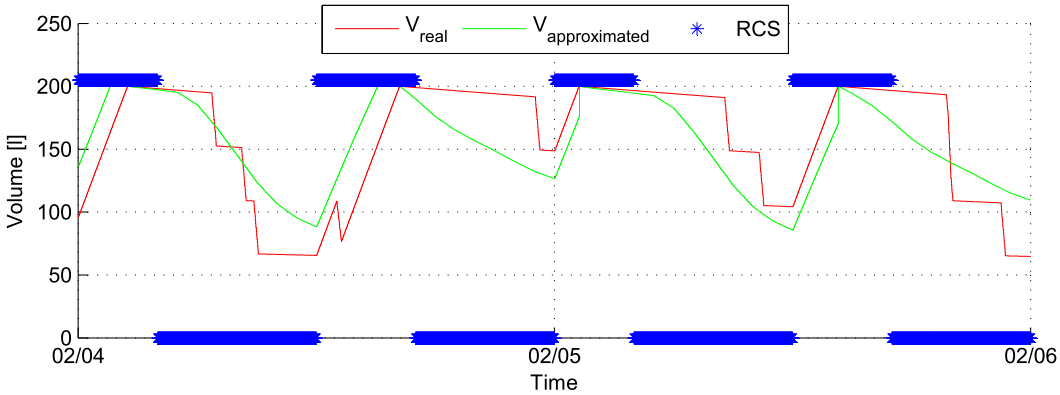

Figure 2.17: Real and approximated amount of hot water stored in the tank

The histogram of the difference $V_{estimate} - V_{real}$ calculated from all minute samples of 1000 days observation period for both data sets A and C is in figure 2.18. They both are very similar.

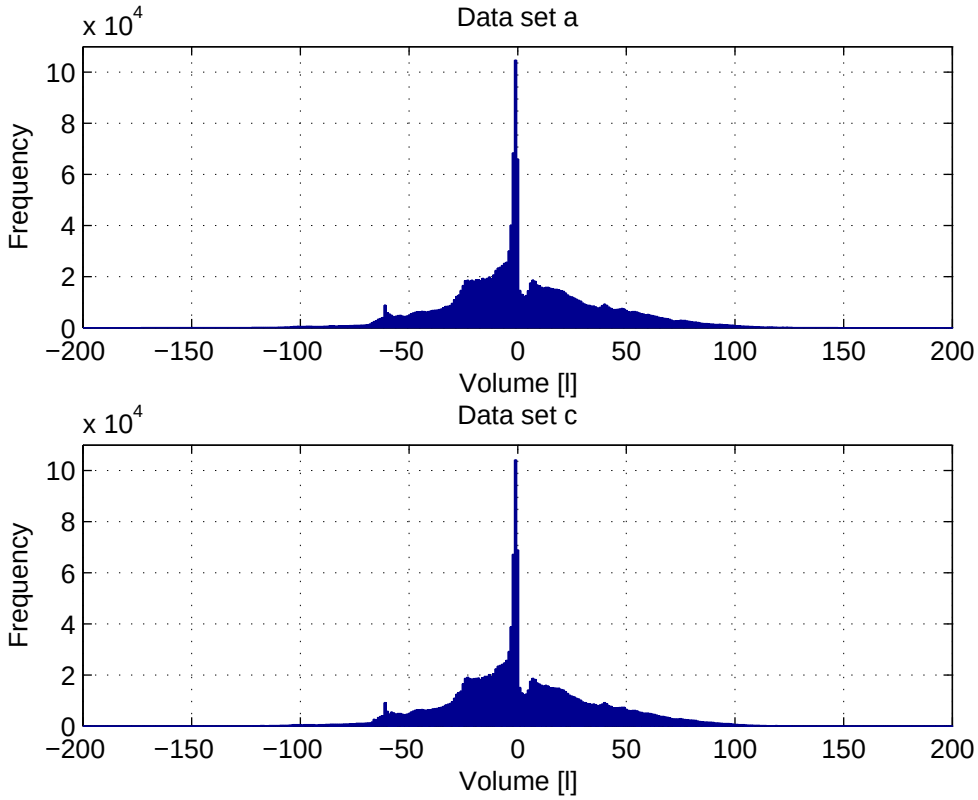

Figure 2.18: Histogram of error $V_{estimate} - V_{real}$

A distribution function was obtained from the empirical distribution of daily error for data set A which is the upper histogram in figure 2.18. The distribution function is shown in figure 2.19. It can be seen that the error is more likely to be negative than positive. The probability is approximately 0.6.

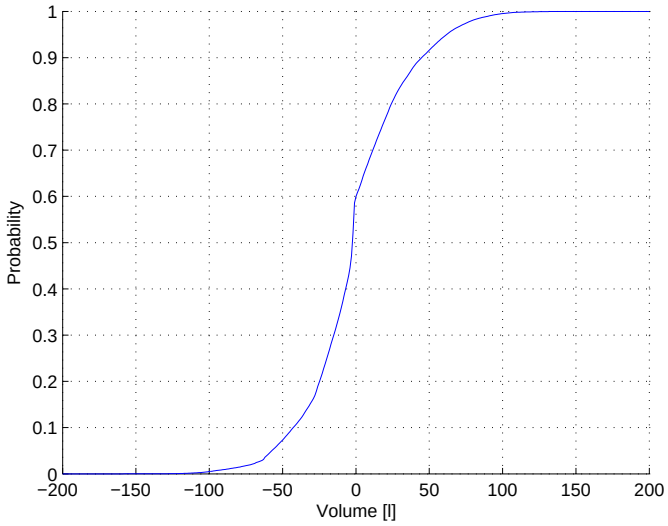

Figure 2.19: Distribution function of the error of estimate of the amount of hot water stored in the tank

Statistical parameters of error from all minute samples for the whole period of 1000 days together with 95% confidence interval are shown in figure 2.20.

data set a - mean [l]	0,53
data set a - STD [l]	34,59
data set c - mean [l]	0,24
data set c - STD [l]	34,48
95% confidence interval for both data sets [l]	(-72,72)

Figure 2.20: Parameters of error

The simulation was repeated with the real load profile of the heater instead of its approximation made by Charging interval detection block. No significant improvement on 95% confidence interval was observed which leads us to the conclusion that the error is caused by the randomness of the hot water consumption.

Conclusion

In this thesis I proposed a method of approximation of the amount of hot water stored in the tank. Chapter 1 dealt with the description of algorithms and demonstrated their function on data from electricity meters which was obtained in project BIOZE. Firstly, the algorithm for estimation of nominal power input of the heater and detection of phase the heater is connected to were proposed. This information was used to identify intervals of charging of the hot water storage tank. The approximation of the daily profile of the hot water consumption was developed based on typical profile, which was adjusted using the estimate of the total daily hot water consumption. Then a model of the heater was developed. The output of this model is the desired estimate of the amount of hot water stored in the tank. For the case that the electricity meter stops providing data, a model of thermostat was created. The algorithm for estimation is capable of overcoming the lack of input data until the error in measurement disappears.

In chapter 2 synthetic load curves were obtained and used as an input to the algorithms. A more advanced method for estimating the daily hot water consumption profile was proposed. A big emphasis was put on evaluating errors of estimation.

The final result of this thesis is the uncertainty of the estimate of the amount of hot water stored in the tank. It is expressed as a 95% confidence interval (-72, 72) [l]. The main reason for the uncertainty is the random nature of hot water consumption. This result is good considering the lack of data available.

Estimation of the hot water consumption from electricity consumption measurement is a cheap, well-functioning method, with no special equipment such as additional sensors required. The only device needed is a smart meter with sufficient computational performance. These methods has potential for development and further uses.

In case the precision of the estimate would be a high priority, the manufacturers of heaters could implement an interface which would provide an estimate of stored hot water based on measuring temperature or by other means. This information could then be transmitted to the smart meter which would forward it to the data center.

Appendix

	Data set a				Data set b				Data set c			
	mean [l]	standard deviation [l]	number of days	mean / stdt %	mean [l]	standard deviation [l]	number of days	mean / stdt %	mean [l]	standard deviation [l]	number of days	mean / stdt %
ID1												
mon	152	45	5	29	202	47	4	23	150	25	2	17
tue	202	47	4	23	170	38	3	22	184	71	2	39
wed	163	51	2	31	147	55	2	38	127	0	1	
thu	147	55	2	37	152	35	3	23	108	0	1	
fri	155	39	3	25	194	38	3	20	114	0	1	
sat	194	38	3	20	151	45	3	30	169	0	1	
san	127	25	2	20	152	44	5	29	110	0	1	
WD	166	47	15	28	167	45	16	27	144	44	7	31
ID2												
mon	253	44	8	17	267	62	9	23	227	27	3	12
tue	268	76	13	28	263	84	12	32	266	113	5	42
wed	279	47	13	17	262	61	13	23	270	43	7	16
thu	260	55	12	21	284	74	12	26	235	65	6	28
fri	229	46	10	20	250	60	10	24	223	13	5	6
sat	270	64	12	24	271	73	12	27	238	15	6	6
san	312	76	9	25	339	198	8	58	258	0	1	
WD	265	57	58	21	272	70	58	26	249	67	27	27
ID3												
mon	135	57	9	42	141	48	9	34	137	17	3	12
tue	161	40	8	25	138	32	8	23	130	31	4	24
wed	145	31	8	21	156	28	8	18	167	23	3	14
thu	128	39	10	30	132	28	10	21	126	34	5	27
fri	138	54	9	39	146	40	9	28	169	30	4	18
sat	232	11	3	5	233	16	2	7				
san	104	36	9	34	108	33	10	31	104	45	5	43
WD	138	42	45	30	139	33	45	24	135	31	20	23
ID4												
mon	36	7	9	20	34	4	7	11	31	4	3	11
tue	39	18	6	46	41	25	4	62	23	0	1	
wed	43	14	7	33	67	70	6	104	43	10	2	23
thu	38	12	6	32	44	18	6	41	44	4	3	9
fri	36	15	8	43	30	15	5	48	38	20	2	53
sat	45	7	8	15	62	59	7	96	53	4	2	7
san	32	10	9	32	40	17	7	43	27	10	4	35
WD	39	12	34	32	46	35	29	76	39	9	12	22
ID5												
mon	45	10	16	23	46	16	17	34	50	18	10	35
tue	42	16	16	39	42	16	16	39	47	18	10	39
wed	47	15	16	32	49	14	15	28	49	7	7	13
thu	49	19	13	39	49	19	13	39	49	21	7	43
fri	69	22	4	32	66	27	3	40	66	38	2	57
sat	80	26	14	33	80	26	14	33	67	30	6	45
san	44	18	14	41	44	19	13	43	43	16	7	37
WD	46	16	74	34	47	17	74	35	49	17	41	35

Figure 2.21: Detected hot water consumptions (WD - working days)

Contents of supplement CD

- PDF version of this document
- Matlab codes of developed algorithms

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