A Predictive Model for Smart Control of a Domestic Heat Pump and Thermal Storage

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Abstract: The purpose of this paper is to develop and validate a predictive model of a thermal storage which is charged by a heat pump and used for domestic hot water supply. The model is used for smart grid control purposes and requires measurement signals of flow and temperature at the inlet and outlet of the storage to determine charged and discharged thermal energy, and electrical energy consumption of the heat pump. The paper reviews possible simulation models and describes a predictive model for the state of charge and for the heat pump power consumption during charging based on experimental data. Simulations are carried out and results are compared with experiments. The model is applied in a case of domestic smart energy control for which results are shown.

1 INTRODUCTION

To reduce carbon dioxide emissions, energy supply systems around the world increasingly integrate energy from renewable sources such as solar Photo Voltaic (PV), wind turbines and biomass conversion. On a local scale of households and small companies this concerns mainly rooftop solar PV systems, urban wind turbines and bio-gas Combined Heat and Power installations (CHP). Due to the daily solar movement, dependence on weather conditions and people's consumption patterns, there is a mismatch between times of energy production and demand. For existing low voltage grids this can cause voltage increase beyond acceptable bounds at times of overproduction or voltage decrease at times when the demand is much higher than the local production.

As pointed out in (Nykamp, 2013), an expensive solution is to strengthen the existing grid. An economically more attractive alternative is to invest in smart grids. The purpose of a smart grid for a low voltage network is to balance local electricity production with demand. A hybrid smart micro grid combines electric production and demand with thermal energy production and demand. The solution contains smart control of flexible devices (i.e. washing machines, dishwashers, heat pumps) and may also contain electric and thermal storage. By controlling flexible devices and storage chargers, grid overloads either due to overproduction or demand peaks are avoided (Leeuwen et al., 2015).

As only part of the demand is flexible and due to increased electrification of household and transportation energy demand, there is often a high level of simultaneous energy demand within an area. Therefore, electrical and thermal storage systems are gaining importance. To control storage charging and discharging, algorithms used for smart energy control need actual information on the state of charge (SoC) of the storage in order to predict the amount of charging or discharging which is possible in the near future. As most smart control algorithms rely on linear programming or control heuristics, and our interest is on application in local embedded systems as part of the storage, the predictive model should be simple. On the other hand it is well known that describing charging and discharging processes for thermal storage systems is rather complex. Therefore the problem statement of this paper is how to predict the state of charge of a thermal storage and required charging power consumption in a simple but sufficiently accurate way. The goal of this paper is to develop mathematical model descriptions for this and to validate the models with experimental data.

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The main contributions of this paper are:

- provide an overview of thermal storage simulation models
- develop models for prediction of the state of charge and charging power consumption
- validate accuracy of model predictions with experimental data

This paper is structured as follows: Section 2 discusses related work on mathematical models for prediction of storage state of charge. Section 3 describes the model and validation experiments. A comparison of model prediction and experimental results is shown and discussed in Section 4, in which also results of a case study are presented which demonstrates application of the model. Finally, Section 5 draws conclusions and introduces future work.

2 RELATED WORK

The behavior of a thermal storage during standstill, charging and discharging is studied by numerous authors. One of most important aspects of a thermal storage is thermal stratification, as this leads to maximum exergy utilization (Rosen, 2001). An overview of research into thermal stratification is reported by (Han et al., 2009), while (Fan and Furbo, 2012) reports on the influence of heat loss on thermal stratification.

Predictive modeling for the temperature distribution within a thermal storage in relation to inlet and outlet flows is a well investigated area. This concerns mainly one-dimensional models, e.g. the lumped capacitance multi-node approximation (Kleinbach et al., 1993) which is implemented in simulation software like TRNSYS. Good results are obtained by approximating the thermal storage with at least 15 nodes or uniform temperature layers. An even more detailed approach of temperature distribution and flow patterns within the storage is possible with a two-dimensional, finite volume model which includes natural and mixed convection boundary conditions (Oliveski et al., 2003). The one and two-dimensional approaches are computationally expensive mainly because of the small time intervals, e.g. seconds to minutes required for simulation. For smart control of the storage and heat pump, such a detailed knowledge of the temperature distribution is not required. Also, time intervals used in smart control are much larger, e.g. 15 minutes to 1 hour. (Halvgaard et al., 2012) uses a lumped capacitance single node model of a thermal storage for model predictions as part of a smart control system. This model essentially describes energy content of the storage and is also introduced by others (Kriett and Salani, 2012), (Henze et al., 2004). This model is straightforward to apply for model predictions as part of smart control, however the relation between heat pump performance and lower temperatures within the bottom part of a thermally stratified storage is lost. Hence, prediction of electricity consumption in time, one of the most important goals of the predictions, is less accurate.

A grey-box model with system identification method is proposed by (De Ridder and Coomans, 2014). The model is the same one-dimensional multi-node approximation discussed earlier but in this case, 5 nodes are proposed together with a parameter identification method based on the Markov-chain Monte-Carlo method. Although the results of this method are reasonable, we foresee two problems in our applications: (1) such identification algorithms are difficult to apply within low cost embedded device controllers with limited available memory and computational power, (2) even with only 5 nodes, for accuracy reasons, evaluation of the model prediction involves time intervals in the order of minutes rather than 15 minutes to 1 hour.

An iterative model which approximates the storage into two layers, one hot layer at the top and one mixed layer with an average temperature below that is reported in (Baeten et al., 2015). This approach is promising and is partly the basis for the present paper. Our model predicts without iterations both the storage state of charge and heat pump electric consumption of a future charging cycle in a one step calculation, based on available data of the inlet/outlet flows.

3 METHODS

A general and widely applicable model for the supply from a thermal storage or electric battery is based on energy conservation which states:

$$\Delta S_t = \Delta C_t - \Delta D_t - \Delta L_t \tag{1}$$

In which the term ΔS_t signifies the change of stored energy, ΔC_t the charged energy, ΔD_t the demand and ΔL_t the energy loss, all within a time interval Δt which in discrete time is the interval $(t-1,t)$. In the following, the terms in Equation 1 will be discussed.

3.1 Type of Thermal Storage

A common storage configuration for domestic hot water supply is shown in Figure 1 for which the mathematical notations are explained in Table 1. Cold water flows in at the bottom, hot water is drawn

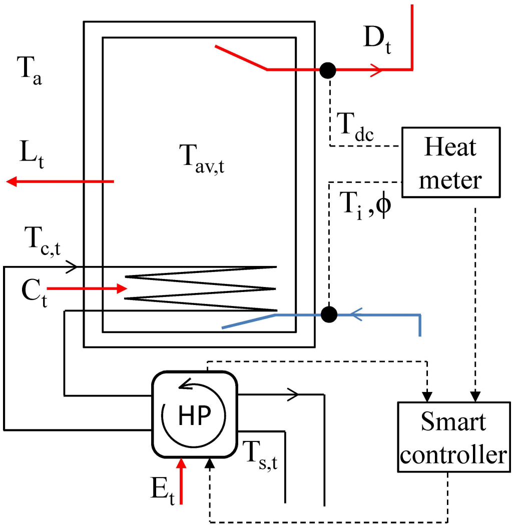

Figure 1: Schematic picture of the thermal storage.

from the top of the storage. A heat pump or solar collector generates heat which is transferred by a coil heat exchanger within the bottom region of the storage tank.

Table 1: Mathematical notations used in Figure 1.

Notation	signification
C_t	charging thermal energy at time t
E_t	heat pump electrical energy consumption
L_t	loss of thermal energy from the storage
D_t	thermal energy demand from the storage
HP	heat pump
Φ	inlet or outlet water flow
T_a	ambient temperature
$T_{c,t}$	charging flow supply temperature
$T_{s,t}$	heat pump source supply temperature
T_{dc}	outlet or discharge water temperature
T_i	inlet water temperature
$T_{av,t}$	average storage water temperature

The size of the thermal storage is typically 200 liters, sufficient for daily hot water consumption of households up to 5 persons. The storage may not be the only hot water system within a house. Hot water for kitchen use, e.g. to wash dishes, may be supplied by a separate 10-15 liters electric hot water storage. The model derived in this section may also be applicable for this type of storage. It is interesting to incorporate such storages in a smart energy control system due to the relatively high power demand, i.e. typically 2500 W for charging periods ranging from 30 minutes to 2 hours. Figure 1 shows connection of the storage to a heat meter and smart controller. The heat meter determines the supplied energy and volume of hot water. The smart controller determines the actual

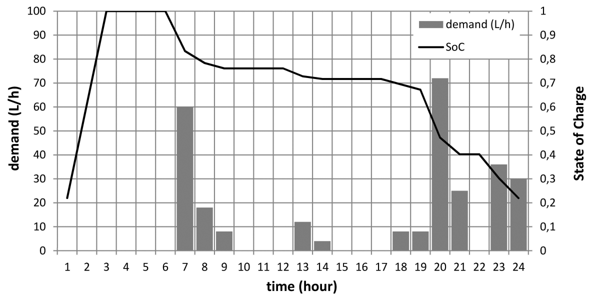

Figure 2: Typical daily hot water demand pattern of a household.

SoC and decides when to start the heat pump (HP) for charging, based on optimization objectives. We will discuss this topic further in Section 4.2.

The thermal storage supplies the daily demand for domestic hot water for a single household. The demand pattern can be learned in time, e.g. as hot water flow per time interval. For a single house, the uncertainty on the demand pattern is large if it is evaluated for small time intervals, but it is smaller if demand is evaluated for larger time intervals, e.g. as total demand per hour. Figure 2 shows a typical daily demand pattern of a 4 person household with an annual domestic hot water energy demand of 9 GJ/y (Leeuwen and Ende, 2016).

The demand pattern is given in liters/hour of 40°C. The thermal storage has a size of 200 liters and is charged to 60°C. The SoC of the storage which is explained in Section 3.2 is charged to 1 early in the night and drops to nearly 0.21 at the end of the day due to the discharge of hot water. The daily SoC pattern shows that for the evaluation of the SoC, a resolution of one hour of the demand prediction is sufficient in this case.

Another aspect to take into account is the comfort of domestic hot water supply. Measures for comfort are the water temperature and the availability in time of warm water. People's expectations of comfort may vary throughout the day. For the control system, information about warm water demand and expected comfort is important in order to decide which amount of water of a certain temperature should be at least available within the thermal storage at certain moments during the day. The predictive model for charging and discharging the storage should be able to provide this information.

3.2 Discharging Model and Experiments

If the storage shown in Figure 1 is ideally stratified, the entire volume of hot water with a uniform tem-

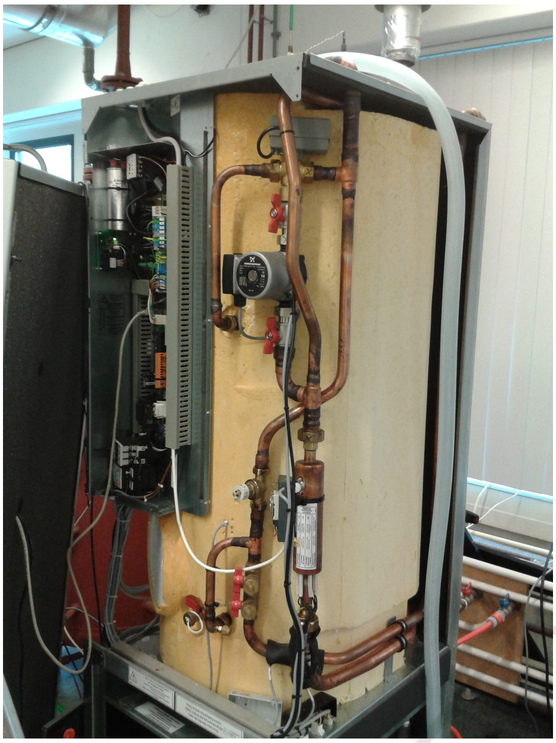

Figure 3: Alpha-Innotec heat pump storage combination used for testing.

perature moves upwards, perfectly separated from a growing volume of cold water from the bottom. However, the incoming cold water flow induces some mixing of cold and hot water. The result is that less water volume with a high temperature can be drawn from the tank than in the perfect stratified case.

To investigate this behavior, experiments are carried out by the energy research lab of Saxion University of Applied Sciences. The experiments involve charging and discharging cycles for two commercially available, combined heat pump/thermal storage units. One is a 200 liter combination with a ground water source heat pump from Alpha-Innotec, refer to Figure 3. The other is a 50 liter combination with an air source heat pump from Inventum.

For the hot water storage and for the glycol source side circuit of the heat pump, the 200 liter combination is equipped with PT-100 temperature sensors at the inlets and outlets and flow sensors at the inlets. The wall socket is equipped with an electric power sensor. The sensors are connected to a National Instruments data acquisition system which is connected to a PC. Labview is used to obtain and log the data. The 50 liter combination was tested at a user's site using a minimum amount of sensors, a PT-100 sensor and a flow sensor on the hot water outlet and an electric power sensor on the wall socket. A portable datataker acquisition unit was used which logs the

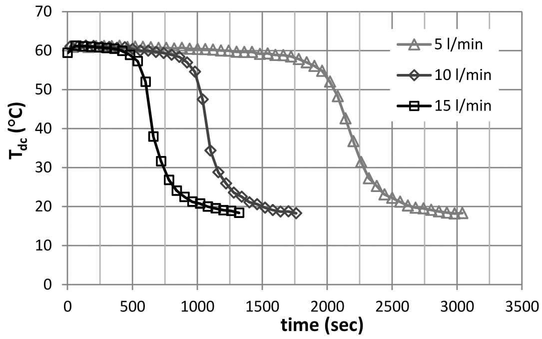

Figure 4: Outlet water temperature at constant flow rates.

data to memory. On the 50 liter combination, only a few charge/discharge cycles with constant flow are carried out to verify the phenomena observed from the 200 liter combination for a combination with a much smaller storage size.

For the 200 liter combination, in Figure 4 the discharge temperature (T_{dc}) is shown for three constant flow rates. When perfectly stratified, the storage should supply hot water with a constant high temperature for 2400, 1200 and 800 seconds for the respective flow rates of 5, 10 and 15 l/min. However, figure 4 shows that allready at 2150, 1050 and 650 seconds, the outlet water temperature has dropped below the minimum use temperature of 40 °C, which demonstrates the effects of mixing of cold and hot water within the thermal storage during discharging.

Purpose of the discharging model is to determine:

- the amount of energy supplied from an initial State of Charge
- the present SoC of the thermal storage
- the amount of useful energy ($T \geq 40°C$) that the storage is still able to supply

Assuming that energy supply from the storage equals energy demand, the supplied energy in time interval Δt is calculated with Equation 2.

$$\Delta D_t = \Delta t \cdot \phi_t \cdot \rho \cdot c_p \cdot (T_{dc,t} - T_{i,t}) \quad (2)$$

In which ρ the water density and c_p the water specific heat. In this paper, ρ and c_p are assumed constant although they vary slightly with temperature. When a heat meter is connected to the thermal storage, the outlet temperature $T_{dc,t}$, inlet temperature $T_{i,t}$ and flow ϕ_t are registered, which is used to learn the demand in time. The heat meter calculates the supplied energy by applying Equation 2. A smart grid algorithm may use this information to determine the actual SoC of the thermal storage. The SoC is calculated by Equation 3.

$$SoC_t = \frac{S_t}{S_{max}}\ ,\ 0 \leq SoC_t \leq 1 \quad (3)$$

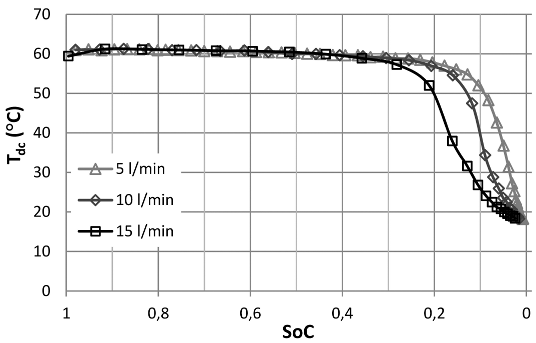

Figure 5: Relation between storage State of Charge and discharge temperature.

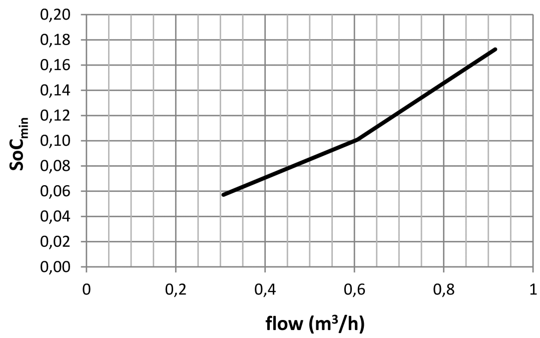

Figure 6: Minimum State of Charge as a function of constant flow rate.

The stored energy at time interval t, S_t is determined by Equation 4. S_{t-1} is the stored energy at the previous time interval $t-1$. The maximum charged energy is determined by Equation 5, which is worked out from the first law of thermodynamics, relating the required thermal energy to the change of enthalpy of the mass of water within the storage (Moran and Shapiro, 2000).

$$S_t = S_{t-1} + \Delta S_t \tag{4}$$

$$S_{max} = V \cdot \rho \cdot c_p \cdot (T_{max} - T_i) \tag{5}$$

In which V the water volume in the storage, T_{max} the maximum, uniform temperature of the storage, i.e. determined by the storage thermostat settings. The inlet cold water temperature T_i is assumed constant in this Equation. In practice, a certain volume of the inlet cold water may warm up to room temperature conditions due to stand-still heat transfer in the inlet pipes. The cold water temperature also varies with the seasons.

The amount of useful energy that can be supplied by the storage is determined by a minimum SoC value. In figure 5 the minimum SoC is determined from the intersection with a supply temperature of $40°C$.

In figure 6, the minimum SoC is shown as a function of flow rate. Assuming negligible mixing effects (or minimum SoC of zero) for a flow rate close to zero, the minimum SoC appears to increase approximately linear with flow rate. In practice, flow rates are not constant but may vary per draw between 5 and 15 l/min. This makes it practicable to use a single value for the minimum SoC, e.g. the worst case which is 0.18. Together with the calculation of the stored energy from Equation 4, the minimum SoC value determines the amount of useful energy that the storage is still able to supply.

3.3 Charging Model and Experiments

During charging, heat is transferred from the coil at the bottom to the water in the storage by the principle of natural convection. From a discharged state, the water in the storage is cold and during charging the temperature increases gradually. The heat pump efficiency decreases with increasing water temperature during the charging process. The heat pump's refrigerant flows through the coil heat exchanger where it condensates at constant temperature. The coil is usually made of thin-walled copper, aluminum or stainless steel with an approximately negligible conduction resistance.

Based on supplier heat pump characteristics (Alpha-Innotec, 2015) and validation measurements, the charging energy of the heat pump ΔC_t appears to be approximately linear with the source temperature $T_{s,t}$. The same characteristics show that the electric energy ΔE is approximately linear with the condenser temperature. Linear equations are developed for C_t and E_t and given in Equation 6.

$$\begin{aligned} \Delta C_t &= a \cdot T_{s,t} + b \\ \Delta E_t &= c \cdot T_{c,t} + d \end{aligned} \tag{6}$$

In which a, b, c, d are constants which are determined from supplier data. For the 200 liter heat pump, these constants are given in Table 2. It is common practice for domestic heat pumps to measure the condenser and source temperature for safety reasons, hence the smart control system should be connected to the heat pump and obtain this data. The source temperature may vary in time but this depends on the heat source, e.g. ambient air varies much more dynamic than ground water.

Neglecting the coil conductive resistance, the coil temperature approximately equals the condenser temperature. The heat transfer from the coil to the surrounding water in the storage is given by Equation 7 which is based on Newton's law of cooling (Moran

Table 2: Heat pump and coil model parameters.

Parameter	Value	Unit
a	0.172	kW/K
b	-42.2	kW
c	0.04	kW/K
d	-10.2	kW
$h \cdot A$	1.191	kW/K

and Shapiro, 2000).

$$\Delta C_t = h \cdot A \cdot (T_{c,t} - T_{w,t}) \tag{7}$$

In which h the coil heat transfer coefficient, A the coil outside area and $T_{w,t}$ the surrounding water temperature within the storage. The product $h \cdot A$ is approximately constant for a complete charging cycle, is obtained from supplier data and given in Table 2. When the surrounding water temperature is known, equating ΔC_t from Equations 6 and 7 yields the condenser temperature $T_{c,t}$ which determines the electric energy requirement ΔE_t. Hence a suitable prediction of the water temperature within the thermal storage around the coil is needed.

When charging from a fully discharged condition, the water temperature within the storage is approximately uniform and the left term of Equation 1 is approximated as:

$$\rho V c_p \Delta T_{w,t} \tag{8}$$

Solving Equation 1 yields the average water temperature which is then substituted into Equation 7.

However, the storage is usually not discharged beyond the minimum SoC. In that case, we learn from Figure 4 that a temperature distribution must exist within the storage, consisting of a layer of hot water at the top of the storage, a cold layer at the bottom and a mixed layer in between. During charging, the hot layer at the top remains in place, while the temperature of the cold and mixed layer increases gradually. In the following, we develop a suitable approximation based on the SoC.

In figure 7 the decrease of the SoC with the total discharged volume from the storage is shown, which indicates a linear decrease down to the minimum SoC level. For the slope, Equation 9 applies.

$$\frac{\Delta SoC}{\Delta V} = \frac{1}{V} \tag{9}$$

The model assumes that during charging, the water volume in the storage consists of 2 layers: an upper layer with a uniform hot temperature and a lower layer with a colder but increasing temperature. For a given SoC_t ($SoC_{min} \leq SoC_t \leq 1$), the remaining volume of hot water $V_{h,t}$ within the storage can be calculated with Equation 9 substituting: $\Delta SoC = SoC_t - SoC_{min}$, which outputs ΔV which is $V_{h,t}$.

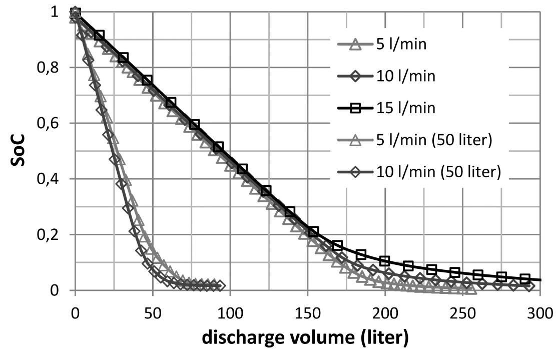

Figure 7: State of Charge as a function of discharged volume.

The average temperature $T_{w,t}$ in Equation 8, according to the model assumption of 2 layers, is the average temperature of the lower layer of mixed water volume in the storage, i.e. $V - V_{h,t}$. This temperature is calculated from Equation 10 in which the stored energy S_{t-1} is known from the state of the previous time interval.

$$S_{t-1} = \rho \cdot c_p \cdot [V_{h,t-1} \cdot (T_{max} - T_i) + (V - V_{h,t-1}) \cdot (T_{w,t} - T_i)] \tag{10}$$

Figure 8 shows the measured heat pump electric power during charging from an empty to a full state of the storage. During charging, the water temperature is measured at two locations, at a quarter of the storage height and at the top. These temperatures also increase approximately linear and differ only a few degrees during charging, so we conclude that during charging from an empty state, the storage temperature is increased isothermal. Hence, electric power increases approximately linear with the water temperature within the storage. It follows that when the charging process starts from an arbitrary SoC state, the average water temperature of the water volume that needs a temperature increase determines the duration and the amount of electric energy.

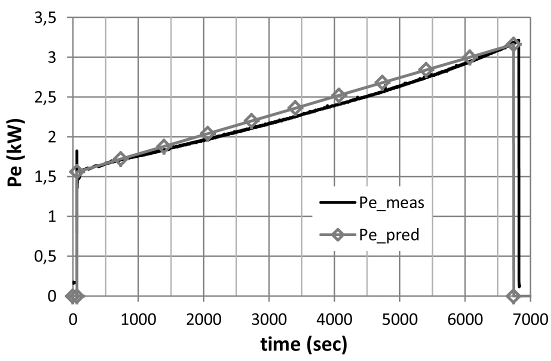

Figure 8: Measured electric power during charging.

The total required thermal charging energy is calculated with Equation 12.

$$C_{tot,t} = (1 - SoC_t) \cdot S_{max} \tag{11}$$

$$SoC_{min} \leq SoC_t \leq 1 \tag{12}$$

The duration of the charging process τ_t is calculated with Equation 13

$$\tau_t = \frac{C_{tot,t}}{\Delta C_t} \tag{13}$$

In which ΔC_t is calculated with Equation 6. The electric power consumption profile P_{e,t^*} of a future charging cycle with discrete time t^* in the future, from a given SoC_t to fully charged conditions, is predicted as a linear function in time, Equation 14 which starts at a value P_{e,t_i^*} and ends with $P_{e,t_i^*+\tau}$. These values are calculated with ΔE_t, Equation 6. t_i^* is some time in the future when charging is initiated, which is a control variable for the smart control system.

$$P_{e,t^*} = P_{e,t_i^*} + \frac{P_{e,t_i^*+\tau} - P_{e,t_i^*}}{\tau} \cdot t^*$$
$$0 \leq t^* \leq \tau \tag{14}$$

The electric energy consumption of the future charging cycle is calculated with Equation 15, which is the integral of Equation 14.

$$E_{tot,\tau} = \frac{\tau}{2} \cdot (P_{e,t_i^*} + P_{e,t_i^*+\tau}) \tag{15}$$

With the parameters given in Table 2 the values shown in Table 3 are calculated for the charging cycle of Figure 8. In this figure, the resulting prediction profile is also shown for comparison and this demonstrates the excellent accuracy of the approach.

Table 3: Comparison between prediction and measurements of electric energy consumption.

Result	Measured	Predicted	Unit
τ	6763	6677	sec
P_{e,t_i^*}	1.45	1.56	kW
$P_{e,t_i^*+\tau}$	3.21	3.16	kW
$E_{tot,\tau}$	15564	15759	kJ

3.4 Energy Loss

When the storage is charged and discharged daily, energy losses from the storage to the surrounding air are insignificant due to good insulation of modern thermal storage tanks. However, when the storage is not discharged for many days and placed in a relatively cold environment, losses may be more significant. The heat loss ΔL_t is calculated by the general heat transfer relation (Moran and Shapiro, 2000), Equation 16.

$$\Delta L_t = UA \cdot (T_{av,t} - T_{a,t}) \tag{16}$$

In which UA the storage heat loss coefficient, $T_{av,t}$ the average storage temperature and $T_{a,t}$ the ambient air temperature which may be assumed constant in time, depending on the situation. Assuming constant water density and specific heat, $T_{av,t}$ is calculated with Equation 17.

$$V \cdot T_{av,t} = V_{h,t} \cdot T_{max} + (V - V_{h,t}) \cdot T_{w,t} \tag{17}$$

3.5 Validation Experiments

Validation of the model is performed by discharging the storage with constant flow ϕ starting at SoC=1 to SoC_{end}, followed by charging to SoC=1. Values for ϕ and SoC_{end} are given in Table 4.

Table 4: Validation experiment settings.

Experiment	ϕ (l/min)	SoC_{end}
1	5	0.6
2	10	0.6
3	15	0.6
4	10	0.4
5	10	0.2

During discharging, flow and temperature are measured of the inlet and outlet water. During charging, electric energy consumption is measured. The model prediction algorithm involves:

1. determine actual SoC from measured flow and temperatures, Equations 1, 2 and 3
2. determine required charging energy C_{tot}, Equation 12
3. calculate duration τ of future charging cycle, Equation 13
4. calculate average water temperature of cold and mixed water layer in thermal storage, Equation 10 and condenser temperature at the beginning and end of a future charging cycle, Equation 7
5. determine minimum and maximum electric power of charging cycle P_{e,t_i^*} and $P_{e,t_i^*+\tau}$, Equation 6
6. determine total electric energy consumption during charging cycle E_{tot}, Equation 15

The validation compares model predictions of duration τ, minimum and maximum electric power P_{e,t_i^*} and $P_{e,t_i^*+\tau}$ and total electric energy consumption E_{tot} which characterize the future charging cycle with the measured charging cycle.

Table 5: Validation results.

Experiment	τ_{meas} (sec)	% error τ	P_{e,t_i^*} (kW)	$P_{e,t_i^*+\tau}$ (kW)	MAX % error ΔP_e	$T_{w,pred}$ $^\circ C$	$E_{tot,meas}$ (kJ)	% error E_{tot}
1	2911	-7.2	2.17	3.20	6.2	31.2	14872	0.3
2	2637	2.5	2.10	3.22	5.6	29.9	14465	3.1
3	2973	-9.1	2.16	3.22	5.4	31.6	15018	-0.7
4	4050	-1.6	1.86	3.22	8.7	27.6	22352	0.1
5	5229	1.1	1.85	3.23	5.2	25.4	29662	0.1

4 RESULTS AND DISCUSSION

4.1 Validation Results

The validation results are shown in Table 5. The measured duration τ_{meas}, measured minimum and maximum electric power consumption P_{e,t_i^*} and $P_{e,t_i^*+\tau}$ and measured total electric energy consumption $E_{tot,meas}$ are listed for each experiment. The error of the predictions is given as a percentage of the measured values. For the predictions, the average water temperature of the cold and mixed water layer $T_{w,pred}$ calculated from Equation 10 is shown, from which the electric power at the start of the charging cycle is predicted.

For the future charging cycle, accurate prediction of the total electric consumption and duration are the most important aspects for smart energy control purposes. Table 5 indicates an excellent prediction accuracy of the total electric consumption, while in most cases the percentage error is smaller than 1%. Although the prediction of duration seems less accurate in some cases, the maximum error of 9.1% is only a difference of 4.5 minutes. Smart energy control algorithms usually evaluate predictions in time intervals of 15 minutes, hence this maximum error is acceptable.

For the prediction of the energy consumption profile, the maximum error (8.7%) is 280 W, which appears at the end of the charging cycle. This error is mainly due to differences in the same order of magnitude between supplier data of electric power consumption which is used for the model and actual measurements of electric power consumption. We verified that if the constants c, d in Equation 6 are based partly on supplier data and partly on the measured power consumption at the end of charging, the prediction profile is more accurate. This information could be made available to the control system by a connected smart electricity meter.

It also has to be taken into account that the errors are in the same order of magnitude as the propagated measurement errors of the used sensors. Therefore we conclude that the predictive model is very well capable to accurately predict the duration, power consumption and power consumption profile for future charging cycles of the thermal storage.

4.2 Case Application

Application of the model is investigated with a case for increased self-consumption of domestic solar PV electricity. Figure 9 shows a reference profile of a day in the spring season. The profile is constructed specifically as a case for this paper and based on measured data on electricity consumption of a four person household and weather data. The figure shows electric power consumption and solar PV generation without smart control. The yearly sum of daily base loads totals 2600 kWh/y and includes electricity consumption of lights, dishwasher, washing machine, washing dryer, television, computer and small electronic devices. The base load is considered non-flexible in this case. The heat pump which charges the thermal storage is a flexible device which can be controlled by a smart controller, as indicated in Figure 1. The reference case shows that solar PV energy generation during the day is mostly exported to the grid, while the occupants are mostly out of the house during the day and come home around 17.00 hours. Financially, this may be unfavorable, depending on the feed-in tariff. Besides this, charging energy of the heat pump and SoC of the thermal storage are shown. The total profile illustrates the load on the power grid, ranging from a feed-in peak of -1380 Wh during the day to a demand peak of 3020 Wh during the night.

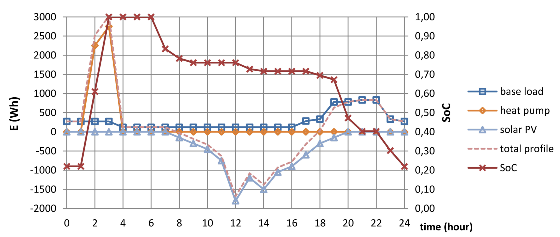

Figure 9: Reference electricity consumption and solar PV generation profile.

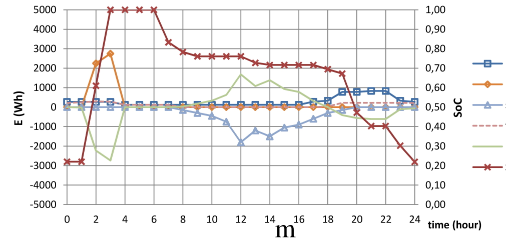

Figure 10: Variant 1: electricity profile with optimized electric battery storage.

Figure 10 shows results for variant 1 which includes an electric battery which is able to charge when there is a surplus of electricity generation and to discharge when there is insufficient generation. The hourly amounts of charged and discharged energy are determined by an optimization algorithm which minimizes peaks of the total profile. The optimization algorithm used is explained in detail in (Fink et al., 2015). The required battery capacity for this profile is calculated at 7.34 kWh. The electricity consumption peak is reduced to 293 Wh during the night.

Figure 11 shows results for variant 2 which includes an electric battery and smart control of the heat pump. Besides minimizing peaks of the total profile, the control algorithm minimizes capacity of the electric battery. The thermal storage and heat pump charging model developed in this paper are included in the control algorithm to predict SoC and electricity consumption. As result, the required battery capacity is decreased to 4.58 kWh and the electricity consumption peak is now 256 Wh which occurs during daytime hours.

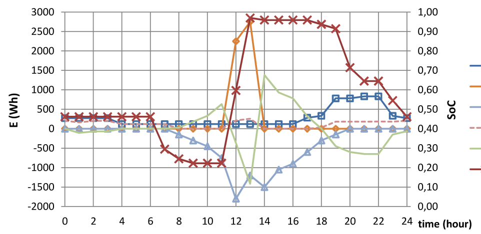

Figure 11: Variant 2: electricity profile with optimized heat pump control and electric battery storage.

The results of variant 2 have several positive effects:

- decreased battery capacity and lower investments compared to variant 1
- lower electricity peak values compared to variant 1
- shift of electricity shortage towards daytime hours, allowing more local consumption of other renewable energy generation in the district

Main purpose of the case study is to show the significance of model prediction of energy for charging the thermal storage. A more elaborate case study involving different households, more days throughout the year and comparisons with thermostat thermal storage control is required to study the effects of smart control more thoroughly.

5 CONCLUSIONS

In this paper a predictive model is developed for a domestic hot water thermal storage which is charged by a heat pump. The model is derived from heat balance equations combined with insights from experimental data. The model involves a set of relatively simple algebraic equations which are easy to evaluate by smart energy control algorithms without iterations. Required inputs are: recordings of measured inlet and outlet water temperature and water flow, which can be performed by low cost heat meters in practice. Outputs of the predictive model are: duration, electric consumption profile and total electric energy consumption of a future charging cycle by the heat pump from the present state of charge to fully charged conditions.

Accuracy of the model is validated by comparing results of model predictions with experimental findings. The percentage error on the predicted duration of the charging cycle is between 1% and 9%, on the electric power consumption between 5% and 9% and on the total electrical energy consumption lower than 3%.

Hence the model can be applied for similar domestic hot water storage configurations, although the relations introduced which describe heat pump electric power consumption, may be different for different types of heat pumps and different heat pump control systems. Changing these relations is however a relatively simple task which involves analysis of the heat pump characteristics, either from supplier data or by executing a few discharging/charging cycle experiments.

Application of the model is investigated with a case of increased self consumption. The developed predictive model is relatively easy to implement into an optimization control algorithm which minimizes peak electricity consumption of a household and electric battery capacity. The results for this type of control show decreased battery capacity, lower electricity peak values and a shift of hours of electricity shortage from nighttime to daytime hours, which is favorable for local consumption of renewable energy generation in a district. Future work is aimed at integration of the model into the Triana smart grid simulator which is used for simulation studies and as base for embedded smart control systems. We will also investigate suitable methods for domestic hot water demand prediction as part of smart energy control of the thermal storage and heat pump.

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