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ORIGINAL ARTICLE

The role of knowledge about user behaviour in demand response management of domestic hot water usage

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Abstract Load balancing is an important topic in smart grid systems. Dynamic pricing is a common approach to achieve a better balance between renewable energy production and energy usage. This assumes that individual households adapt their energy usage patterns based on energy prices. However, the actual behaviour of consumers in a household is an uncertain factor that might influence the effectiveness of pricing strategies. In this paper, we investigate to what extent knowledge about actual user behaviour can contribute to local optimization of energy usage. We use simulations to study whether a smart heating system that applies a pre-heating strategy for domestic water during periods of low prices can benefit from good predictions of the user behaviour, in financial terms or in terms of energy saving. Also, we use the simulations to investigate the effect of different goal temperatures for the pre-heating strategy. The results show that pre-heating does not make a difference with respect to the energy efficiency, but that during cold months, pre-heating can result in a financial benefit. In addition, we calculate what certainty about the user behaviour is needed to be able to effectively use pre-heating during the warmer summer month. These results can help to design residential energy optimization systems.

Keywords Behavioural information · Smart thermostat · Domestic energy management · Domestic hot water

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Introduction

Electricity generation by non-schedulable renewable sources is quickly growing and implies challenges for the management of electricity grids because of possible imbalances between the supply and demand of energy. Information and communication technology provides promising solutions to efficiently overcome the problem. Remote scheduling of appliances and dynamic pricing of electricity are seen as ways that can help to shift the demand. However, the role of information about the actual behaviour of the user in smart grids is limited in current research. In most research around smart grids, it is usually assumed that users are just rational economic entities, but we take the uncertainty of the user's behaviour into account. In fact, there are more factors that influence the choices of users. In this paper, we investigate to what extent knowledge about actual user behaviour can contribute to local optimization of energy usage.

In particular, we investigate to what extent knowledge about the pattern in the usage of hot water in a house can lead to cost savings or energy reduction. For this purpose, we propose a smart algorithm. Our approach is based on overheating the hot water storage before high-peak hours (like Loesch et al. 2014), in order to get a higher degree of freedom for scheduling, especially for peak hours when a high usage is also expected. However, overheating increases the energy loss, and unnecessary overheating leads to high energy wasting. Our assumption therefore is that it is important to have a correct prediction of the usage during a high-peak period.

Our hypothesis is that the ability to predict the user behaviour will result in strategies that are more energy efficient. To validate this hypothesis, we use a simulation of a house with an electrical heater and thermal energy storage (a hot water tank). We simulate two scenarios in which the predictions about high usage are either correct or incorrect. Based on this, we show for which level of precision of the behaviour prediction it is beneficial to use a pre-heating strategy. In addition, we perform simulations with different goal temperatures for the pre-heating. Based on these results, we can draw conclusions about the most efficient goal temperature in different situations. Although our simulations refer to a specific case study, similar analyses can be conducted for other configurations and control strategies and other demand-response management (DRM) programs. Our findings enable us to draw useful conclusions about the role of behavioural information in the framework of DRM plans.

In this paper, we first extensively discuss the background of our work. Then, we introduce the different controlling strategies, which are used in the simulations in section "Energy and cost effects of pre-heating." The simulation results are analyzed in section "Optimal target temperature for pre-heating." Finally, the paper concludes with our most important findings and suggestions for future work.

Background

Demand side management in residential settings

According to data published by US Energy Information administration,[1] about 40% of the total US energy in 2015 was consumed in residential and commercial buildings, and more than half of it was used for heating purposes (space and water heating).

Smart grids are aimed at the management of both electricity generation and consumption, in order to provide a better integration and exploitation of renewable energy sources. A major component of the future smart grid is an adaptive demand side that allows handling the fluctuating power supply based on renewable energies. Demand response management, DRM, includes all programs designed to influence the customer's energy use, focusing on changing the shape of the load and thereby helping to optimize the whole power system.

Price response strategies are core elements of this process and consist of the optimization of the amount of electricity consumed by the end-user by dynamically adapting electricity prices on an hourly basis by the electricity provider (Schibuola et al. 2015).

Residential premises contain electrical devices that have a lot of hitherto unused flexibility. Their operation can either be delayed (dishwashers, washing machines, etc.), or they contain an energy buffer (Vanthournout et al. 2012). The latter can be an electrical, i.e. batteries, or a thermal buffer. As the cost of water-based thermal buffers is low compared to batteries, these are especially interesting. The more because the thermal demand of a household represents a major portion of the total energy usage. Based on an Australian study, up to 28% of CO_2 emission of houses in 1998 were from the operation of hot water systems (Crawford and Treloar 2004). Also, the charging of thermal buffers can be shifted invisibly for the user and without comfort impact. Therefore, the work presented in this article focuses on buffered electric domestic hot water systems (from now on: DHW) as a source of flexibility to be used in demand response systems.

Using hot water as thermal buffer

The usage of DHW is highly variable: it depends on the geographical situation, also on people's habits, on the time of the year and of course on the type of building usage. Above all, it depends on the inhabitants' specific lifestyle (Meyer and Tshimankinda 1998; Ndoye and Sarr 2008). Nevertheless, residential DHW consumption might show diverse daily consumption profiles at a standard temperature, depending on the inhabitants' demands along the week (Ndoye and Sarr 2008). Because the instant hot water needed throughout the day is different, a heat source that would be needed to supply the instant demand has to be oversized, which is inefficient. Therefore, storing DHW in tanks in order to have water prepared for consumption at the desirable

[1] http://www.eia.gov/tools/faqs/faq.cfm?id=86&t=1

temperature whenever inhabitants require it is more efficient and convenient.

Considering that buildings account for more than 40% of the total energy consumption in the European Union, mainly for space heating and hot water, these are relatively large demands that can be controlled and adapted to perform a DRM function (Arteconi et al. 2013). In winter-dominated climates, the DHW loads can contribute as much as 30% of the total household load (Nehrir et al. 1999). The DHW load profile and average daily global energy load profile follow a similar pattern, meaning that these loads significantly contribute to peak load values (Nehrir et al. 2007). Moreover, DHW is an ideal candidate for DRM because the hot water in the tanks acts as energy storage.

Modelling domestic hot water systems

There is extensive literature on the modelling of electrical DWHs. A novel domestic hot water heater model to be used in a multi-objective demand side management program is suggested in Paull et al. (2010). The model incorporates both the thermal losses and the water usage to determine the temperature of the water in the tank.

Research on DHW buffers for use in smart grid environments either focuses on specialized coordination systems for DHW buffers (e.g. Lane et al. 1996; Du and Lu 2011) or focuses on modelling the behaviour of DHW buffers. Examples of the latter are Lane and Beute (1996), which presents a model to predict the load caused by electric DHW buffers (Kreuzinger et al. 2008), which proposes a methods to estimate the detailed temperature profile of a DHW buffer based on limited temperature measurements.

Vanthournout and colleagues (Vanthournout et al. 2012) present a generalized interface for electric DHW buffers, based on four key indicators that together represent the flexibility state of the buffer, while hiding all implementation details of the device. The correct behaviour of these key indicators has been validated by means of simulations and measurements in a lab prototype that they developed.

In Rodríguez-Hidalgo et al. (2012)), the size of a storage tank is determined for usage in a solar thermal system. It shows that the storage volume not only affects the accumulated energy but also is related to the heat exchanger and collector performances. In consequence, its size will influence in a significant way the performance of the whole DHW solar plant.

In addition to the technologies like thermal energy storages, it seems that smart algorithms are very important, and improper management of heating and storage system could result in negative effects on the energy costs and also on the electrical grid (Loesch et al. 2014).

Controling strategies

In this section, we first review constraints on the temperature of stored water. Then, two common strategies for controlling the heating system (according to the temperature of tank) are presented.

Constraints on the temperature of tank

There are some constraints on the temperature of hot water stored in the tank. First of all, the temperature of tank cannot go higher than the boiling point of storage medium; thus, for tanks which use water, the temperature cannot exceed 100 °C. Moreover, the higher the temperature, the higher the energy loss due to both conduction and possibly the evaporation of hot water.

On the other side of the temperature spectrum, there are discussions about the minimum safe temperature for storing water in tanks. If the temperature of the stored water is too low, the rate of pathogens, particularly legionella (which can cause legionellosis), will increase. According to Bartram (2007), temperature affects the survival of legionella in water as follows:

- above 70 °C: legionella dies almost instantly
- at 60 °C: 90% dies in 2 min
- at 50 °C: 90% dies in 80–124 min, depending on strain
- at 48 to 50 °C: it can survive but will not multiply
- between 32 and 42 °C: ideal growth range

The risk of bacteria colonies (legionella) in water is potentially life threatening. The European Guidelines for Control and Prevention of Travel Associated Legionnaires' Disease recommend that hot water should be stored at 60 °C at least.

Regular controlling strategy

The regular controlling strategy is based on a hysteresis of the storages' temperature. It means that the allowed temperature of the hot water storage is defined as a range. If the minimum temperature is reached, the heater will turn on to increase the temperature; it will work until the temperature reaches the maximum.

$$Controlling\ Signal\ (\mathrm{t}+\Delta\mathrm{t}) = \begin{pmatrix} On & \mathrm{T(t)} < \mathrm{T_{min}} \\ Off & \mathrm{T(t)} > \mathrm{T_{max}} \\ Controlling\ Signal\ (\mathrm{t}) & Otherwise \end{pmatrix}$$

The area between the minimum and maximum temperature offers a degree of freedom for shifting the heater runtime to a certain degree.

Pre-heating strategy

In Loesch et al. (2014), it is suggested to increase the temperature of water stored in tank to a new higher maximum just before the peak hours. By doing so, there is less need to turn on the heater during peak hours and it could thus lead to a decrease in the costs. In fact, in this case, a higher degree of freedom for the heater is possible (due to overheating). Technically, it is implemented by increasing the maximum temperature limit.

Energy and cost effects of pre-heating

To assess the effectiveness of two explained strategies in different situations, a simulation program has been implemented. The behaviour of the system has to be analyzed dynamically to study the temperature of stored water, energy usage, and costs under different scenarios. The simulations of the system were done using TRNSYS (Klein et al. 2004), a well-known simulation environment for thermodynamics. In this section, the main parts of our simulation are described.

Assumptions in the simulations

Time-based pricing

A common way to encourage the customers to shift their power usage to off-peak hours is time-based pricing. In our simulations, it is assumed that there is one daily period of peak hours starting from 19:00 for 3 h. The price of electricity during these period is 0.36€/KWh; it is 0.20€/KWh for off-peak hours.

Hot water usage

For the amount of hot water usage in different hours, two different scenarios are simulated. In both scenarios, it is assumed that there is no water usage during the nights (from 11:00pm to 6:00am) and that there is a constant usage in all other hours, with the rate of 20 l/h. There is one exception: in the second scenario (showering scenario), it is assumed that the residents have a high usage for a short period of time. In this case, there is a peak in the usage, which lasts for 30 min, starting at 21:00, with the rate of 400 l/h (so, in addition to the normal rate of 20 l/h, this results in total rate of 420 l/h). In this scenario, the showering is happening during the peak hours, and it is possible to shift the energy usage from peak hours to not-peak hours by an overheating strategy. We have chosen this scenario as an example in which the behaviour of the human affects the efficiency of a heating strategy. Of course, different behavioural patterns are very well possible. As illustration, Fig. 1 shows the price and the usage in the second scenario for 24 h.

In addition, it is assumed that the hot water at the tap point is used at a temperature of 40.5 °C (which is achieved by mixing hot and cold water). In our

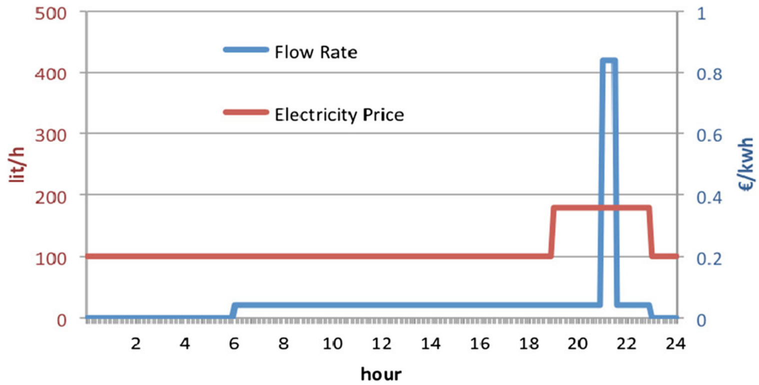

Fig. 1 Electricity price (red) and warm water usage in the showering scenario (blue) in different hours

simulations, the temperature of hot water is the same as the temperature of the stored water at the top of the tank and the temperature of the cold water is the same as the outdoor temperature (in some cases in reality, it might be colder, especially when pipes come through the ground, and a lot of water is consumed). In our simulations, we have used 1-year weather data of Kloten, Zurich, Switzerland, which is available in TRNSYS package. This data is based on Remund and Kunz (2003).

Storage tank

As described above, we assume that the required hot water is stored in a tank. In our simulations, we have used a fully mixed tank with the volume of 0.5 m^3 (capacity of 500 l). The loss coefficient of tank is 3 kJ/h.m^2.°C (it means that due to 1 °C difference between the temperature of stored water (T_{Tank}) and ambient air (T_{Amb}), it will lose 3 kJ energy from per square meter of its surface). The rate of energy loss has a linear relation with the temperature difference between stored water temperature and ambient air:

$$\textit{Lost Energy in Period A} = \varepsilon \times \int_{\textit{Period A}} (T_{\text{Tank}} - T_{Amb})dt \qquad (1)$$

where ε represents the loss coefficient of tank.

Because the energy loss is related to the temperature difference and the tank temperature is decreasing, this results in a pattern in which the energy loss per time unit is higher in the beginning than in the end.

When the controller turns on the heating system, a flow of water from the bottom of the storage tank goes to a heater and returns (after heating up) to the tank. The properties and functionality of heater are described in the next subsection. When some hot water is used at the tap point, it is replaced by cold water (ambient temperature) in the bottom of the storage tank.

Heater

An auxiliary electrical heater is used to increase the temperature of the flowstream of water, coming from (and returning to) the storage tank. The heater is designed to add heat to flow stream at the maximum rate of 180,000 kJ/h whenever the controlling signal is on. The set point temperature for the outlet water of heater is 95 °C.

Controlling strategies

The two different controlling strategies are specified as follows.

Regular strategy: this strategy is the conventional strategy based on hysteresis. It means that during active hours (between 6 and 23), the temperature of water stored in the tank is kept between 60 and 70 °C. The only exception is the last active hour (22–23am) which if the temperature goes below 60 °C, it will heat it up to 65 °C instead of 70 °C. The reason is that since there will be no usage after 23am, extra heating of stored water is a waste of energy.

Pre-heating strategy: this is the strategy based on the idea of overheating. Its goal is to reduce the energy costs by heating up the stored water to a higher temperature before the peak hours. It increases the minimum and maximum temperature for the last 4 h (15:00–19:00) before the start of the peak hours (T_{max} = 90 °C, T_{min} = 85 °C). The minimum and maximum temperatures for the other hours are the same as in the regular strategy. Figure 2 shows the minimum and the maximum temperatures for both strategies.

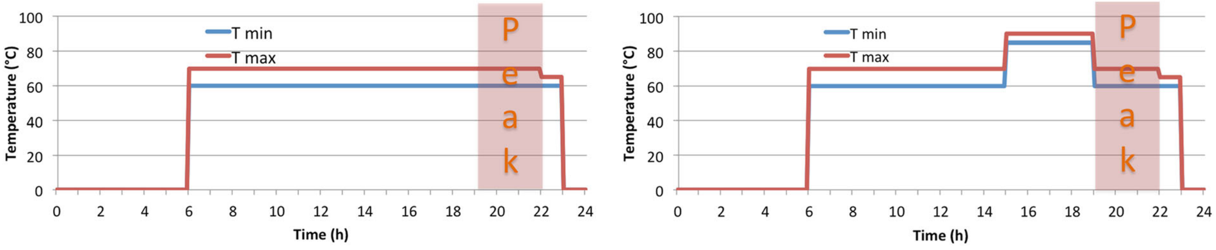

Fig. 2 Minimum and maximum temperature for the regular strategy (left) and the pre-heating strategy (right)

The graphs in Fig. 3 show the results of different controlling strategies for both scenarios, for one sample winter day.

As can be seen in upper graphs, whenever the temperature of tank is high, less hot water is mixed with cold water.

Analysis of simulation results

The two controlling strategies (section "Controling strategies") are applied to both scenarios. To study the influence of the differences in weather (i.e. the ambient temperature), one complete year is simulated, with a time step of 5 min. Figure 4 shows the average daily usage of the different strategies and scenarios for different months. The following observations can be made:

– The pre-heating strategy always consumes more energy. This is expected, as an inherent property of all kinds of energy storages, e.g. batteries, is that they lose energy during the storing period. Consequently, some part of the stored energy in the tank is always lost due to its loss coefficient. It is clear that storing energy for longer time leads to more loss. Also, the larger the difference between the temperature of the tank and the surrounding air, the more energy is lost.

– As expected, the usage in cold months is higher than usage in warmer months. To understand this from a theoretical perspective, one can have a look at Eq. 1: during winter days, the value of T_{amb} is lower; as a result, there is a larger difference between the temperature of the tank and the ambient air, which increase the rate of energy loss.

– The difference between the energy usage in the two strategies is larger in the warm months. Especially, in the non-showering scenario for July, the pre-heating strategy uses 27% more energy than the regular strategy. The reason is the high temperature of the tank during non-active hours (23:00 to 6:00). If the stored energy in the tank is not

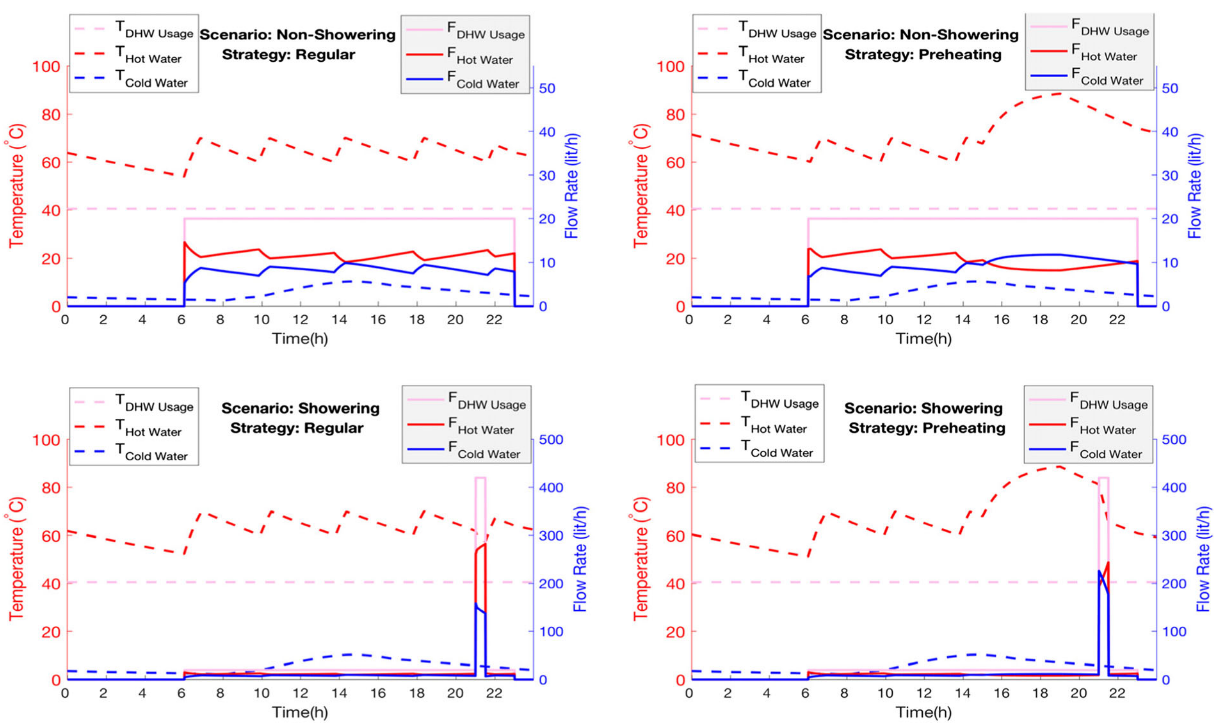

Fig. 3 Comparison of two strategies for two different scenarios. In these graphs, dashed lines show the temperature (left axis) and continues lines show the rate of stream flow in pipes (right axis). It should be noticed that range of right axis in bottom graphs are different from upper graphs

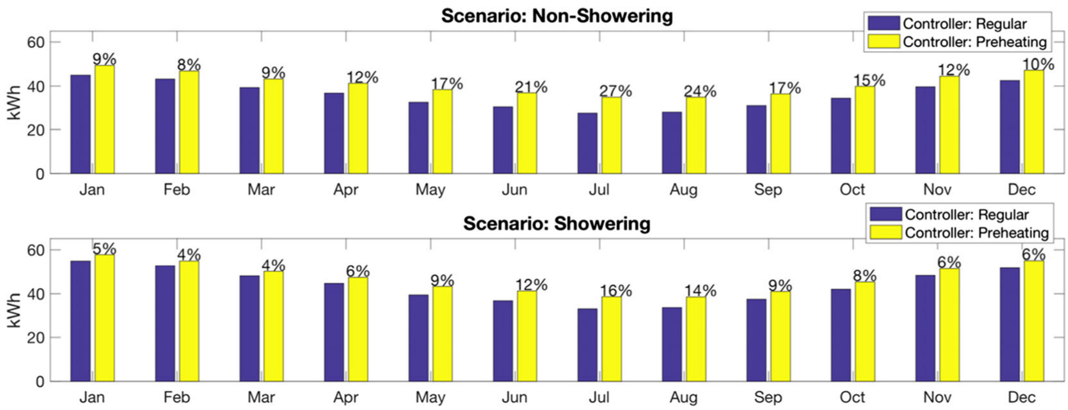

Fig. 4 Average daily usage for both controlling strategies. Up: non-showering scenario; bottom: showering scenario

used during active hours, it will (mostly) be wasted during the night. So, the best case is that at the last moments of the active hours (before 23:00), the temperature of tank would be around the minimum possible temperature (60 °C). However, this does not happen in many cases.

When pre-heating is happening and a large amount of energy is stored in the tank, but there is not much usage after that (non-showering scenario), most of the energy that is added during the preheating phase will be wasted during the night. According to Paull and colleagues, the temperature of the water in a domestic water tank drops exponentially when no water is used (Paull et al. 2010). For instance, in Fig. 3, when the pre-heating strategy is applied and no showering is taking place (Fig. 3, top right), the temperature of the stored water increases up to 88.4 °C. However, due to lack of usage in subsequent hours, at the beginning of the non-active period (23:00), there is still a lot of energy stored in the tank (i.e. the temperature of tank at 23:00 is 74.10, which will be waste during night). It should be mentioned that this graph is from a cold day (January). In warm days, the temperature of tank at 23:00 is even higher.

Table 1 compares the temperature of tank at the beginning of non-active hours for a cold and for a hot day, for different scenarios and different strategies.

Figure 5 shows average daily cost of different scenarios according to each controlling strategy.

As is depicted in the bottom graph, when there is a high usage during peak hours, for all months, the cost of the pre-heating strategy is lower than the costs for the regular strategy, in spite of the higher energy usage. The reason lies in the main idea of the pre-heating strategy. The strategy pretends to reduce the energy usage during the hours with high price, by overheating the water before the peak hours. Even though part of stored energy will be wasted, in case of high usage (showering scenario), the overall costs are lower than in the regular strategy. So, in the cases that we are sure about a large usage during peak hours, overheating of the stored water before the peak hours is a wise strategy.

However, there is a different story for the first scenario (upper graph in Fig. 5). As can be seen, during the colder months, overheating is still cheaper than the regular strategy. However, in warmer months, it is more expensive. This is because in the warmer months, most of the added energy is not used, as the cold water that comes in via the pipe is warmer than during the winter, and consequently less hot water is used. Therefore, most of the added heat is wasted during the night.

In general, for this set up (prices, efficiency, scenarios, minimum and maximum temperatures, etc.) for cold days, overheating is cheaper, while for warmer days, it is

Table 1 Temperature of tank at the beginning of non-active hours

	Cold day January		Warm day July	
	Regular strategy	Pre-heating strategy	Regular strategy	Pre-heating strategy
Non-showering	64.0 °C	74.1 °C	61.3 °C	79.0 °C
Showering	64.0 °C	60.8 °C	67.7 °C	71.7 °C

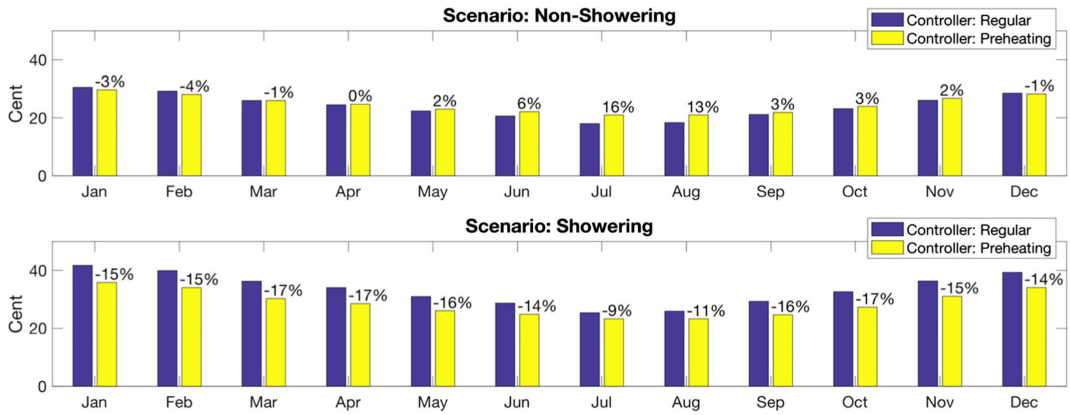

Fig. 5 Average daily costs for both controlling strategies. Up: non-showering scenario, bottom: showering scenario

only better in case of high usage during the subsequent hours. Consequently, knowledge about the user behaviour (will there be usage of hot water) is needed to decide on the optimal strategy.

Discussion of simulation results

In this section, we provide a further analysis of the effect of different probabilities of the behaviour on the choice for a specific strategy.

On a particular day, it is affordable to use the pre-overheating strategy when the prediction of its cost is less than the prediction of the cost of regular strategy:

$$Cost_{OverHeating} < Cost_{Regular} \quad (2)$$

By using machine learning algorithms, a smart thermostat can learn the probability of a high usage during peak hours for different days. Assume that, for a particular day, the probability of taking a shower[2] is P. Then,

$$Cost_{\mathrm{Regular}} = \mathrm{P}\ Cost_{Regular-Shower} + (1-\mathrm{P})Cost_{Regular-NoShower} \quad (3)$$

$$Cost_{OverHeating} = \mathrm{P}\ Cost_{Overheating-Shower} + (1-\mathrm{P})Cost_{Overheating-NoShower} \quad (4)$$

Then we can rewrite (2) as follows:

$$\mathrm{P}\ Cost_{Overheating-Shower} + (1-\mathrm{P})Cost_{Overheating-NoShower} < \mathrm{P}\ Cost_{Regular-Shower} + (1-\mathrm{P})Cost_{Regular-NoShower} \quad (5)$$

or

$$\mathrm{P}\left(Cost_{Overheating-Shower} - Cost_{Regular-Shower}\right) < (1-\mathrm{P})\left(Cost_{Regular-NoShower} - Cost_{Overheating-NoShower}\right) \quad (6)$$

Therefore, by using the information from Fig. 5 ($\mathrm{Cost}_{OverHeating\text{-}Shower}$, $\mathrm{Cost}_{Regular\text{-}Shower}$, $\mathrm{Cost}_{OverHeating\text{-}NoShower}$, $\mathrm{Cost}_{Regular\text{-}NoShower}$), it would be possible to find the threshold value for P. When the estimated probability of taking shower is higher than this threshold, it is better to switch from the regular strategy to pre-overheating. This threshold is calculated for different months and the result is reported in Fig. 6. The figure makes clear that during the cold months from December to March, it is always cost efficient to pre-heat. And, for the warmest month, July, the probability of showering

[2] A more realistic implementation would have been to use a distribution of chances of taking a shower at different time points. However, for investigating the added value of knowledge about showering our implementation suffices.

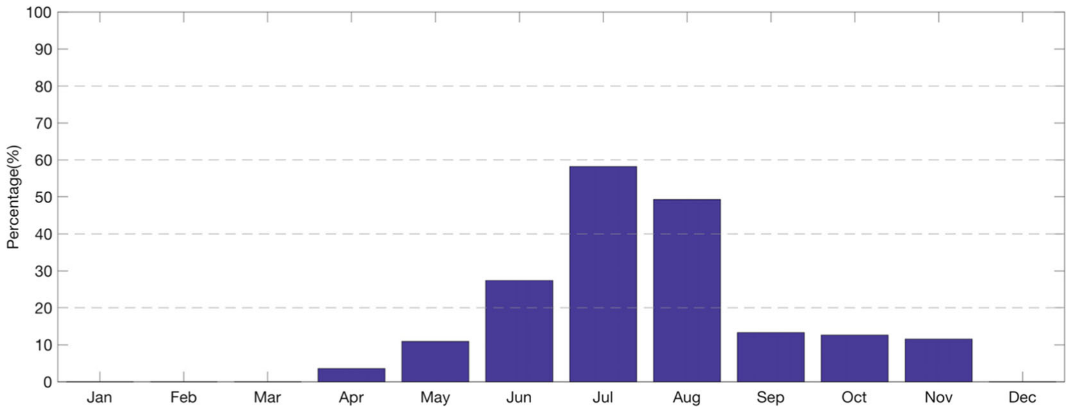

Fig. 6 Required level of certainty about user behaviour for pre-heating to be cost-efficient

should be at least 60% to switch to the pre-overheating strategy.

This result shows that knowledge about the behaviour of consumers and the pattern of their energy usage (e.g. usage of hot water, time of showering) can help to decide about cost-effective heating strategies. This knowledge can be provided by residents or can be learned by an energy management system (smart thermostat). Different approaches for such a prediction have already been proposed in the literature (e.g. Edwards et al. 2012; Ahmad et al. 2014).

Optimal target temperature for pre-heating

Simulation

In the simulations of pre-heating in the previous section, a fixed target temperature $T_{max} = 90$ °C was used. In this section, we investigate the effect of different values for T_{max}, both on the electricity usage and the costs in the pre-heating strategy. Again, we consider the two scenarios (showering and non-showering). All other characteristics are similar to the previous simulation. Figure 7 shows the effects of different target temperatures, T_{max}.

In the energy usage simulations (the graphs on the left in Fig. 7), the intuitive characteristics of the simulations are present. First, the energy usage is increasing when a higher T_{max} is chosen, which holds for all months. Also, it is visible that colder months result in higher energy usage. Finally, in the showering scenarios, more energy is needed than in the non-showering scenarios.

The graphs of the costs (the graphs on the right in Fig. 7) show more interesting patterns. For the most of the scenarios, the costs are initially decreasing with an increase of the T_{max}, but after some time, they start increasing. This results in a monthly optimum value of T_{max}, which is depicted by a small asterisk in the graph. The optimum value is higher in colder months. Also, the optimum in the showering scenarios is much higher than in not-showering scenarios (e.g. for September 83 versus 74). In the next subsection, these results are discussed in more detail.

In the showering scenario, some non-monotonicity is visible in the colder months (like January): first the costs decrease with a higher T_{max}, then they increase and later they decrease again. Both in the energy and costs graphs, it can be observed that at some point, the energy and costs stabilize: higher temperatures for pre-heating do not increase the energy usage nor the costs.

Discussion of simulation results

In this section, we discuss and interpret a number of observations in the simulations. First, we discuss the *flat tail* of the graphs. The figures show that energy and costs do not further increase anymore after some value of T_{max}. The reason behind this phenomenon is that the length of time for pre-heating in our simulations is limited (3 h). Because also the maximum power of the heater is fixed (180,000 kJ/h), there is a maximum temperature of the water that can be reached during the pre-heating period. Increasing T_{max} to higher values does not have any practical effect. In colder months, this maximum is lower as the start temperature is lower. For example, for January, the highest reachable

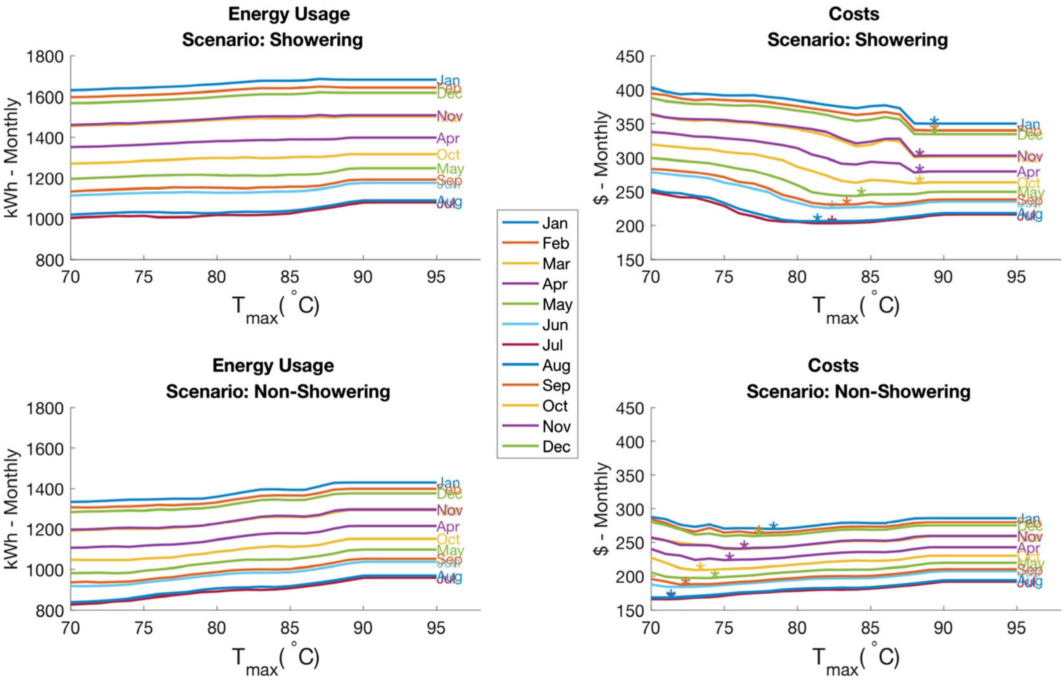

Fig. 7 Energy usage (left) and costs (right) of pre-overhearing strategy with different T_{max} for different months. The optimum T_{max} (minimum cost) for different months are showed by an asterisk in the costs graphs

temperature during the pre-heating period is 89, and increasing T_{max} to higher temperatures is ineffective. For July, this value is 91°.

A second issue to discuss is the sudden changes in the slope of the lines, which is especially visible in the graphs of the costs in the showering scenarios. We would expect that the costs are higher for values of T_{max} that are lower than the optimum value. The reason is that the amount of energy that has been generated during the pre-heating period is not sufficient for the demand during the peak hours; therefore, the heater needs to be turned on during the expensive period. This can be seen when the costs for $T_{max} = 84$ are compared with the costs of $T_{max} = 82$. However, it is not the case when we compare $T_{max} = 84$ with $T_{max} = 86$. To explain this, we should look in more detail at what is happening during the pre-heating period. Figure 8 shows the simulation results for both scenarios for the month January.

The figure shows that the scenario in which T_{max} is 86°, the temperature drops below the threshold for heating ($T_{max} = 5$) just before the start of the pre-heating period. In comparison, in the scenario of $T_{max} = 84$, this happens earlier. As a result, the second heating phase in the pre-heating period is longer and results in a higher temperature at the end of the pre-heating. Therefore, in the first scenario ($T_{max} = 86$), the temperature is too low in the last minutes of the peak hours, and heater has to be turned on in the expensive period.

In short, there are two main reasons that explain the higher cost for $T_{max} = 86$ in comparison to the case when $T_{max} = 84$. First, the $T_{max} = 86$ scenario needs more energy during off-peak hours. Second, as the temperature at the beginning of peak hours is higher in the second scenario, there will be enough stored energy for passing peak hours, while when T_{max} is 86, stored energy is not enough and the heater will be turned on at the last minutes of peak hours.

These results show that not only T_{max}, but also the length of overheating period affects the energy usage and costs. If the length of this period is too short, then there is not enough time to reach to T_{max}. On the other hand, if it is too long, then part of energy will waste and the stored energy might even be not enough for the demand during the peak hours. In short, the best length for overheating is the time needed to heat up the water in the tank to T_{max}. The optimal length for overheating can be calculated by a smart thermostat based on its prediction about the T_{amb}, and the amount of water usage in the following hours.

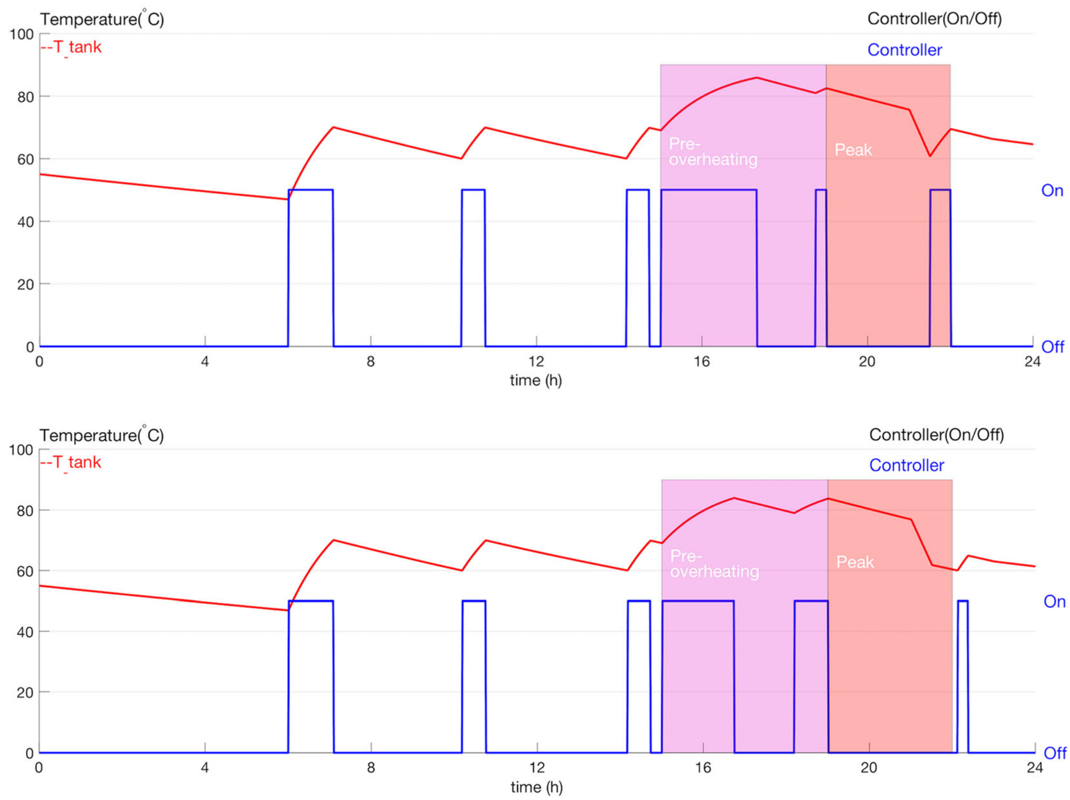

Fig. 8 Simulation of the temperature in the tank and the heating periods for the month January. At the top, the scenario for $T_{max} = 86$; at the bottom, the scenario for $T_{max} = 84$

Conclusions and future works

The main aim of this research was to investigate to what extent understanding of human behaviour can help to produce better controlling strategies for water heating systems, in the sense that they are more energy efficient or lead to reduced costs. We did this by comparing simulations of different controlling strategies (pre-heating versus non pre-heating) in combination with actual behaviours, and by investigating what maximum temperatures for pre-heating should is the best choice. It is clear that pre-heating does not lead to more energy efficiency, but it might lead to reduced costs in scenarios of dynamic prices, especially during the colder winter months.

The sensitivity of results to different aspects is a sign that it is important to make detailed predictions that take the probabilities of user behaviour into account when determining the effectiveness of different strategies and the effects of different changes. Apart from the two aspects that are investigated in this paper (time of usage, maximum temperature), other aspects might influence the efficiency of the strategies as well, for example: the amount and the temperature of the water used, the ambient temperature, the type and size of the tank, length of peak hours period, etc. In addition, economical aspects can have a significant effect on the results. For example, a larger difference in the energy price during peak and non-peak hours makes the pre-overheating strategy more beneficial. However, studying the effect of each of these aspects is beyond the subject of this article and requires simulations different scenarios. It is an interesting topic for future work.

Another interesting future task is the validation of the results. This would require actual data of hot water usage of several houses with different types of households (single, couple with children, elderly).

An important conclusion about the pre-heating temperature is that the length of the pre-heating period is very relevant to determine the most cost-effective solution. If it is too large, energy is wasted because it is kept at a high temperature for a too long period; on the contrary, if it is short, then the amount of stored energy water will not reach to the goal temperature. Therefore, the length of the pre-heating needs to be calculated based on the current temperature, goal temperature, size of thermal tank, the outdoor temperature and the maximum power of the heater.

As emphasized in this paper, the effectiveness of any strategy for controlling the temperature of tank is dependent on our knowledge of the hot-water usage pattern of the residents. As a consequence, a useful direction of research is the automated learning of personalized usage patterns. Those patterns can then be used to predict the usage of hot water in next hours and can be implemented as smart heating strategies by the system.

Space heating and water heating are two main places that we use energy in our houses, around 40 and 20%, respectively. In many houses, these two kinds of usage are integrated and there is one system (or maybe one heater and two storage tanks) for both purposes. Therefore, it is better if we also study both usages together and try to design one efficient controller (with one or two tanks) for both.

Nowadays, alternative domestic heating systems get much attention, such as the use of heat pumps. A heat pump takes thermal energy from the environment (from air, water or ground) and uses it to heat water of a central heating system in the house. Air source heat pumps, ASHP, are more common for domestic usage (Tabatabaei et al. 2015). As a possible future work, in our simulations, we can replace the old fashion electrical heater by a modern ASHP. This alternation will make both simulation and controller more complex, because the performance of ASHP is not a constant (like electrical heater) but vary by changes of temperature of ambient air and stored water.

In addition, when DHW is heated by a solar thermal plant, usually the consumption is not coupled with the solar irradiation daily profile. Since usually, solar irradiance will not always be enough to raise the water temperature up to 60 °C, an auxiliary boiler completes the plant. Therefore, having solar thermal plants make our system more efficient, but the optimum controlling will be a more challenging task, which can study as an interesting future work.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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