Multiobjective Optimisation of Water Heater Scheduling

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ABSTRACT: *In this paper we present our work on the optimisation of water heater scheduling. The goal is to develop intelligent strategies for controlling the electric heater and heat pump in commercial combined water heaters. Strategies try to find the best compromise between comfort and price, based only on information about the temperature of water in the reservoir. A simulation and testing environment has been implemented to compare the performance of existing and new strategies.*

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1. Introduction

Hot water heating is the biggest component of electricity consumption in residential homes, contributing as much as 20% to the total electricity consumption in an average Slovenian household [11]. Water heater manufacturers continually develop improvements to the mechanical aspects of water heating. However, the potential for savings by smarter power scheduling is quite unexplored. Most water heater controllers tend to keep water temperature at pre-set levels throughout the day, with the exception of user-defined schedules. This results in increased heat loss and, more importantly, bigger loads on the power grid during peak hours. An intelligent controller would be able to find and optimised schedule of water heating, customised for the habits and wishes of users. It is important not only to minimise the price of heating, but to do so with a minimal increase in user discomfort level.

2. Related Work

Some research on the topic of electric water heaters has already been done. All stated sources are dealing with devices using only an electric heater, whereas our research focuses on combined devices. Much of existing work perceives user discomfort as a constraint, rarely incorporating it as one of the objectives.

In [1] solutions are provided for an electric water heater that is connected to an electrical grid where the electricity tariff is dynamically changed in real time, and mainly focuses on optimisation in regard to this tariff system. In [2] a model is presented, which addresses the extraction of household water usage patterns with the goal of peak-shaving and reducing the load on the power-grid. In [3] similar goals are addressed, while approaching the problem from a different angle, utilising fuzzy logic to control electric water heaters. Similarly, in [4] the focus is on a solution that decreases peak load on the grid by scheduling heating outside peak hours. In [5] a simulation platform to model electric water heaters and test demand response control strategies in a smart grid is introduced.

3. The Problem

The aim is to develop intelligent strategies for the scheduling of water heating. There are several types of water heaters on the market, the difference being their source of energy. The most interesting are combined water heaters that have both an electric heater and a heat pump at its disposal. The control unit of a combined water heater is able to control the different heaters separately. At any given moment the controller decides whether a heater is to be turned off or on. Water heaters typically have a single thermometer installed, usually on the top of the water reservoir. This measurement is the only information an intelligent controller gets about the state of the water in the reservoir and the consumption habits of the users.

The development of intelligent strategies is a multiobjective optimisation problem. The first objective is the electricity cost and the second is some measure of discomfort of the users. Any strategy will have to be a trade-off between the two. Our solution will be a set of strategies, among which the user will be able to choose the one with the desired trade-off between price and comfort.

4. Strategies

We have implemented a number of different strategies. Each falls into one of two categories that differ by the information that is available to the controller.

The simplest strategies are static strategies that use only predefined settings and current measurements. These could be date, time, temperature and the temperature in the previous minute. Static strategies follow a predefined set of rules. While they do not learn or modify their behaviour, different rule-sets may be defined for different periods of the day, or days in the week. Some static strategies:

1. On-Off Control (lower T, upper T, electric heater, heat pump) is the strategy used in most commercial water heaters. Sometimes called Bang-Bang Control. The boolean constants electric heater and heat pump specify if the strategy is allowed to use electric heater and heat pump. When the temperature drops below lowerT all available heat sources are turned on until upperT temperature is reached.

2. Intervals (list of intervals with appropriate strategies) uses different strategies in different parts of the day (e.g. when electricity is cheaper or when the user expects higher water consumption). At initialisation we can specify any number of intervals and corresponding strategies. One example is a sub-strategy called Heat Less at Noon which uses On-Off Control(40, 41, False, True) between 9 am and 3 pm and On-Off Control(45, 50, False, True) at other times. This strategy is similar up to constants values to some real strategies consumers use.

3. New On-Off (lower boundary for electric heater, lower boundary for heat pump). When the temperature drops below the predefined lower boundary for electric heater the electric heater turns on until the temperature is higher than this boundary. The heat pump works on the same principle but with a different boundary temperature, which is usually higher.

4. Rules Z. A day is divided in N regions that are set by the user. In each region a set of boundary temperatures, as well as boundary temperature changes is defined. The two different heaters are turned on or off based on the boundary conditions for the current region.

Oracle strategies are given the future water consumption schedule that they use to calculate the plan of how and when they will heat the water. We use these strategies to get the best trade-off between discomfort and price. There is no other strategy with a strictly better performance in both objectives.

1. Brute Force makes decisions at discrete time intervals of predefined length, usually 1 or 10 minutes. At every step four options are available: no heating, only electric heater, only heat pump, or both. Brute force simulates every possibility, looking for the optimal one. Theoretically every possible strategy would be tested by Brute Force, allowing us to find the true Pareto front. This approach is not practical due to its computational inefficiency.

2. Bulk starts with a decision to never heat. It simulates the water heater until it reaches discomfort. Then it starts rewinding time back and turning the heat pump on until the discomfort reaches zero. If this cannot be achieved with the heat pump alone, Bulk begins utilising the electric water heater. This way, any heating is done directly before water consumption. It can also be modified to heat during the lower price tariff to accumulate heat. This way Bulk produces a result with minimal discomfort at an almost minimal price.

There is also a third category of strategies that learn from the past and adjust their decision-making to best fit the user habits. This kind of strategies are the final goal of our research.

5. Methods

The basic method applied in this research is the testing and comparison of various scheduling strategies. We utilise computer simulations, as running these tests on real water heaters would require a lot of time and resources, which we do not have at our disposal. To this purpose, we have developed a water heater simulator and a water consumption simulator.

5.1 Water Heater Simulation

Real specifications [9, 10] of commercial water heaters were used, namely: dimensions of the reservoir, power of heaters, coefficient of performance (COP) of the heat pump, thermal conductivity of the insulation and maximum flow rate. Typical water heaters are shaped cylindrically, with cold water entering the reservoir at the bottom and hot water leaving on the top. The position of the heating element varies with the model. Some manufacturers choose to position the heater at the bottom, to encourage the convection of hot water, others attempt to heat uniformly along the vertical axis, or some other option. In current tests water is heated uniformly. Combined water heaters have two types of heaters: electric heater and heat pump. With the electric heater, the thermal power it produces is equal or close to equal to the electric power it consumes. As such, its heating power is fixed. The heat pump, on the other hand, produces more thermal energy than the amount of electric energy it uses. The ratio between the two – COP – typically falls into a range from 2 to 5.5. The COP of a heat pump depends on the temperature of the heat source, often the outside air, and the temperature of water. During the heating process, as water temperature increases, the COP drops.

The simulation does not attempt to simulate the complex thermodynamics and fluid mechanics happening in the water heater. It rather uses a simplified model that manages to emulate the responses of the built-in thermometer to various inputs. The water in the reservoir is divided into 20 layers along the vertical axis. All the water in one layer has the same temperature. The water heater is simulated with a one minute step. Each step, energy losses are calculated for each layer, taking into account the water temperature, outside temperature and the thermal conductivity of the container walls. Heat exchange between neighbouring layers is simulated with an experimentally set heat transfer coefficient to match real data. When heating is turned on, each layer receives its share of thermal energy. As the simulator receives a request for hot water, it removes the appropriate volume of water from the top layers and adds cold water layers at the bottom. The number of layers and their individual size is kept in check by joining neighbouring layers with similar temperatures. Manufacturers usually take special care to minimise the mixing of water in the reservoir. This provides the consumer with a better experience that is, the outgoing water stays at the almost the same temperature during a shower, unless all hot water is used up. Our simulator is able to reproduce this behaviour to a sufficient degree.

5.2 Water Consumption Simulation

A number of sources [6, 7, 8] for water consumption measurement were used to develop a simulation of water consumption during weekdays and weekends. When a household with a specified number of members is generated, each individual is assigned a semi-random consumption pattern. A specific consumption schedule is then generated based on the patterns of individuals, with added variance using Gaussian distributions. We separate two types of events. 3 to 10 small events (e.g. washing hands) per user are randomly scattered throughout the day, taking one minute and using less than 1 litre of hot water. Large events (showers) happen 1 to 3 times per day per user, and take between 5 and 30 minutes, with 1-6 litres of water per minute at a mean 38C.

Both real and simulated water consumptions vary greatly on a day to day basis. Figure 1 shows the distribution of simulated hot water consumption over a longer time period.

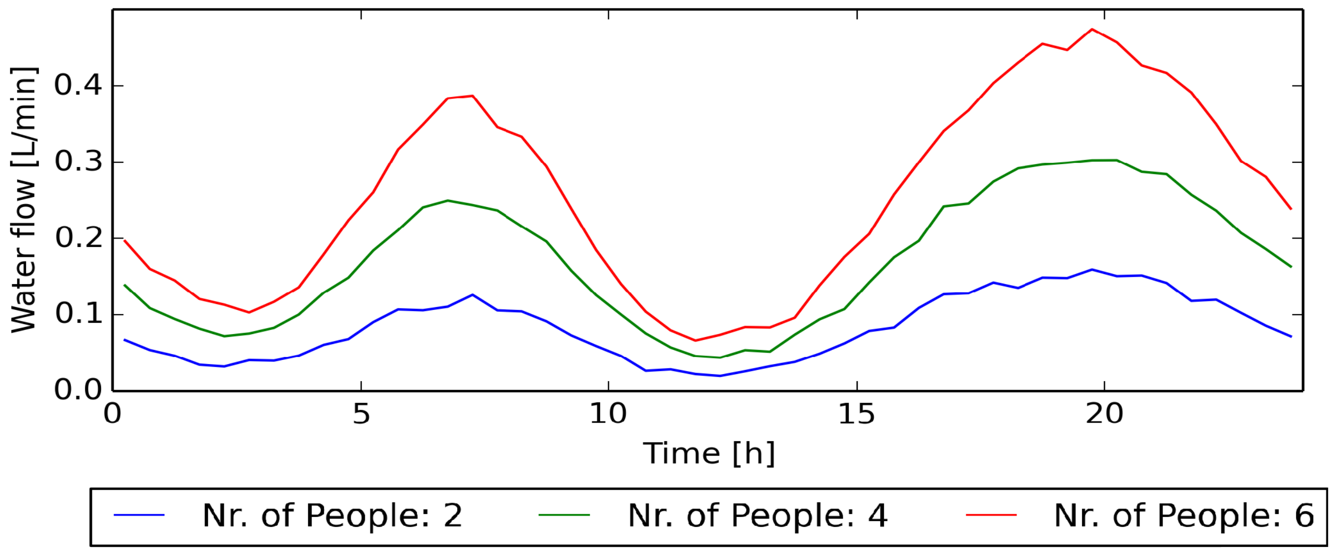

Figure 1. Simulated hot water consumption, averaged over 50 week days for 100 different households

5.3 Discomfort and Price

Different strategies under different water consumption profiles were evaluated using discomfort and price as criteria. Discomfort for a minute of our simulation is defined as:

$$discomfort = \begin{cases} 0 & if\ T_o \geq T_r \\ \dfrac{(T_r - T_o) * V}{1000} & if\ T_o < T_r \end{cases} \quad (1)$$

where T_r is the requested temperature by the user, T_o is the outflow temperature and V is the volume of water with the corresponding temperature. The total discomfort of a measurement is defined as the sum of individual discomforts.

The calculations of price have to take into account different price tariffs. The majority of Slovenian electricity providers use a two-tariff system, with the lower tariff from 22.00 to 6.00 and during weekends and the higher tariff from 6.00 to 22.00 during week days. The prices vary between suppliers. We use a lower tariff price of 0.04320 €/kWh and a higher tariff price of 0.07795 €/kWh [11].

6 .Testing and Results

At the beginning of the test, the generator of water consumption produces a semi-random plan of consumption. The water heater is simulated with a one minute step for the specified duration of the experiment, usually several weeks. Water is used according to the schedule, while the heating of the water heater is controlled by the tested strategy. The process is repeated for other strategies using the same consumption schedule. The whole experiment is ran multiple times with different consumption schedules. The result of the experiment are the average price and discomfort for each of the tested strategies (Figure 2).

As anticipated, Bulk achieves the best comfort, which is usually near zero. Other strategies with comparable comfort achieve it at a much higher price. A generally best performance is achieved by On-Off Control, using only the heat pump heater. Most of our static strategies are dominated by On-Off Control and Bulk.

Each strategy has a number of parameters that can be varied to achieve different results. By varying the boundaries of On-Off Control we produce three fronts, one for each type of heating (figure 2). Varying the parameters of Oracle strategies would produce another front. Ideal solutions would dominate On-Off Control – type strategies, while being dominated by Oracle strategies.

7. Conclusion

The project is aiming to develop intelligent strategies for the scheduling of water heating in commercial water heaters. So far we have developed a complete testing environment for comparing different strategies. We have implemented and tested most commercially used strategies. For comparison we have also implemented one Oracle strategy that achieves the best comfort possible.

In order to find a good approximation of the Pareto front for our consumption simulator, we intend to develop a set of Oracle strategies that are capable of achieving a specific tradeoff of price and comfort.

We also plan to utilise evolutionary algorithms to optimise the various static strategies. Finally, we want to develop intelligent strategies that adapt by learning from the past.

An immediate application of our system is to provide the user with a more intuitive way of choosing the most appropriate strategy. As it stands, users manually choose the On-Off

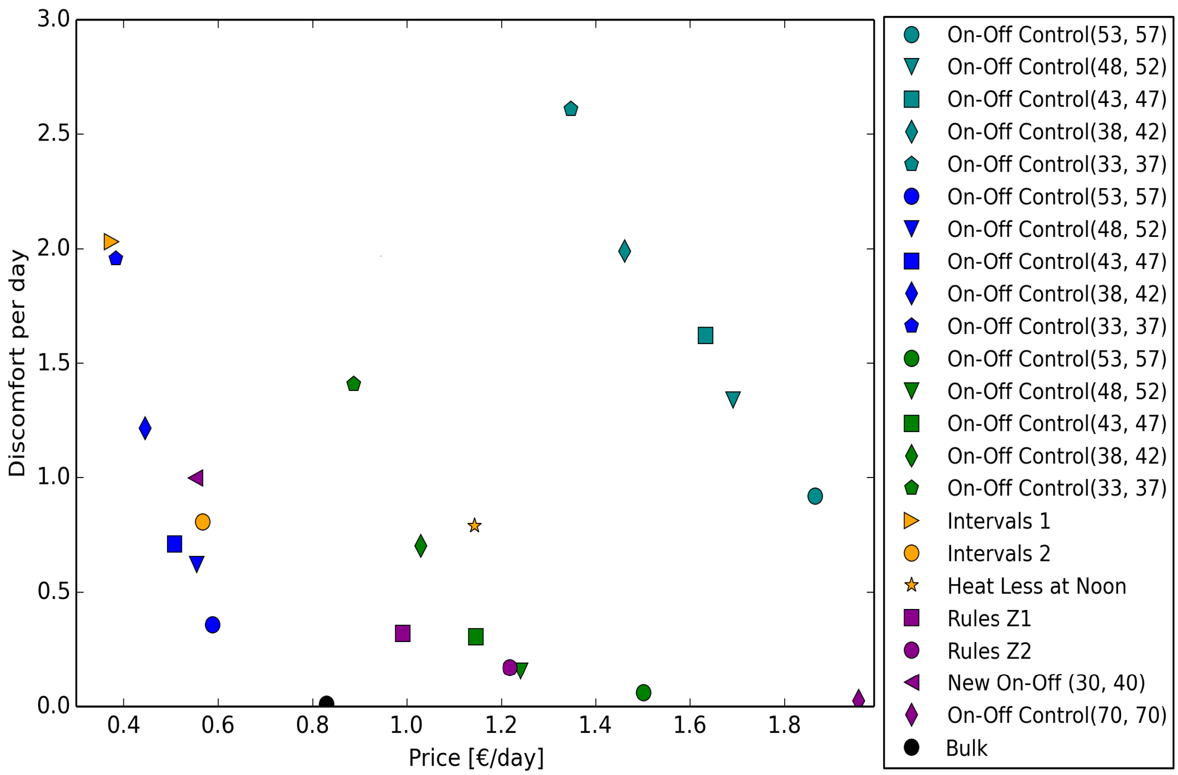

Figure 2. Averaged price and discomfort for a number of static strategies and Bulk. The colours dark cyan, blue and green represent static strategies using only the electric heater, only the heat pump and both, respectively. Strategies coloured orange are variations of Intervals. Other static strategies are coloured purple. Oracle strategies are black. Household with 4 members, using a 230 L water heater with a 1500 W electric heater and a heat pump with a heating power of 2000 W and a COP of 3.3 at 35ºC

Control settings, which is generally the preferred water temperature. With our simulation, users would only need to decide on a price to comfort trade-off, and the controller would choose the best strategy and settings to improve their comfort while lowering their costs.

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