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Field testing of demand side management via autonomous optimal control of a domestic hot water heater

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ABSTRACT

While many approaches for using domestic hot water heaters (DHWH) for demand side management (DSM) have been proposed, only few of these approaches, have been implemented and tested in the field. Results from an implementation of autonomous optimization of a DHWH for DSM based on one-way communicated pseudo cost functions (PCF) are presented. An off-the-shelf DHWH was equipped with sensors and actuators. In-house software running on a Raspberry Pi handles data acquisition and optimization. Day-ahead prices serve as the PCF and are communicated via a publish/subscribe messaging service. The device was deployed in a two-person household for a period of 36 days. The first 18 days, the DHWH was operated conventionally by power line communication based on time of use-tariffs (TOU). During the second half of the field test, it was operated by optimization. In accordance with prior simulations, monetary and energy costs went down without loss of comfort. The average reduction of costs per unit electric energy was approximately 3.6%, the average reduction of cost per unit heat was approximately 12.3%, and optimization-based operation improved the thermal efficiency from 63.0% to 69.3%.

1. Introduction

A range of strategies for integrating the increasing share of renewable energy generation have been proposed in recent years [1]; real time price (RTP)-based autonomous demand side management (DSM) is one of them. In particular, small distributed thermal storage units, such as domestic electric hot water heaters (DHWH), can make a significant contribution in this regard, if the technological and economical costs for activation can be kept small [2].

DHWHs provide relatively high nominal power ratings of typically 2–3 kW combined with high capacities of 8–12 kWh. Using DHWHs via time-of-use (TOU) tariffs for demand shifting has a long history. In recent years, several field tests have been conducted to test dynamic DSM strategies with DHWHs [3–5].

Saele and Grande [5] reported on a field test in Norway using 40 DHWHs for remote load control (RLC) by the distribution system operator (DSO). The study showed that customers generally accept RLC as long as no loss in comfort is to be expected.

A more sophisticated use of DHWHs for DSM was tested in the Pacific Northwest GridWise^{TM}Testbed [3], where 35 DHWHs were used for residential demand response (DR) based on real-time pricing (RTP) for the duration of one year: water heaters were controlled by a probabilistic approach, leading to load curtailment whenever the market clearing price exceeded the average historic price. For comparison, additionally, two equally sized DHWH groups were controlled based on TOU tariffs and fixed prices, respectively.

Sundström et al. [4] used DHWHs controlled via e-meters to provide regulation power capacity for the transmission system operator (TSO). Power metering data was used to estimate the state of charge (SOC) of each individual thermal storage and to deduce daily average power demand probability distributions. Results indicate that a higher accuracy on both, the SOC and the estimated demand are needed to avoid comfort loss for the customer.

To tackle these issues, Kepplinger et al. [6] proposed a one-way communicated pseudo-cost function (PCF) driven autonomous on-site optimization of DHWHs for DSM. In short, the PCF serves as the cost function for an optimization problem constrained by temperature limits. The expected hot water demand is estimated using sensor data collected and processed on site. Results presented in [6] are based on simulation, assuming perfect knowledge of the average temperature within the hot water heater and using historic day-ahead prices from the Austrian electricity market as PCF [7].

In the current work, a hardware prototype based on an off-the-shelf 150 l DHWH is developed and field tested in a live

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Table 1
Calibration results for the temperature measurement chains in the relevant temperature ranges. Coefficients β and ϵ of the linear regression line given by $T_c = (T_m - \epsilon)/\beta$, where T_c and T_m signify the corrected and measured temperature, respectively. Sample standard deviation s of the resulting corrected measurements from the reference measurement.

Sensor	T-range (°C)	β (–)	ϵ (°C)	s (°C)
T_{in}	10–30	0.940	−0.473	0.795
T_{out}	10–70	0.972	−0.245	0.247
T_1	10–70	0.964	0.181	0.295
T_2	10–70	0.967	0.044	0.322
T_3	10–70	0.965	0.452	0.285
T_4	10–70	0.962	0.367	0.313
T_5	10–70	0.964	0.717	0.289

environment. The prototype features autonomous PCF-driven optimal control. Data from 5 weeks of field testing is analyzed and compared to TOU tariff driven operation with respect to thermal efficiency, energy demand, user comfort and costs.

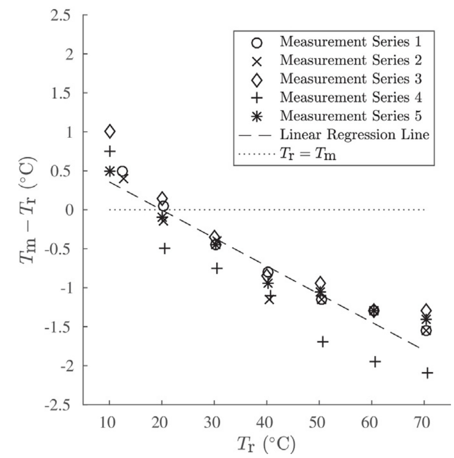

Fig. 1. Example calibration of T_5, where T_r and T_m signify the reference measurement and the temperature measured for T_5, respectively. The linear regression line (dashed) is given by $T_r = (T_m - 0.717)/0.964$.

2. Experimental setup

The experiment is conducted to determine if the method used for the simulation study in [6] can be applied to real-world situations. The implementation should lead to energy savings, no loss in quality of service, and the appropriate load shift response. The data necessary to answer these questions is also needed for the autonomous control of the device. To this end, it is collected by the micro-controller attached to it as part of the deployed software.

For the field test, a standard 150 l Austria Email EKH-S 150 U DHWH [8] is equipped with sensors and actuators as shown in Fig. 2. Water temperatures, T_1–T_5, are measured via five K-Type thermocouples positioned uniformly along the DHWH's central axis. This sensor arrangement is backed by the study by Cruickshsank et al. [9], which indicate that horizontal temperature variation in DHWHs is small compared to vertical temperature variation due to stratification. The studies by Fernandez-Seara et al. [10,11] and Castell et al. [12] identified a similar stratification behavior as observed by our experiments. Additionally, the ambient temperature T_{env} and the temperature at the water inlet and outlet, T_{in} and T_{out}, respectively, are measured. Power consumption $\dot{W}_{el}$ is registered by a power meter (type eac WSZ-50A [13]) at a resolution of δ_{el} = 1 Wh per impulse and a relative error in accuracy of <1%. Hot water demand $\dot{m}$ is measured using a magnetic inductive flow meter (type ifm electronic SM8100 [14]) at a resolution of $\delta_v = 0.1$ l per impulse and a relative error in accuracy of <2%. The DHWH is actuated via a relay that is controlled by the control signal u. Data acquisition, demand prediction and optimization is carried out using a Raspberry Pi Model B [15] with a Gertboard I/O extension board [16].

Temperature-measurements are based on seven independent chains of K-type thermocouples and thermocouple amplifiers (type Adafruit MAX31850K [17], see Table 1).

Each measurement chain is calibrated relative to a reference measurement (FLUKE 287 [18]) in five measurement series. One series spans the temperature interval between 0 °C (ice water) and 100 °C (boiling water) in steps of 10 °C. Sensor calibration is based on linear regression in the relevant temperature range (Table 1). The sample standard deviation of each corrected measurement chain with respect to the reference measurement is then calculated and used as the error estimate. Relevant temperature ranges, coefficients of the linear regression, and the resulting sample standard deviations are given in Table 1. Fig. 1 illustrates the calibration method. The analyses and results presented in Section 4 are based on the corrected temperatures.

A simulated price obtained via a publish/subscribe service implemented by IBM Research Zurich via JMS is used as the pseudo cost function (PCF).

3. Autonomous DSM

The DSM approach proposed in [6] relies on a linear optimization problem, which is derived using a bulk model for the DHWH and a k-nearest neighbors (kNN) algorithm to estimate future hot water demand. The dynamic model of the heater is based on the open system energy balance. The resulting ODE reads

$$m \cdot c_w \frac{dT}{dt} = -\dot{Q}_{dem}(t) + \dot{W}_{el}(t) - \dot{Q}_{loss}, \tag{1}$$

where m is the water mass in the boiler, c_w is the specific heat capacity of water, T is the average water temperature, t is time, $\dot{Q}$ signifies a heat rate and $\dot{W}$ is power.

$$\dot{Q}_{dem}(t) = \dot{m}(t) \cdot c_w \left(T(t) - T_{in}\right), \tag{2}$$

$$\dot{W}_{el}(t) = P_{el} \cdot u(t), \quad u(t) \in \left\{0, 1\right\}, \tag{3}$$

$$\dot{Q}_{loss} = UA_s \left(T(t) - T_{env}\right), \tag{4}$$

where UA_s is the overall heat transfer coefficient times heat transfer area. Assuming a given PCF $c(t)$, shifting the load to low peak times

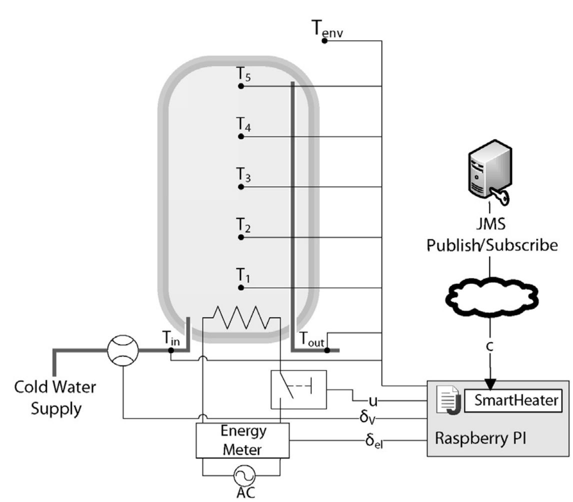

Fig. 2. Experimental setup [19].