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Cost/comfort-oriented optimization algorithm for operation scheduling of electric water heaters under dynamic pricing

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ABSTRACT

This paper presents a heuristic algorithm, which schedules the operation of electric water heaters (EWHs) under dynamic electricity pricing. The algorithm takes into account cost and comfort preferences/constraints as well as energy pricing and hot water consumption and minimizes the energy cost without significant compromise of the perceived comfort level, operating either in a cost- or comfort-oriented mode. Its performance was evaluated through simulation assuming a day-ahead real-time pricing (DA-RTP) tariff and a time-varying bound on power consumption, taking into account the user's daily hot water consumption rate. A comparison between the proposed heuristic algorithm and an optimal scheduling algorithm showed identical performance, in terms of energy cost reduction. Also, a parametric analysis studied the effect of several critical parameters (maximum water tank temperature, EWH's rated power and capacity) on the performance of the scheduling algorithm. A significant feature of the proposed algorithm is its low computational complexity, which extends its applicability to low-cost embedded controllers.

1. Introduction

Buildings are responsible for more than 40 percent of global energy use and one third of global greenhouse gas emissions, both in developed and developing countries (UNEP, 2009). Growing efforts to supply affordable, reliable, secure and clean electric power are based at most on energy efficiency. While energy efficiency is the most prominent component of these efforts, Independent System Operators (ISOs) use demand response (DR) as a basic tool towards reduction of both total energy consumption and peak demand (Goldman et al., 2010). By applying DR, customers' electricity consumption is constrained at critical time periods or in periods of high whole market prices. Existing DR measures include time-based rates and incentive based programmes. DR plays an important role in the smart grid technologies that manage electricity demand in response to supply conditions. (U.S. Department of Energy, 2006). On the other hand, by making the demand side more sensitive to price signals, part of the generation adequacy challenge could be solved (Aghaei and Alizadeh, 2013). In energy systems mainly relying on photovoltaic and wind power, DR may furthermore contribute to system stability and increase the renewable energy share, playing a role of growing importance in the future electricity system, mainly due to benefits regarding economic efficiency, system reliability and environmental benefits (Gils, 2014).

Considerable research work aiming at reducing energy cost of residential electric appliances under price-based DR schemes via suitable controlling of their operation schedule has been already conducted. Among various domestic electric appliances, EWHs have certain characteristics, such as high nominal rated power and significant thermal storage capacity, which make them ideal candidates for implementing operation scheduling control. In certain areas, EWHs can consume up to 30% of household load and contribute significantly to the peak load (Diao et al., 2012). The already proposed strategies for controlling electric power demand of EWHs' load can be divided in two categories: a) Utility-centered strategies, applied by electricity providers, which aim at reducing peak-load of aggregate EWH load in order to provide balancing/regulation services, using techniques for water temperature adjustment (Diao et al., 2012), voltage control (Nehrir et al., 2007) or ON/OFF control (Diduch et al., 2012; Ericson, 2009; Kondoh et al., 2011) and b) customer-centered strategies, which aim at reducing the household's energy bill in response to dynamic price signals

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Nomenclature

A	Surface area of the water heater [m^2]
C	Specific heat capacity of water [4184 J/(kg·K)]
$\{p_1, \ldots, p_n\}$	Electricity tariff profile [cents/kWh]
$cost_i$	Energy cost at time slot i [cents]
$cost_{max}$	Maximum energy cost [cents]
$cost_{min}$	Minimum energy cost [cents]
$cost_{perc}$	Percentage cost difference between the tolerable and the minimum energy cost [%]
$discomfort_i$	Comfort cost (discomfort) at time slot i [°C·kg]
$discomfort_{max}$	Maximum discomfort [°C·kg]
$discomfort_{min}$	Minimum discomfort [°C·kg]
J_i	Objective function at time slot i
J_{min}	Minimum value of the objective function
$\left\{M_1^{bath}, \ldots, M_n^{bath}\right\}$	Bath water usage profile for all (1 to n) time slots [kg/s]
M	Mass of tank water [kg]
M_i^{inlet}	Mass of water from cold water inlet at time slot i [kg]
M_i^{bath}	Mass of bath water at time slot i [kg]
M_{max}^{bath}	Maximum mass of bath water [kg]
P_i^{bound}	Bound on power consumption at time slot i [W]
$P_i^{critical}$	Total power demand of critical loads at time slot i [W]
Q	Rated power of the water heater [W]
s_i	Operation indicator (0 = OFF, 1 = ON) at time slot i
$S^* = \{s_i^*, \ldots, s_n^*\}$	Set of optimal operation indicators for all (1 to n) time slots
$slots_{acc}$	Maximum tolerable number of time slots with water temperature below T_{pref}
$step$	Step for the increase of $\lambda_{discomfort}$ at each iteration
t	Time [sec]
T	Tank water temperature [°C]
T_{amb}	Ambient temperature [°C]
T_{inlet}	Temperature of inlet water [°C]
T_{max}	Maximum water temperature [°C]
T_{min}	Minimum water temperature [°C]
T_{min}^*	Modified minimum water temperature [°C]
T_{pref}	Preferred water temperature [°C]
T_i^0	Tank water temperature at the beginning of time slot i [°C]
T_i^h	Tank water temperature at the end of time slot i, before water draw [°C]
T_i^w	Tank water temperature at the end of time slot i after water draw [°C]
U	Standby heat loss coefficient [W/(m^2·K)]
w_i^{cost}	Normalized energy cost at time slot i
$w_i^{discomfort}$	Normalized discomfort at time slot i
$w_{average,j,k}^{discomfort}$	Average normalized discomfort from j to k slot
Δt	Time slot duration [sec]
λ_{cost}	Weighting factor of energy cost
$\lambda_{discomfort}$	Weighting factor of discomfort

(implicit or price-based DR), by shifting their demands automatically to the off-peak hours. The presented paper belongs to the second category (customer-centered) and thus a brief presentation of relevant papers is necessary.

Lu and Katipamula (2005) have presented certain strategies for set point control of EWH loads aiming at shifting power consumption from the high-price to the low-price period in order to reduce both peak-load and electricity cost, while keeping tank water temperature above a minimum acceptable level.

Goh and Apt (2004) developed three different strategies which aim at achieving maximum cost energy savings for the consumer when dynamic pricing is applied. The most effective of these strategies is changing the set-point temperature between a minimum and a maximum value, according to electricity price. Nevertheless, this strategy does not take into account the comfort aspect and thus it does not always guarantee an acceptable tank water temperature. Specifically, there is not a rule for setting the minimum and maximum set point temperatures. Thus, if maximum set point temperature has been set to a low value, there is possibility of unacceptable (low) hot water temperature during periods of high water consumption and high electricity prices.

Sepulveda et al. (2010) proposed a binary particle swarm optimization algorithm in order to calculate the optimal load demand schedule for minimizing the peak load demand while maximizing the water heater temperature. These two conflicting objectives were mapped to a fitness function, by using weight factors for the aggregated load and the water temperature. The trade-off between the load demand and the temperature of the water was adjusted by setting the values of the weight factors.

Du and Lu (2011) proposed an appliance commitment algorithm, which schedules thermostatically controlled appliances (TCAs), such as EWHs, in such a manner that electricity bill is minimized, taking into consideration constraints set by comfort requirements.

Zimmerman et al. (2011) introduced a linear programming (LP) model in which a client-side agent implements strategies aimed at cost optimization under a real-time pricing scheme. In order to define user's comfort, a range of acceptable water temperature is proposed. However, the results lack a high degree of accuracy, due to some simplifications that are applied, i.e. constant standby heat loss.

Kepplinger et al. (2015) studied the potential of applying demand side management to electric water heaters. The goal was to minimize electricity cost while keeping tank water temperature above a predefined minimum temperature in time periods with hot water demand. The optimization problem was formulated as a binary integer program and the subsequent presented optimal strategy was based on both the expected demand and a piecewise constant energy cost function.

Shah et al. (2016) approached the problem by using a greedy algorithm, aiming at to reduce electricity costs of EWHs, considering a TOU pricing scheme, while it used thermal storage in order to adapt to possible variation of hot water usage profiles. Concerning the comfort aspect, the algorithm strived to keep tank water temperature within an acceptable range. However, the algorithm uses a rather complicated process to tune an optimization factor, which is used for the calculation of the standby loss.

Passenberg et al. (2016) developed a stochastic Dynamic Programming (DP) algorithm that optimized the heating schedules of electric water heaters using forecasted consumption and weather data, in order to reduce the energy cost while maintaining the water tank temperature between a minimum and a maximum value. The algorithm was taking into account possible uncertainties about the prediction of hot water consumption and thus, it