Electric Power Systems Research 80 (2010) 1446–1451

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

A novel domestic electric water heater model for a multi-objective demand side management program☆

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ARTICLE INFO

Article history:
Received 11 September 2009
Received in revised form 3 May 2010
Accepted 10 June 2010
Available online 14 July 2010

Keywords:
Demand side management
Domestic hot water heater
Power system efficiency
Load control

ABSTRACT

This paper presents a novel domestic hot water heater model to be used in a multi-objective demand side management program. The model incorporates both the thermal losses and the water usage to determine the temperature of the water in the tank. Water heater loads are extracted from household load data and then used to determine the household water usage patterns. The benefits of the model are: (1) the on/off state of the water heater and temperature of the water in the tank can be accurately predicted, and (2) it enables the development of water usage profiles so that users can be classified based on usage behaviour. As a result, the amount of ancillary services and peak shaving that can be achieved are accurately predictable and can be maximized without adversely affecting users.

1. Introduction

The efficiency of the power grid is of great importance as environmental concerns related to the combustion of fossil fuels increase. One important way to reduce losses and increase power system stability is through advanced control algorithms on the load side. This idea is broadly referred to as demand-side management (DSM). Different objectives have been considered by past DSM programs found in the literature, such as peak shaving and valley filling [1], and providing ancillary services like synchronous reserve [2], frequency regulation [3], and voltage stability [4]. The pilot project that is underway in Saint-John, New Brunswick, tries to balance all of these objectives for maximum overall benefit. Other multi-objective DSM projects have been attempted but in these cases, the impact on the user is treated as an objective [5,6]. In the present project, a control objective function has been developed similar to the one presented in Ref. [7] where minimal impact on the users is treated as a constraint. In order to satisfy this constraint, a more advanced mathematical model of the domestic electric water heater (DEWH) is required.

DEWHs are ideal candidates for DSM projects because the hot water in the tanks acts as energy storage. In winter-dominated climates, the DEWH loads can contribute as much as 30% of the total household load [8]. In addition, the DEWH load profile and average daily load profile follow a similar pattern, meaning that DEWH loads significantly contribute to peak load values [9]. DEWH loads have been used in the past to achieve DSM, most recently [10] among many others.

The heat transfer characteristics of the DEWH tank are well known, and are presented in Section 2. In most cases, when the DEWH is used for DSM, the individual DEWH heat transfer model is used to develop an aggregated DEWH model. For example, Ref. [11] uses a Monte Carlo rejection method to aggregate individual models, Ref. [12] uses a state-queuing model to account for uncertainties in user behaviour, and Ref. [9] replaces the deterministic parameters of the model with normal random variables. These aggregated models allow many DEWHs to be controlled together, thereby simplifying the control algorithms needed. However, aggregation of the model allows the temperature of the water in individual tanks to be at an unacceptable level at times when the user requires hot water. This adversely affects user comfort and can permit the growth of unwanted and potentially dangerous bacteria [13]. For the widespread acceptance and integration of the program, it is critical to avoid these situations.

This paper develops a predictive model that is not aggregated. Each household that is part of the DSM project has its own model with most parameters determined through inspection of the site. DEWHs will be controlled remotely using high frequency communications, and smart meters record household load data on 15 min intervals.

Although the aggregated model produces undesirable results, it is useful to classify similar users. The benefits are that control algorithms can be simplified, and users with habitual water usage

☆ Thanks to the National Science and Engineering Research Council, the New Brunswick System Operator, and Saint John Energy for their support.
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doi:10.1016/j.epsr.2010.06.013

patterns can be identified. In previous literature, classification is performed on the household load data rather than the data for the remotely controlled load [14], which may introduce a significant source of error. The algorithm presented here allows the water usage data to be determined from the household load data, and a water usage profile can be developed as will be shown. It is much more effective to classify users based on their water usage patterns rather than the household load profile shape. It is important to note that although users are being classified for reduced control algorithm complexity, the individual models are still available so that the user comfort constraint is never violated.

The novel aspects of this model that make it advantageous over those presented in previous literature include:

- It can be implemented in near real time so that the on/off state of the individual heaters and the temperature of the water in the tanks can be accurately predicted. The result is that the exact amount of frequency regulation, synchronous reserve, or peak shaving that can be achieved is known before a control action is taken.
- Water usage profiles can be developed so that users may be classified in terms of water use rather than household load profile.

The result of these two benefits is that load control becomes predictable and the multiple objectives can be maximized with an absolute minimum impact on the users' comfort. It is the first known model to be developed that uses an analysis of past load data to determine exact water usage patterns, a facet which is integral in the modeling of the DEWH and is overlooked in all of the previous literature.

The previously established thermal model of the tank is presented in Section 2. The proposed methods of extracting water usage are presented in Section 3. The model is validated and results are shown in Section 4. Finally, the conclusions are presented in Section 5.

2. Background on DEWH thermal model

There is extensive literature on the modeling of DEWHs [9,11,15,16]. A differential equation model of the thermal characteristics of the water heater is presented in Refs. [9,11]. This model is based mainly on energy flow analysis and yields a method to determine the temperature of the water in the tank as a function of time. The differential equation describing the temperature of the water in the tank is

$$C\dot{T}_H(t) = -SA\left(\frac{1}{R}\right)[T_H(t) - T_{\text{out}}] - D \times W_D(t)C_p[T_H(t) - T_{\text{in}}] + Q(t) \quad (1)$$

A solution is given by

$$T_H(t) = T_H(\tau)\,e^{-(1/R'C)(t-\tau)} + \{GR'T_{\text{out}} + BR'T_{\text{in}} + QR'\} \times [1 - e^{-(1/(R'C))(t-\tau)}] \quad (2)$$

where τ is the initial time (h); $T_H(\tau)$ is the initial temperature (°F); T_{in} is the incoming water temperature (°F); T_{out} is the ambient air temperature outside tank (°F); $T_H(t)$ is the temperature of water in tank at time t (°F); $Q(t)$ is the energy input rate as a function of time (W); R is the tank thermal resistance (m^2 °F/W); SA is the surface area of tank (m^2); $G = SA/R$ (W/°F); $W_D(t)$ is the water demand as a function of time (L/h); C_p is the specific heat of water (J/(°F kg)); D is the density of water = 1 kg/L; $B(t)$: $D \times W_D(t) \times C_p \times 1\,\text{h}/3600\,\text{s}$; (W/°F); C: (volume of tank) $\times D \times C_p$ (J/°F); $R' = 1(B/G)$ (W/°F).

It is important to note that the values of Q and B are time dependent. Q, as the energy input, is dependent on whether the element is on or off, and B is a function of the usage of water. Therefore, the value of τ and $T_H(\tau)$ must be updated every time there is a change in B or Q. All of the other parameters are measured from the site and must be known for accurate prediction of the temperature.

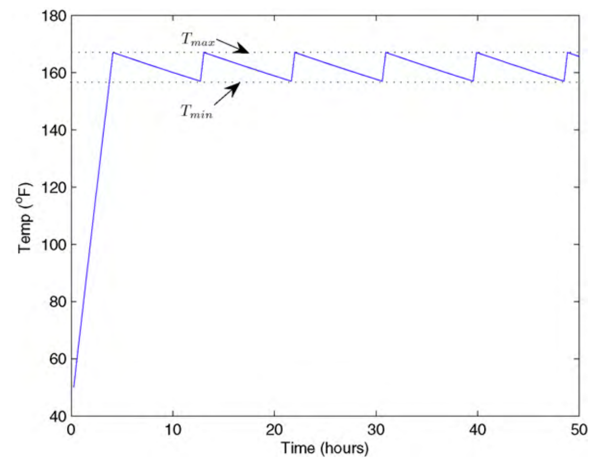

Fig. 1. Temperature of water in the tank with no water usage.

The element turns on and off in a hysteresis fashion as the temperature varies between the minimum and maximum setpoints, $T_{\min}$ and $T_{\max}$. The value of Q is either 3000 W or 0, and is determined from (3):

$$Q(t + \Delta t) = \begin{cases} 3000\,\text{W}, & T_H(t) < T_{\min} \\ 0, & T_H(t) > T_{\max} \\ Q(t), & \text{else} \end{cases} \quad (3)$$

During no water usage operation of the DEWH, the temperature of the water exponentially decays and rises between the two temperature setpoints at shown in Fig. 1.

The other time dependent variable, B, which is a function of the water usage, is more difficult to predict. Past projects treat the water usage as known [11] or as constant [9]. The assumption that the water usage is constant leads to significant errors in the prediction of the temperature of the water in the tank. The present study will use past household load data to develop a water usage model for accurate prediction of individual water heater temperature.

3. Proposed method

The development of the water usage profile requires three steps. First, the DEWH load data must be extracted from the household data. Next, the water usage amounts are determined from the DEWH load. Last, the water heater profile is determined from large amounts of DEWH load data.

3.1. Extracting water heater load data from household load data

It is known that the water heater elements in the study are 3 kW. The household load data is analyzed for drops or jumps that account for this 3 kW load. In general, there are two types of scenarios under which the water heater element turns on: (1) the temperature of the water has dropped below the minimum setpoint as a result primarily of conduction heat losses; and (2) a large amount of water has been drawn and replaced with colder incoming water. In the first case, the temperature of the water in the tank is at the minimum setpoint, and the element will be on for a consistent and predictable amount of time. In the second case, the water temperature can be far below the minimum temperature setpoint, and the length of time that the element is on will be variable, depending on the amount of water drawn.