Applied Energy 211 (2018) 104–112

Contents lists available at ScienceDirect

Applied Energy

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

A minimal simulation of the electricity demand of a domestic hot water cylinder for smart control

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HIGHLIGHTS

- A fidelity measure for comparing simulated with monitored electricity time series of a hot water cylinder is proposed.
- A simple simulation of hot water cylinder electricity use is presented that meets these fidelity requirements.
- The approach is useful for simulating individual households to evaluate smart home management scenarios.

ARTICLE INFO

Keywords:
Demand flexibility
Demand side management
Domestic hot water
Energy storage

ABSTRACT

In many countries domestic electric hot water storage cylinders have high penetration and account for a large proportion of electricity demand. Their ability to store energy makes them a significant opportunity for emerging smart home energy management systems. One approach to evaluating the potential of hot water cylinders under smart control is to simulate electricity demand via a physical model of a cylinder together with assumed hot water usage patterns. Determining the accuracy of these simulations is made difficult by the lack of detailed data on cylinder variables and household hot water usage. This results in simulation methods that potentially miss essential features or are overly complex. To address this issue, we first propose a statistical fidelity measure that can be used to compare simulated with monitored electricity demand time series from an individual cylinder. We then present a minimal simulation method that achieves reasonable fidelity with monitored demand. The proposed method is particularly useful for simulating individual households using only electricity time-series data for the purpose of evaluating smart home management scenarios.

1. Introduction

Demand flexibility is increasingly considered a key enabler for greater expansion of variable renewable electricity supply [1,2]. Coupled with developments in smart control technology, this has sparked a renewed interest in the role of domestic appliances in demand side management (DSM) [2–13]. By reducing, increasing or shifting electricity demand at certain times of the day, DSM of appliances can provide benefits to the electricity system by reducing the need for expensive investments in generation and transmission infrastructure, while enabling the accommodation of higher levels of variable renewables [2,3,13–15]. DSM of appliances can also provide benefits to individual households by enabling the exploitation of time-of-use (TOU) tariffs [10] and maximizing self-consumption of domestic generation such as rooftop photovoltaics (PV) [9,16–18].

Due to their ability to store large amounts of energy for later use, electro-thermal appliances for space and domestic hot water heating are of increasing interest for DSM [19–24]. Electric hot water tanks offer a particularly promising opportunity as they are a large proportion of residential electricity consumption in many countries [25,26] and represent a significant year-round load shifting opportunity. In New Zealand, for example, approximately 70% of households have electric hot water cylinders [26]. These cylinders range from 130–200 litres yielding a storage capacity of ~10 kWh per household, comparable in size to typical residential battery storage options. Centralized control of hot water tanks by utilities for load shedding has been widely implemented for a number of decades [27–33]. However DSM of hot water cylinders is receiving renewed interest due to the possibility of much more flexible and intelligent control.

A common approach to explore the DSM potential of appliances

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https://doi.org/10.1016/j.apenergy.2017.11.044
Received 14 June 2017; Received in revised form 18 September 2017; Accepted 5 November 2017

Nomenclature

Δt	time interval
μ	log normal parameter
γ	log normal parameter
ϕ	normalized power input
ρ	density
σ	standard deviation
τ	duration time of on-event
Θ	heaviside step function
θ	usage event variable
A	surface area
C_V	heat capacity
F	volumetric flow
f	dimensionless flow
F_{std}	standard shower flow
H	height
i,j	index of discrete time
k	index of on-events
L	number of data points in 24 h
P	probability
Q	power input
q	dimensionless power input
Q_R	power rating of element
R	radius
R^2_{diff}	coefficient of determination
R_{value}	insulation R-value
s	start time of on-event
T	temperature
t	time variable
T_0	atmospheric temperature
T_{in}	input water temperature
T_{max}	max thermostat temperature
T_{min}	min thermostat temperature
T_{std}	standard shower temperature
U	heat transfer rate
u	dimensionless heat transfer rate
V	volume
v	tempering valve flow rate
z	thermocline position
z_{init}	initial value of thermocline
$\mathscr{T}$	start-time distribution
$\mathscr{A}$	autocorrelation function
$\mathscr{D}$	duration distribution
$\mathscr{K}$	start-time-duration distribution
$\mathscr{P}$	business day power profile

under intelligent control is via bottom-up models that simulate an appliance's electricity demand through the combination of (i) a physical model of the appliance and (ii) some method of simulating household appliance usage [33,34]. By separating behavioral from physical aspects, these models can be used to simulate control scenarios for the physical device and then determine the impact of these scenarios on service to the household. Most approaches consider simplistic appliance models and a large number of aggregated households to determine the DSM potential at a macro-scale. However, these approaches do not capture the variation in individual household electricity demand required for increasingly individualized DSM control strategies [9,16,17]. In addition, lack of detailed data on tank variables and household hot water usage, means that it is difficult to determine the accuracy of these simulations at the individual household level. This results in simulation methods that could either be overly complex or, miss essential statistical patterns in the electricity demand of the appliance.

The contribution of this paper is twofold. First we address the issue of accuracy of simulations by proposing a potential fidelity metric between simulated and measured electricity demand of a hot water cylinder based on a detailed statistical characterization of electricity demand time-series data. Second we develop a minimal simulation method consisting of a model of a thermally stratified hot water cylinder and usage behaviour that can accurately simulate electricity demand (based on the introduced metric). This simulation approach thus achieves a balance between simplicity and being able to accurately simulate the electricity demand of a domestic hot water cylinder, making it ideal for simulating DSM control scenarios at the individual household level.

This paper is arranged as follows. Section 1.1 gives a brief review of hot water cylinder models. In Section 2 we explore the patterns in monitored electricity use of hot water cylinders and develop methods for characterizing the data. From this analysis we derive a measure of fidelity that a simulation needs to meet to be an accurate representation of the monitored electricity use time series. In Section 3 we develop a simple simulation of hot water cylinder electricity use based on a bottom-up model and show that it meets these fidelity requirements. Section 4 provides a discussion of the results and a conclusion.

1.1. *Hot water cylinder models for DSM*

Control scenarios for hot water tanks for both individual [16,17] and aggregated [29,30,35] households have been investigated via bottom up models that consist of physical models of hot water tanks and simulations of household hot water usage.

Approaches to physically modelling hot water tanks vary. The simplest approach is to assume that the water in the cylinder is fully-mixed and described by a single temperature variable [16,17,31,36–39]. This approach has the benefit of being very easy to implement numerically and requires few parameters. However, fully-mixed models do not replicate the thermal stratification that is observed in the most common electric hot water tank: the vertical hot water cylinder. This means that these models are unable to capture key aspects of hot water service. More sophisticated treatments consider a one dimensional vertical temperature profile composed of discrete zones of temperatures between the top and bottom of the tank [23,32,35,40]. These more sophisticated models require more computation than simple fully-mixed models and the specification of a greater number of parameters. In this paper we propose a simple two temperature model of a stratified hot water cylinder that achieves a middle ground between these two approaches.

Household hot water usage has been simulated in a variety of ways. Widén et al.used self-reported usage in time-use diaries as the basis for determining household usage over a specified time period [41]. Simulations for longer periods of time take a statistical approach. For example, in some approaches the start times and durations of usage events over a single day are selected from probability distributions that take into account a range of variables in the household, such as occupancy levels [29,30,34,35].

Physical models for specific tanks have been validated by detailed comparisons of simulated and monitored electricity demand over short intervals where hot water usage is known [17,35,41]. However these results do not easily generalize to other systems where tank parameters are unknown. They are also not useful for validating simulations of electricity demand that include both the behaviour of the physical hot water tank and simulated hot water usage by households. Other validation approaches compare simulated and measured energy use over a certain time period (e.g. days or years), however this obscures details of the electricity demand that varies on much shorter timescales. The lack