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Recursive parameter estimation of thermostatically controlled loads via unscented Kalman filter

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ABSTRACT

For thermostatically controlled loads (TCLs) to perform demand response services in real-time markets, online methods for parameter estimation are needed. As the physical characteristics of a TCL change (e.g. the contents of a refrigerator or the occupancy of a conditioned room), it is necessary to update the parameters of the TCL model. Otherwise, the TCL will be incapable of accurately predicting its potential energy demand, thereby decreasing the reliability of a TCL aggregation to perform demand response. In this paper, we investigate the potential of various unscented Kalman filter (UKF) algorithm variations to recursively identify a TCL model that is non-linear in the parameters. Experimental results demonstrate the parameter estimation of two residential refrigerators. Finally, simulation results demonstrate the incorporation of the recursive parameter estimation methods into a model predictive controller for demand response.

1. Introduction

1.1. Background and motivation

Large populations of thermostatically controlled loads (TCLs) hold great potential for performing ancillary services in power systems. The advantages of responsive TCLs over large storage technologies include: (i) they are already well-established technologies; (ii) they are spatially distributed around the power system; (iii) they employ simple and fast local actuation; (iv) they are unimpaired by the outage of individuals in the population; and (v) they – on the aggregate – can produce a quasi-continuous response despite the discrete nature of the individual controls [1–3].

Because TCLs are controlled according to a temperature setpoint and deadband range, customers are generally indifferent to precisely when electricity is consumed. The inherent flexibility of TCLs, such as refrigerators and electric water heaters, makes them promising candidates for provisioning power system services. In fact, direct load control (DLC) and demand response (DR) programs are increasingly controlling TCLs, among other electric loads, to improve power grid stability [4,5].

1.2. Relevant literature

Past literature on the modeling and control of TCL populations has focused on the development of aggregation methods with centralized control. Malhame and Chong's study [6] is among the first reports to use stochastic analysis to develop an aggregate model of a TCL population. The coupled Fokker–Planck equations, derived in [6], define the aggregate behavior of a homogeneous population. More recently, [7] develops a diffusion–advection partial differential equation (PDE) model and parameter identification scheme for an aggregated population of heterogeneous TCLs. In [8], the authors present a deterministic hybrid PDE-based model for heterogeneous TCL populations, analyze its stability properties, and derive a power reference tracking control law.

In [9], the author uses a linearized Fokker–Planck model to describe the aggregated behavior of a TCL population. Direct control is achieved by broadcasting a single time-varying setpoint temperature offset signal to every agent. Numerical results demonstrate how small perturbations to the setpoint can enable TCLs to perform wind generation following. The work in [10] builds upon [9] by proposing a sliding mode control algorithm for direct control of air conditioning loads. A "state bin" modeling framework is used to describe local states (On/Off) in a discrete temperature-related manner.

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In [11], the authors employ a linear time-invariant (LTI) representation of a TCL population. As in [10], a "state bin" modeling framework is used and the aggregate probability mass is allowed to move through these bins. A Markov Chain-based approach is used to predict the evolution of the TCL population. In [2], the authors propose a proportional controller which, at each time step, broadcasts a switching probability, η, to all the TCLs in the population. If $\eta < 0$, all TCLs that are on must switch off with a probability of η and if $\eta > 0$, TCLs that are off switch on with a probability of η.

Recognizing that system frequency is a universally available indicator of supply–demand imbalance, a number of researchers have developed fully decentralized techniques for performing frequency services with TCLs. In [12], the authors show the suitability of TCLs to perform frequency services using system frequency as a control signal and the potential for a population of TCLs to respond to a sudden loss of generation. This demand response capability reduces the dependence of grid operators on rapidly deployable backup generation.

In [13], the authors develop a TCL model in which devices adjust their setpoints linearly according to the system frequency, allowing the population to act as a fast frequency controlled reserve. To address problems of long-term instability, Angeli and Kountouriotis develop a decentralized stochastic controller in [14] that is capable of maintaining desynchronization among the TCLs while regulating overall power consumption. In [15], the authors present a stochastic controller whereby each TCL in the population independently targets a reference power profile. The result is a stable and fully decentralized system that requires only the locally available control signals of frequency and time.

Recent trends in the field of convex optimization, in particular the introduction of the alternating direction method of multipliers (ADMM), have enabled researchers to pursue distributed methods of load control [16,17]. With these distributed control schemes, individual TCLs coordinate amongst each other or with an aggregator to drive the population towards a shared global objective. In [3], the authors employ a sharing ADMM algorithm to coordinate the electricity demand of a TCL population to perform generation following. By allowing each TCL to locally model its dynamics and enforce constraints, the authors demonstrate the capability of their algorithm to accurately control a heterogeneous TCL population.

A consensus coordination algorithm is developed in [18] that enables the aggregated power consumption of a population of air conditioners to follow a power generation forecast. With each TCL modeling its dynamics locally, the fully distributed algorithm is able to achieve fast convergence with only limited communication between neighboring TCLs in the network. In [19], the authors present a distributed model predictive control (MPC) scheme that enables a population of TCLs to provide load balancing services. The results demonstrate that as the number of TCLs in the population increases, the distributed MPC scheme achieves a higher efficacy than an aggregation method with centralized control.

Unlike centralized control schemes with aggregation models, decentralized and distributed control schemes rely on the individual TCLs to locally optimize their behavior. Therefore, it is necessary for every agent in the population to model its own behavior and to predict its energy demand. TCLs with poorly fit models will undermine the ability of the population to accurately perform ancillary services. Given that most TCLs experience regular changes to their physical characteristics (e.g. the contents of a refrigerator, the flow through a water heater, or the occupancy of a conditioned room), a linear time-invariant model is likely to prove inadequate. Also, for TCLs like radiant heaters and air conditioners, it is not possible for the manufacturer to predetermine the physical characteristics of the spaces that will be conditioned. Therefore, to improve the performance of decentralized and distributed TCL control methods, it is advantageous to employ recursive or online parameter estimation algorithms to fit and continuously update each TCL's model.

1.3. Main contributions

This manuscript contributes to the development of recursive parameter estimation algorithms for TCLs by investigating various unscented Kalman filters for the estimation of a TCL model that is non-linear in the parameters. We present four closely related filter methods (single, joint, dual, and triple) employing both the standard Kalman filter (KF), and unscented Kalman filter (UKF) algorithms. Specifically, we consider: (i) a single filter approach in which one UKF estimates the TCL parameters; (ii) a joint filter approach in which one UKF simultaneously estimates both the parameters and the state; (iii) a dual filter approach in which one UKF estimates the parameters and one KF estimates the state; and (iv) a triple filter approach in which one UKF estimates the parameters, one KF estimates the state, and another KF estimates the model inputs. We present experimental parameter estimation results using real temperature data from two residential refrigerators. Finally, simulation studies demonstrate the incorporation of the single filter approach into a model predictive controller for demand response.

1.4. Paper outline

This paper is organized as follows. Section 2 discusses the TCL model and Section 3 overviews the parameter estimation problem. Sections 4 and 5 provide background for the standard Kalman filter (KF) and the unscented Kalman filter (UKF), respectively. Section 6 formulates four filter methods for recursive parameter estimation of a TCL. Section 7 provides numerical examples of our proposed algorithms applied to real temperature data from two residential refrigerators. Section 8 presents simulation studies showing fast parameter convergence and the application of the single filter approach to the model predictive control of a TCL population for demand response. Finally, Section 9 summarizes key results.

2. TCL model

The literature is rich with models for representing the dynamics of a diversity of thermostatically controlled loads. These models address different challenges with respect to fidelity, user or occupant behavior, unobserved inputs or states, and suitability for controls applications. For example, in [12], the authors employ a refrigerator model which represents the energy flows between 4 thermally coupled masses (fridge structure, fridge contents, freezer structure, and freezer contents), allowing the researchers to accurately estimate the thermal storage capacity of the system.

Stochastic gray-box techniques are employed in [20,21]. In [20], the authors estimate the thermal mass, evaporator thermal resistance, insulation thermal resistance, and coefficient of performance (COP) for a residential refrigerator using maximum likelihood estimation. An electrical power consumption to temperature model for a residential freezer is developed in [21], allowing authors to apply model predictive control to shift the demand.

In [22], the authors develop a control-oriented multi-state thermal model and parameter estimation method for heating, ventilation, and air-conditioning (HVAC) systems in commercial buildings. A piecewise linear model of a residential heating system is presented in [23] which is able to approximate higher order thermal dynamics within the system.