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Dual estimation: Constructing building energy models from data sampled at low rate

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HIGHLIGHTS

- Estimation of equation-based energy models from data.
- Unmeasured states and parameters of building energy models are jointly estimated.
- Implicit discretization method to cope with the low sampling rate of data.
- Observability analysis of the equation-based building energy model.
- Validation using historical data from a real-life building.

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ABSTRACT

Estimation of energy models from data is an important part of advanced fault detection and diagnosis tools for smart energy purposes. Estimated energy models can be used for a large variety of management and control tasks, spanning from model predictive building control to estimation of energy consumption and user behavior. In practical implementation, problems to be considered are the fact that some measurements of relevance are missing and must be estimated, and the fact that other measurements, collected at low sampling rate to save memory, make discretization of physics-based models critical. These problems make classical estimation tools inadequate and call for appropriate dual estimation schemes where states and parameters of a system are estimated simultaneously. In this work we develop dual estimation schemes based on Extended Kalman Filtering (EKF) and Unscented Kalman Filtering (UKF) for constructing building energy models from data: in order to cope with the low sampling rate of data (with sampling time 15 min), an implicit discretization (Euler backward method) is adopted to discretize the continuous-time heat transfer dynamics. It is shown that explicit discretization methods like the Euler forward method, combined with 15 min sampling time, are ineffective for building reliable energy models (the discrete-time dynamics do not match the continuous-time ones): even explicit methods of higher order like the Runge–Kutta method fail to provide a good approximation of the continuous-time dynamics which such large sampling time. Either smaller time steps or alternative discretization methods are required. We verify that the implicit Euler backward method provides good approximation of the continuous-time dynamics and can be easily implemented for our dual estimation purposes. The applicability of the proposed method in terms of estimation of both states and parameters is demonstrated via simulations and using historical data from a real-life building.

1. Introduction

There is a growing interest in research and industry to extract in real-time additional insights from data collected by building automation systems (BAS). Examples of the additional value include real-time fault detection and diagnostics [1], energy saving supervisory control [2–5], real-time performance validation and energy usage analysis [6], real-time estimation of energy consumption in connection with user behavior [7–9], real-time estimation of the user behavior for improved control decisions [10–13], real-time estimation of thermal comfort models [14]. These real-time applications share the common goal of checking correct evolution of energy dynamics and/or thermal comfort, and detecting

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Nomenclature

T_z	zone temperature	u	input to the system
T_n	neighbor zone temperature	w	parameters of the system
T_o	outside temperature	y	output of the system
T_m	building mass (envelope) temperature	v	process noise of the system
C_a	thermal capacitance of zone air	n	observation noise of the system
C_m	thermal capacitance of building mass	f, F	state transition maps
α_{am}	conductance zone air/mass	h, H	output maps
α_{om}	conductance outside air/mass	T_s	sample time
$\hat{\chi}_k^-$	predicted (augmented) state estimate	χ_k	augmented state (state and parameters)
P_k^-	predicted covariance estimate	Q_k	covariance of process noise
$\tilde{y}_k$	innovation residual	R_k	covariance of observation noise
S_k	innovation covariance	$X(k\|k-1)$	matrix of sigma vectors
K_k	near-optimal Kalman gain	$L_f^k h$	Lie-derivative of order k
P_k	updated covariance estimate	dG	(nonlinear) observability matrix
$\hat{\chi}_k$	updated (augmented) state estimate		
x	state of the system		

anomalies and their causes [15]. To this purpose it is necessary to develop appropriate estimation tools that can detect, online from real-time collected data, whether the system is running according to a nominal model, or it is deviating from it.

In building applications the practical aspect and constraints are particularly important, since the majority of customers (building owners, landlords and tenants, as well as facility managers and energy service companies) are not willing to substantially invest in the solutions, at least until a short payback period is guaranteed. As a result, there is an opportunity for analytic engines capable of operation on legacy BAS systems which log only limited number of data points with limited sampling rate and resolution. While in industry there exists a variety of rule-based solutions for the individual BAS application listed above (e.g. Attune by Honeywell [16], SmartStruxure Lite solution by Schneider Electric [17], envisage* Energy Management System by General Electrics [18] and many others), researches have shown that a model-based approach is expected to provide a common basis to be shared by most of the advanced features and outperform rule-based methods [19–22]. The model-based approach requires the development of an appropriate model for the system dynamics, and the use of data to interpret in real-time the model parameters and their possible variations.

A model is a product that represents a system of interest, and quoting George Box "all models are wrong, but some are useful": in the following we will elaborate on which models are useful to our real-time purposes. Several building energy models and related software are available, which can be categorized as *steady-state* building energy simulation models and *dynamic* building energy simulation models. Models like the ISO 13790 [23] fall in the first category, because of the steady-state assumption that the building is heated or cooled for the thermal comfort of people. Models like EnergyPlus, TRNSYS, Modelica and RC models [24,25] fall in the second category, because they take into account (to different extent depending on the specific software) the dynamic behavior of heat and mass transfer. Steady-state building energy simulation models are used for long-term simulations and predictions, especially given the fact that in many buildings energy use is collected on monthly or weekly basis. However, they cannot be adopted for real-time energy monitoring and control. For real-time purposes we need to use dynamic building energy simulation models, well suited for buildings equipped with automated meter reading, where data are collected at a rate typically in the range from units of minutes to one hour. Taking into account hourly or per minute thermal dynamics allows using these models not only for long-term simulations and predictions, but also for real-time management and control purposes. Collection of data on a weekly or monthly basis makes not only real-time monitoring and control impossible, but it has been also identified as one of the main reasons for having huge gaps between the estimated and the actual building energy consumption [26].

Summarizing, we are interested in dynamic building energy simulation models. Using the classification of Lawrence Berkeley National Laboratory [27], when can further distinguish dynamic building energy simulation models into:

- Procedural energy modeling (like EnergyPlus and TRNSYS).
- Equation-based energy modeling (like Modelica and RC models).

Procedural modeling is usually more complex, because it is based on partial differential equations. For this reason modeling the physics is mixed with the implementation of numerical solution algorithms, and these building simulation programs typically do not allow specifying initial conditions for all state variables, which makes it impossible to use these models for model predictive control purposes or anti windup of control action or other optimization and monitoring tasks. Equation-based modeling is usually simpler, because based on ordinary differential equations with lumped parameters: this simplifying assumption allows defining state variables, specifying their initial conditions and controlling their evolution. Within the scopes of this paper, estimation of energy models from equation-based modeling is to be preferred over procedural modeling, because they allow easier real-time interpretation of the (lumped) model parameters [28].

Estimation of equation-based energy models is equivalent to estimating the parameters of the heat transfer equations (thermal resistance, conductance etc.) and/or some variables that cannot be measured (e.g. envelope temperatures). Estimation of equation-based energy models from data becomes challenging when combined with the following two issues:

(1) In most practical cases, many measurements are missing, due to the expensive sensors that would be required to acquire these measurements. For example, in building thermal dynamics, it is easy to get zone temperatures, but more difficult to get envelope temperatures. Envelope temperatures can be as important as zone temperatures in understanding the state of the building, so it is relevant to estimate them.