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Parameter estimation for grey-box models of building thermal behaviour☆

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ABSTRACT

Good models for building thermal behaviour are an important part of developing building energy management systems that are capable of reducing energy consumption for space heating through model predictive control. A popular approach to modelling the temperature variations of buildings is grey-box models based on lumped parameter thermal networks. By creating simplified models and calibrating their parameters from measurement data, the resulting model is both accurate and shows good generalisation capabilities. Often, parameters of such models are assumed to be a combination of different physical attributes of the building, hence they have some physical interpretation. In this paper, we investigate the dispersion of parameter estimates by use of randomisation. We show that there is significant dispersion in the parameter estimates when using randomised initial conditions for a numerical optimisation algorithm. Further, we claim that in order to assign a physical interpretation to grey-box model parameters, we require the estimated parameters to converge independently of the initial conditions and different datasets. Despite the dispersion of estimated parameters, the prediction capability of calibrated grey-box models is demonstrated by validating the models on independent data. This shows that the models are usable in a model predictive control system.

1. Introduction

A large part of the world's energy production is used for heating and cooling buildings. The fraction of total energy production consumed for utilities in commercial and residential buildings has been estimated at 32% by the International Energy Agency (IEA), according to [1]. Even though modern building techniques are able to reduce the energy used for heating, the renewal rate of buildings is low. Berthou et al. [2] reports renewal rates of 1% per year in France. This illustrates the need for good building energy management systems (BEMS) in existing buildings as well.

A model predictive control (MPC) system is an attractive solution for use in a BEMS. Models of building thermal behaviour can be used to predict the heating and cooling time of a building. In a MPC system, a model is used to simulate the system ahead in time in order to find a sequence of inputs that controls the system to the desired state. In a BEMS, the use of MPC will allow for improved tracking of the temperature setpoint as well as minimization the energy consumption [2,3]. Predictions of future system inputs are readily available from weather forecasts, which helps to facilitate the use of MPC.

There have been several publications studying the use of MPC for building thermal control. In [4] the authors use both active heating and passive solar blinds to control indoor air temperature. The paper also gives a thorough introduction to the various MPC control methods, such as deterministic and stochastic MPC. In [5] a complete building model is developed as a set of layered models and used in an MPC. The authors report an energy saving of 63% in thermal energy and 29% in HVAC electric energy, for a four-month test period. These examples show the potential benefits of using MPC for building thermal control. They also show the importance of a good prediction model for MPC to be feasible.

There are a number of different modelling approaches that can be used to model the thermal behaviour of a building in an MPC system [6]. In Perera et al. [1], a white-box model based on mass and energy balance is derived and calibrated for specific buildings. This type of model gives a set of ordinary and/or partial differential equations (ODE/PDE) that must be discretised and solved. For complex models, a large number of parameters are required that can be difficult to identify. Another approach to modelling is the use of black-box models, which relies solely on measurement data without any prior knowledge of the building, e.g. ARMAX [7,8] or PLS-R [9,10] models. These types of models show high prediction accu-

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racy, but do not usually allow the application of physical knowledge to define the model. This approach also produces models with low generalisation between different buildings, which makes building-to-building comparisons of models difficult [11]. Comparing the thermal behaviour of buildings can be of interest for the purposes of energy consumption classification.

Another approach to modelling thermal behaviour of buildings is the use of grey-box models [2,3,12,13]. A grey-box model is based on a simplified structure derived from a cognitive understanding of the physics involved. For the heating of buildings, the model structures may consist of thermal networks [14], i.e. resistor–capacitor circuit equivalent lumped parameter models. Rather than deriving the full model as in [1], the simplified model structure is developed from an understanding of the heat transfers involved in a building, which provides directly a reduced order model. This process can be referred to as 'cognitive' model development [14]. The parameters of such models are lumped parameters, i.e. each parameter represents a combination of multiple physical quantities. Such parameters must be identified from measurement data, since they are generally difficult to compute based on technical building specifications. A grey-box model therefore uses a combination of the white- and black-box approaches [15].

It is often assumed that the parameters of such models can be assigned physical meaning. The identified parameters are compared to the physical properties of the building [16,17]. For interpretation of model parameters to be justified, we suggest that the results of the parameter estimation process must show a low degree of dispersion, e.g. be independent of the initial guess parameter vector for the estimation algorithms. Estimation of parameters is required to give similar results when using different datasets from the same building.

The estimation of parameters requires the measurement data to contain enough dynamic information about the system to accurately calibrate the model [16,18–20]. Since the subject of this work is physical buildings, the experimental design is challenging. The outdoor weather conditions acts as a model input, particularly the outdoor temperature. Further, it is of interest to estimate the parameters under realistic conditions for an occupied building. Hence the choice of excitation of the system is limited. Lack of dynamic information in the data is known to give problems with practical identifiably [19].

Since all the parameters of a grey-box model must be estimated, an additional challenge with calibrating grey-box model parameters is over-parameterisation [16]. This is known to give non-convergent parameter estimates, since an over-parameterised model has undetermined optimal parameters, i.e. infinitely many solutions exist.

While challenges caused by practical identifiably and/or over-parameterisation may give reason to question the physical interpretation of the estimated parameters the models may still be usable in an MPC. In this work, the dispersion of parameter estimates under different experimental conditions is investigated using multiple sets of experimental data from a real building. Further, calibrated models are validated on independent data to show that they are capable of predicating the thermal behaviour of the test building, hence rendering them usable in an MPC system.

2. Model, methods and measurements

A common approach to parameter estimation is the use of numerical optimisation [19], either directly [2] or in the form of a maximum likelihood (ML) method [17,21]. When using numerical optimisation, it is of interest to investigate the dispersion in the estimated optimal parameters under different experimental conditions. In particular, it is interesting to study if the initial guess for the optimisation affects the estimated parameters.

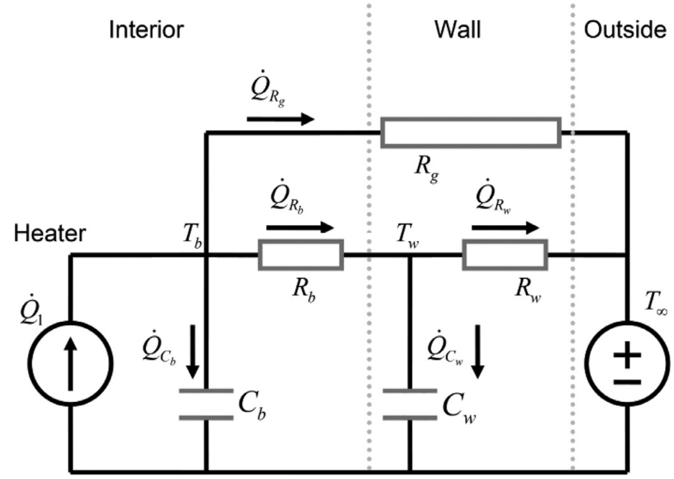

Fig. 1. The R3C2 thermal network model.

2.1. Model and parameters

The model used in this paper is a thermal network model of a building [3,14,16,17,20,22], presented using an electrical circuit equivalent model. Thermal resistance is modelled as resistors and thermal capacitance as capacitors. The resulting model is a circuit where the temperature is used as the driving potential, and the flow through the circuit is the heat flow. This approach has been used in a number of published papers on modelling building thermal behaviour, e.g. [3,13].

The focus of this paper is estimation of the model parameters. For simplicity, only one model is investigated, and the model structure is chosen as a minimalistic representation of the experimental building from which the calibration data is collected. The model is shown in Fig. 1. This model is similar to the R3C2 model used in [2], but the resistance for ventilation is removed since there is no ventilation system installed in the test building.

The model consists of two states T_b and T_w, which correspond to the interior temperature of the building and the wall temperature respectively. Wall temperature is measured on the inner surface of the wall. For each state there is an associated capacitance, C_b and C_w. These capacitances represent the building's ability to store thermal energy in the interior and the building envelope, e.g. walls, floor and ceiling. The remaining three model components are resistances. R_b represents the thermal resistance between the building interior and the wall. R_w is the resistance to heat flow through the wall, i.e. between the state T_w and the outside temperature. The third resistance R_g represents the resistance to heat flow through the parts of the building envelope that are not included in the state T_w, such as windows and the door. The driving forces of the system are $\dot{Q}$ and T_∞, where $\dot{Q}$ is a heat flow source, e.g. an electric heater. The outside temperature is modelled as a potential source T_∞.

Deriving equations from a thermal network model can be done with, for example, Kirchhoff's node potential law [23,24]. Each state in the circuit, T_b and T_w, is assigned to a circuit node and the flow into and out of each node is balanced. The model can be written in state-space form as a set of ordinary differential equations (ODEs) [18]:

$$\frac{dT_b}{dt} = -\left(\frac{1}{C_bR_b} + \frac{1}{C_bR_g}\right)T_b + \left(\frac{1}{C_bR_b}\right)T_w + \left(\frac{1}{C_b}\right)\dot{Q}_1 + \left(\frac{1}{C_bR_g}\right)T_\infty \quad (1)$$