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Parameter estimation of internal thermal mass of building dynamic models using genetic algorithm

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Abstract

Building thermal transfer models are essential to predict transient cooling or heating requirements for performance monitoring, diagnosis and control strategy analysis. Detailed physical models are time consuming and often not cost effective. Black box models require a significant amount of training data and may not always reflect the physical behaviors. In this study, a building is described using a simplified thermal network model. For the building envelope, the model parameters can be determined using easily available physical details. For building internal mass having thermal capacitance, including components such as furniture, partitions etc., it is very difficult to obtain detailed physical properties. To overcome this problem, this paper proposes to present the building internal mass with a thermal network structure of lumped thermal mass and estimate the lumped parameters using operation data. A genetic algorithm estimator is developed to estimate the lumped internal thermal parameters of the building thermal network model using the operation data collected from site monitoring. The simplified dynamic model of building internal mass is validated in different weather conditions.

Keywords: Lumped thermal parameter; Building internal mass; Thermal network model; Simplified model; Genetic algorithm; Dynamic thermal performance

1. Introduction

For diagnosis purposes of a whole building [6,16], or for thermal mass control strategies [1,12,18], or even for energy saving by system retrofitting [4,5,27], a reference model of the building is essential for load prediction or cost saving estimation. At the building level as a whole process, many researchers have developed different reference models that can be categorized into physical models and data driven models.

Physical modeling, also called forward modeling, begins with a description of the building system or component of interest and defines the building being modeled according to its physical description. Most simulation models are based on first principles, such as EnergyPlus [7], DOE-2 [20]. However, a large number of parameters are needed as inputs for the simulation model. The process of collecting a physical description

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Nomenclature

A	area (m^2)
C	thermal capacitance ($J/(m^2K)$)
d_f	difference between two maximum fitness values
f	fitness function
J	objective function
Q	cooling/heating load or heat (kW)
R	thermal resistance (m^2K/W)
T	air temperature (°C or K)
t	time (s)

Greek symbol

ε_f	threshold value

Subscripts

act	actual cooling load
conv	convective heat
e*i*	associated with external wall at *i*th orientation
est	estimated
fr	fresh air
im	associated with building internal mass
in	inside, indoor air
la	latent heat
r	associated with radiation
rf	associated with roof
rtn	return air
sol	associated with solar air temperature

is time consuming and often is not cost effective, or may even be impossible for some cases (the thermal properties of furniture, partitions etc.). In the modeling process, such indefinite properties are usually assumed. Unsuitable assumptions can make the model deviate from reality, thus decreasing the confidence in models.

Data driven models, also called inverse models, include steady [26,28] and dynamic ones [10,17,24,30], which are capable of capturing dynamics such as mass dynamics to some extents and are better suited to handle inter-correlated forcing functions or independent parameters. Applying regression techniques to the above can lead to models. It is generally necessary to acquire data over a long period of time with widely varying conditions in order to train the models for accurate predictions under all conditions. Furthermore, it is not known how well the models would perform in predicting building energy use if there were a major change in the control strategies employed, such as would occur when going from a night set up control to a precooling control strategy, because those parameters do not respect the proper physics or the parameters cannot represent the physical properties [2].

Therefore, a kind of simplified models, which can represent the physical properties of the building system are preferred for diagnosis, optimal control etc. Braun and Chaturvedi [2] developed an inverse gray box thermal network model for transient building load prediction. In the approach, a second order transfer function was established from an assumed 3R2C (three resistances, two capacitances) thermal network model to predict building load. All the parameters of the 3R2C models for the external walls, roof, internal walls etc., whose values are assumed in certain ranges, need to be identified by a non-linear regression algorithm to minimize errors between the predictions of the transfer functions and the measured operation data. Liao and Dexter [22] developed a method to establish a simplified second order physical model to simulate the dynamic behavior of existing multi-zone heating systems of a residential building. In their method, the total resistance and capac-