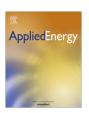
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# Estimating hourly cooling load in commercial buildings using a thermal network model and electricity submetering data



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#### HIGHLIGHTS

- Three hourly cooling load prediction models, called "RC-S" models, are proposed.
- Parameter optimization method with GA algorithm is proposed.
- Internal mass RC models compared to measured data are completed and analyzed.
- Internal mass RC models compared to EnergyPlus simulated data are done and analyzed.
- Better model is selected and it can provide reasonable estimation of cooling load.

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#### ABSTRACT

One major obstacle in Heating, Ventilation and Air Conditioning (HVAC) system Fault Detection and Diagnostics (FDD), retrofitting and energy performance evaluation is the lack of detailed hourly cooling load data. Cooling load measurement in commercial buildings is expensive and sometimes very difficult to implement. Detailed building simulation models, such as EnergyPlus, are too complicated to build and also must be calibrated. In this paper, an hourly cooling load prediction model, called the "RC-S" model, is proposed. This new cooling load calculation approach consists of a simplified thermal network model of the building envelope, a thermal network model for the building internal mass and the internal cooling load model from the submetering system. One existing RC model is introduced as reference model and three types of "RC-S" models are set up in this study. Genetic algorithm (GA) is selected to optimize the parameters in those models. Measurement data collected from a real commercial building and simulation data obtained from EnergyPlus model of the same commercial building are used to train and test the four models. The results prove that the proposed "RC-S" cooling load calculation method is more accurate than the existing RC model and much simpler than whole building simulation models. It can provide reasonable estimations of cooling loads for HVAC FDD and other performance evaluations.

#### 1. Introduction

The building sector is a major consumer of energy worldwide and a large amount of energy is used for Heating, Ventilation and Air Conditioning (HVAC) [1–5]. One cause of high consumption in HVAC systems lies in their frequent failure to operate as intended after a period of operation, even with correct commissioning [6,7]. In many buildings, energy performance is not a concern as long as building comfort can be maintained. Many previous studies have focused on enhancing the operating efficiency of HVAC systems. These studies can be categorized by topic, such as Fault Detection and Diagnostics (FDD), supervisor optimal control, retrofit and

\* Corresponding author. Tel.: +86 021 65989750. E-mail address: xupeng@tongji.edu.cn (P. Xu). continued commissioning. Reliable data on energy consumption and cooling loads form an indispensable basis for these functions.

In the last decade, interval metering and submetering of commercial building systems have become more popular in various countries and regions of the world. The energy meter structure is depicted in Fig. 1. Data on these meters are normally collected every 5–15 min, so over time, overwhelming amounts of data accumulate, providing a good platform for FDD and optimizing control for HVAC systems.

However, unlike electricity, few buildings have their cooling load metered. Cooling loads are typically measured using the supply and return temperatures and flow rates of chilled water. Cooling load measurement is not very expensive for a newly constructed system. However, it is often neglected because contractors' main concern is to meet the comfort requirements with

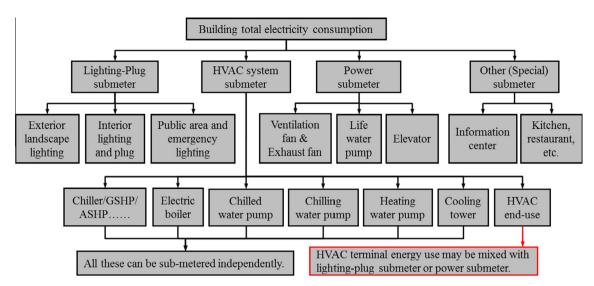


Fig. 1. Submetering system schematics and classification levels.

the lowest investment cost. In newly constructed buildings, the temperature and flow sensors are buried inside the chilled water pipe. The data are relatively accurate at the beginning, but sensors will drift and degrade over time. In existing buildings, it is necessary to drill holes to install sensors. Many building owners and operators forbid drilling into high-pressure pipes because of liability issues. In many cases, peeling off insulation and installing temperature and ultrasonic flow sensors attached to pipes is also prohibited.

In view of the importance of the cooling load and the difficulty of installing meters, an increasing number of scholars are dedicated to the study of calculating building loads with kinds of models. The paper is organized as follows. Section 2 is the literature review. Section 3 elaborates the previous RC model and three newly introduced models. This section also describes the principles of the parameter calibration process for the external building envelope and internal mass. Section 4 mainly describes the building information for the case study commercial building and its data acquisition. Section 5 is composed of three parts. Section 5.1 introduces the parameter calibration process for the external building envelope. Measured data and simulated data are utilized to compare and validate four models in Sections 5.2 and 5.3, respectively. Finally, the results from measured data and simulated data are further compared and summarized.

#### 2. Literature review

In the 2001 ASHRAE Handbook—Fundamentals models are divided into two basic categories: 'forward modeling' and 'inverse modeling' [8]. Forward modeling generally begins with a physical description of a building. This includes the building's construction materials, lighting, equipment, occupants and the type of HVAC system. This type of model is typically used for designing a building and its HVAC system. Inverse models are derived from empirical historical data and are expressed in terms of one or more driving forces and a set of empirical parameters. A model form is predetermined and measured data are used to get the parameters that provide the most accurate representation for the chosen model form and data set. This type of model can be used for retrofit analysis, performance monitoring, FDD and on-line optimal control.

Forward models, also known as law-driven models, physical models or white box models, are the universally used method in

the field of building load prediction. However, as mentioned above, the input parameters for these models are complicated and often are not available. It takes time and effort to establish and calibrate models, even for specialists with many years' experience, but the precision of the model still cannot be guaranteed [9–14]. Inverse modeling, also called data-driven modeling, can be generally classified into black and gray models. Black box models include traditional regression models [15-17], artificial neural network (ANN) models [18-21] and support vector machine (SVM) models [22-24] and so on. Black box models are trained and driven by a set of data. The training data set has stringent requirements on quality and time span. Furthermore, the training data are supposed to provide as much coverage of various conditions as possible. Many inverse models tend to have poor precision and weak robustness due to the lack of high-quality training data. Gray box models sit between white and black box models. Their approaches differ from black box approaches in that they use certain parameters identified from a physical system model. Examples of gray box models are decision tree models [25,26], Fourier series models [27–29] and thermal network models (RC model) [30]. Considering that the building loads have explicit components, RC models are more accurate because their parameters have obvious physical meanings and the models require less data than data-driven models. Therefore, RC models need less training and are more robust. Based on circuit principles and Kirchhoff electric current theory, a building thermal network model is presented as a simple simulation model of transient heat transfer through the building envelope and internal mass, which is called the "RC model". R is the thermal resistance of the material, and *C* is the heat capacity of materials.

The approaches to calculating the cooling load coming from a building envelope using RC models are detailed in a book written by Kreider and Rabl in the 1990s: 'Heating and Cooling of Buildings: Design for Efficiency' [30]. Braun and Chaturvedi [31] proposed an inverse gray thermal network model for transient building load prediction. Liao and Dexter [32] developed a gray second-order physical model to simulate the dynamic behavior of the existing heating system of a multi-zone residential building. Mitchell [33] postulated that the nodal placement of the 3R2C model could be obtained by matching the theoretical frequency response characteristics of the building envelope with the frequency response characteristics of the simplified model using a genetic algorithm. The numbers in front of *R* and *C* stand for the numbers of resistance and capacity factors in the model. Seem

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