

Automatic generation of RC models using IoT data from commercial buildings

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Abstract

Automatic generation of accurate building models is essential for applying advanced control technologies and understanding the thermal dynamics of buildings. In this paper, a method for automatically generating RC models of commercial buildings is proposed. The method defines the simplest RC model and iteratively adds model parameters while using Bayesian information entropy to judge the quality of the model. When the quality of the model no longer improves, the method ends the model. This method was validated in an office building in Foshan, and the results showed that the final model could predict indoor temperature accurately with fewer efforts in modeling.

Highlights

- Achieving automatic generation of RC models that can input data and output model parameters end-to-end
- Ensuring that the model structure is simple enough
- Extending the RC model to large commercial buildings

Introduction

The heating, ventilation, and air-conditioning (HVAC) systems are responsible for approximately 50% of the total energy consumption in buildings, and they consume the greatest proportion of energy compared to all other end-user systems (S. Li et al., 2022). To reduce the energy consumption of HVAC systems, many advanced control technologies have been explored and verified. Among them, Model Predictive Control (MPC) has become a hotspot because it can not only reduce energy consumption but also maintain thermal comfort (Oldewurtel et al., 2012; Žáčková et al., 2014).

To implement MPC, it is crucial to develop a proper building energy model. The process of establishing and calibrating the model typically accounts for approximately 70% of the project's effort (Henze, 2013). Additionally, many researchers consider the absence of practical and automated technology for developing precise building energy models as the primary obstacle to applying MPC in practice (Drgoňa et al., 2020).

There are three approaches to establishing building energy models, namely white-box, black-box, and grey-box models. White-box models are established based on physical principles and require detailed building

information (Fathi et al., 2020). In contrast, black-box models rely on historical data to estimate the energy consumption of buildings (C. Wang et al., 2022). The grey-box model combines the benefits of both white-box and black-box models. It includes a certain degree of physical principles, making it more interpretable than black-box models, while also being simpler to establish than white-box models (Y. Li et al., 2021). One of the widely used grey-box models is the resistance-capacitance (RC) model, also known as the thermal network (A. Li et al., 2017).

To establish an RC model, the initial step is to define its structure and estimate its parameters. If the structure is overly complex, it may lead to parameter redundancy and unreliable parameter estimation based on measured data (Raue et al., 2009). Conversely, a model with a structure that is too simple will not accurately reflect the thermal dynamics of the building. Therefore, it is common practice for researchers to carefully select a suitable RC model structure.

In the process of model selection, usually, several possible model structures are selected as candidates and then they are compared based on statistical tests, frequency responses, or validation criteria to determine the best one (Bacher & Madsen, 2011; Harb et al., 2016; Saberi Derakhtenjani et al., 2015). Wang et al. propose a model simplification method to obtain suitable RC models for residential buildings (Z. Wang et al., 2019). The method begins with a complex model and iteratively removes parameters based on the standard error ratio. By verifying the method in a house in Canada, results show the selected model not only has good interpretability but also obtains accurate indoor temperature prediction. Bacher and Madsen develop a forward selection algorithm that progressively increases parameters in the model and ends the process when the more complex model fails to exhibit statistical improvements in model quality (Bacher & Madsen, 2011). Results show the selected model can reflect well in the thermal dynamics of the residential building. Vallianos et al. combine a forward selection algorithm and model simplification method to propose an automatic generation method for RC models. (Vallianos et al., 2022). The method begins with the simplest model and iteratively removes parameters based on Bayesian Information Criterion (BIC). When the model quality does not improve anymore, the method reversibly removes parameters based on BIC. By verifying in a house in Canada, results show the

selected model can predict 24-h ahead zone temperature with an RMSE of 0.44 °C.

Currently, most of the research focuses on residential buildings. Residential buildings usually have limited room and can be zoned by the physical envelope. When the RC model is applied in commercial buildings, there exist some differences, resulting in the fact that the previous method cannot be simply transferred. Commercial buildings usually have a larger room and May include open areas with different envelopes to that in residential buildings. This means that its internal thermal dynamics are more complex. However, commercial buildings consume lots of energy as well. By understanding their thermal dynamics, optimal control can be applied and energy can be saved. Therefore, the research attempt to develop an automatic generation method to obtain reliable and simple RC models for the thermal dynamics of commercial buildings for optimal control.

In Section 2, an approach for automatic model development, selection, and evaluation is presented. Following this, Section 3 describes the commercial building and its associated measured data. Section 4 provides a comprehensive discussion of the obtained results, while Section 5 concludes the article.

Methods

This section outlines the process of developing a simple and dependable RC model through an automated approach. The framework involves three stages: model generation, model training, and model selection. During the model generation phase, the necessity and formulation of RC models, along with their associated assumptions, are thoroughly examined. In the model training phase, the model parameters are estimated. Finally, in the model selection phase, the criteria for model selection are presented. The proposed methodology is based on the fundamental concept of starting with a simple model structure and gradually refining it to a more appropriate one.

Model generation

A RC model is created using a blend of prior physical knowledge and statistics, specifically, the information embedded in data. The prior physical knowledge is represented by a set of first-order stochastic differential equations, which are also known as a stochastic linear state-space model in continuous time. These equations illustrate an integrated model of the building's thermal dynamics. It should be noted that the interpretability of the model's parameters is dependent on how the building is divided into entities in the model. The whole process is shown in Figure 1.

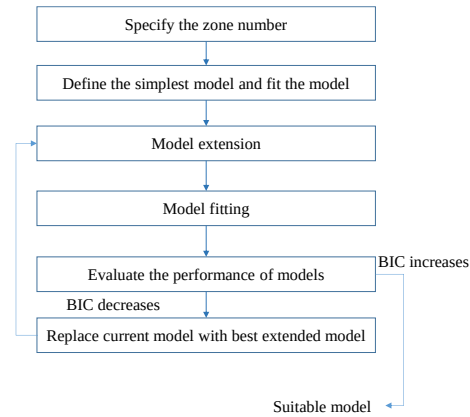


Figure 1: The workflow of automatic generation of RC model

Considering the complex envelope and interior, the automatic generation of RC models mainly focuses on these components. Figure 2(a) is defined the simplest model, which consists of three resistors and three capacitors. The internal mass and envelope become increasingly complex during the iteration process, with a pair of thermal capacitors and thermal resistors added each time, as shown in Figure 2(b) and (c).

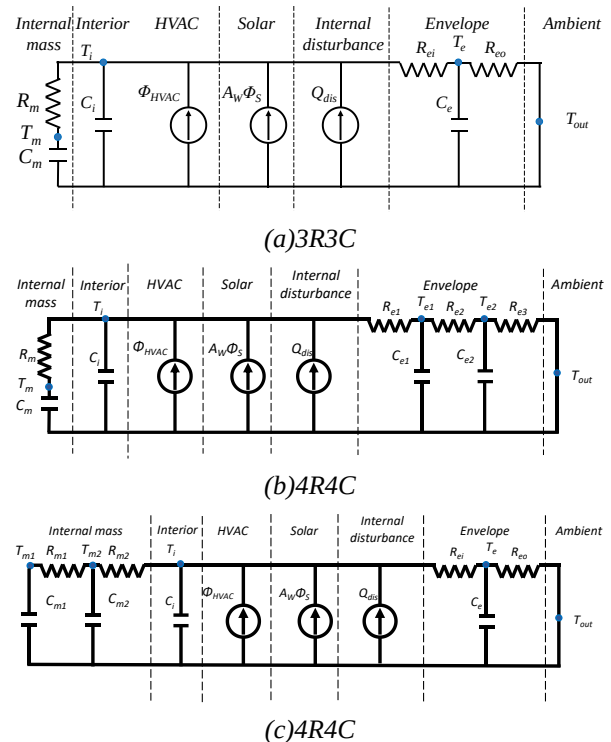


Figure 2: The example of the development in Automatic Generation of RC Models

In the study, the zone temperature is considered as uniform output in the whole room, and ambient temperature, solar radiation, thermal energy from the HVAC system, and heat disturbance from the occupants, equipment, and lighting are chosen as model inputs. Then according to the RC network, the mapping relationship between inputs and outputs can be represented by Equation (1).

$$C_k \frac{dT_k}{dt} = \sum_h \frac{T_h - T_k}{R_{h,k}} + \sum Q_i \quad (1)$$

Where T_k represents the temperature in the k th node, C_k is the thermal capacity in the same node, T_h is the temperature in the h th node next to the k th node, $R_{h,k}$ is the thermal resistance between the k th and h th nodes, and Q_i represents the i th heat disturbance in the k th node.

Model training

During the process of model training, the parameter of RC models is estimated using the genetic algorithm (GA). By minimizing the mean square error (MSE) between the real data and the estimated indoor temperature, the GA is able to obtain the optimal parameters. Once the MSEs reach a minimum, the estimated parameters are considered the final results by the GA.

Model selection

During the process of model selection, we use the Bayesian Information Criterion (BIC) to compare different models. The BIC is based on information theory and aims to strike a balance between model complexity and mapping capability (Liu et al., 2022). Generally, a lower BIC indicates a better model. The calculation formula is shown in Equation (2).

$$BIC = N \ln \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{N} + m \ln N \quad (2)$$

Where N represents the number of samples, y_i is the real data, $\hat{y}_i$ is the prediction data, and m represents the number of model parameters.

The study automatically generates RC models by iteratively adding parameters to the model. Each time a resistor and a capacitor are added to the model, the increasing complexity of the envelope and internal mass are taken into account. The model selection ends when the BIC no longer reduces.

Case study

This method is validated in a 26-story office building located in a hot summer and warm winter region, with a curtain wall composed of fully glazed facades and a VAV system for maintaining indoor thermal comfort through cooling or heating. Sensor data such as weather data, ventilation rates, and supply/return air temperature are collected to estimate the parameters of the RC model.

Firstly, heatmap analysis is conducted on the building's ventilation rates to extract its operation schedule as shown in Figure 3. Based on the analysis, the operation mode of the building can be divided into two types: weekdays and non-weekdays. By averaging the data, an approximate heat disturbance schedule is obtained, as shown in Figure 4. The other heat disturbance such as lighting, equipment, and occupant determined based on design standards, and the specific setting is shown in Table 1 (Lu, 2008).

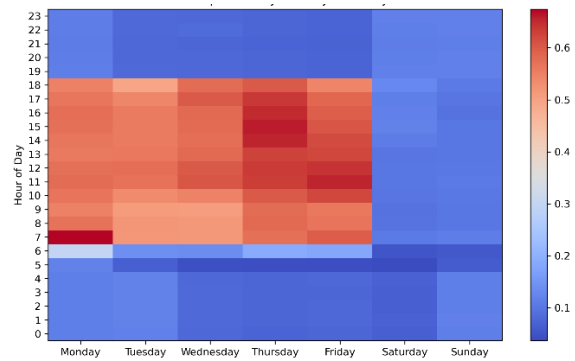


Figure 3: Heatmap analysis of the building's ventilation rates

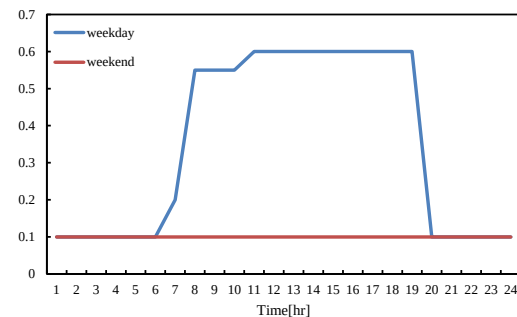


Figure 4: Heat disturbance schedule

Table 1: The setting of heat disturbance

Item	Design density
Occupant	10 m ² /person
Lighting	9 W/m ²
Equipment	15 W/m ²

Based on the schedule and design density, the internal heat disturbance can be estimated. Other input can be collected from different sensors. The prediction interval is 15 minutes.

Results

The results of BIC during the model generation process are summarized in Table 2. The entire model generation process starts from the simplest model, and two models are generated in each iteration process, with the same number of parameters. In the first iteration process, the model that increases the complexity of the enclosure structure is selected because it has a smaller BIC index. Subsequent models are then extended based on this model until the BIC no longer decreases. From the table, it can be seen that when the model is iterated for the third time, the BIC no longer decreases, so the model selection process stops. In addition, the value of BIC shows that the degree of decrease gradually decreases during the first two iteration processes. In the second iteration process, the model improvement is less than 7%. The entire model selection result increases the 5R5C model with increased internal structural complexity as a more suitable RC model, as shown in Figure 5.

Table 2: BIC for the extended models in the process of model selection

Iteration	Model	
Beginning	3R3C	
	-600	
1	4R4C (envelope)	4R4C (internal mass)
	-877	-549
2	5R5C (envelope)	5R5C (internal mass)
	-932	-937
3	6R6C (envelope)	6R6C (internal mass)
	-871	-870

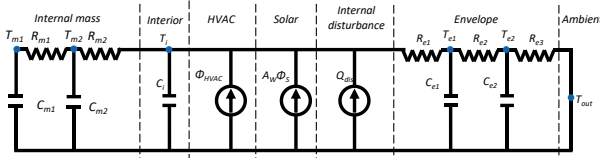


Figure 5: The chosen model in the end

The model uses one day of data to train and predicts indoor temperatures for the next six days. The predicted results are shown in Figure 6. It can be observed that the model's prediction results are better on the training set, but the prediction accuracy gradually decreases on the testing set. For weekdays, the model can track the changes in indoor temperature well, with prediction errors less than 0.5°C for the first three days of the testing set, and some errors reaching up to 1°C on the fourth day. However, for weekends, the model's prediction performance is relatively poor, with temperature change trends differing from the actual trends, and most prediction errors around 1°C . The possible reason is that the model is trained using only weekday data, and the parameters of the weekday RC model may differ from those of the weekend RC model, leading to inaccuracies in predicting indoor temperatures on weekends. In addition, the model has a larger prediction error when the indoor temperature is low. In future work, modeling for weekdays and weekends separately can be done, and improvements can be made to the model's performance when the indoor temperature is low.

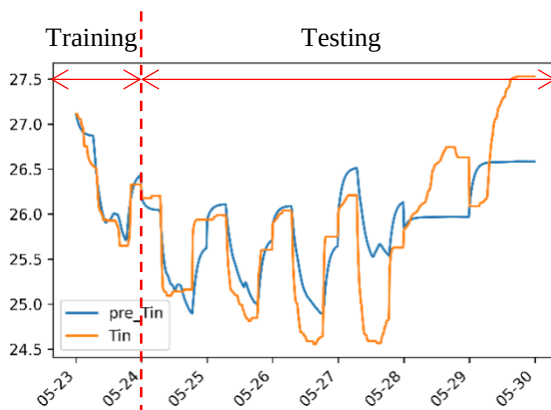


Figure 6: Prediction results based on the chosen model

Conclusion

Automatic generation of accurate building models contributes to applying advanced control technologies. In this paper, a method for automatically generating RC models based on BIC is proposed. The method applies BIC to evaluate the performance of RC models, which can ensure the balance of the complexity and accuracy of models. The results showed that the final model could predict indoor temperature accurately with fewer efforts in modeling.

Acknowledgement

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