

Development and validation of rapid building energy simulation engine based on novel multi-thermal-zone RC network modeling method

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Abstract

This study presents RCBldEng, a fast simulation method for multi-thermal-zone building energy consumption based on Resistance-Capacitance (RC) models. While existing building energy simulation tools like EnergyPlus provide reliable results, they require substantial computational resources and detailed input parameters. To address this limitation, we developed and evaluated four RC model configurations (4R1C, 6R1C, 7R1C, and 7R2C) with progressive levels of interzonal thermal coupling complexity. The models were validated against EnergyPlus simulations using a U.S. Department of Energy (DOE) prototype buildings—a medium office building—three distinct climate conditions representing diverse thermal challenges across China: Shanghai (ASHRAE 3A - warm and moist), Guangzhou (ASHRAE 2A - hot-humid subtropical), and Shenyang (ASHRAE 6A - cold continental). The 7R2C model demonstrated superior performance across all climate zones, achieving r-squared values approaching 99% in office buildings under diverse climatic conditions. Cross-climate validation results confirm the model's robustness, with consistent accuracy maintained across heating-dominated (Shenyang), cooling-dominated (Guangzhou), and balanced load (Shanghai) thermal environments. Notably, the introduction of dual-capacitance mechanisms and interzonal thermal coupling significantly improved prediction accuracy during transitional seasons. The results indicate that while all coupled models showed improvement over the baseline 4R1C model, the 7R2C configuration offers an optimal balance between accuracy and computational efficiency. This research provides architects and engineers with a lightweight yet reliable tool for rapid comparison of design alternatives during early-stage building design and renovation projects.

Keywords: Building simulation; RC model; Heating load; Cooling load; Energy use

Key Innovations

The study introduces RCBldEng, a fast multi-thermal-zone building energy simulation method using RC models with progressive interzonal thermal coupling complexity. The dual-capacitance 7R2C model achieves high accuracy compared to EnergyPlus while significantly reducing

computational requirements, particularly excelling in transitional season predictions.

Practical Implications

Our developed RCBldEng provides architects and engineers with a lightweight alternative to computationally intensive simulation tools. Its optimal balance of accuracy and efficiency enables rapid comparison of multiple design alternatives during early-stage building design and renovation projects, supporting sustainable design decisions without sacrificing prediction reliability.

Introduction

As climate change and urbanization are posing challenges to curb building sector energy use and carbon emission (Shen & Yang, 2020), how to design energy-saving new constructions or to effectively renovate existing buildings (S. Li et al., 2022) in a more computationally efficient manner (Shen, 2024) has become an critical research focus considering that emerging parametric optimization based on heuristic method entails intensive computation. Building thermal load and energy consumption simulation calculations are essential for evaluating energy consumption and carbon emission levels during building operations. While architects and engineers use various simulation models throughout different design stages (Hong, Chou, & Bong, 2000; Weisberg, 2012; Wittchen, Johnsen, & Sørensen, 2007; Yan et al., 2008), there's a growing need for efficient simulation tools during conceptual design and renovation phases. Currently mature energy simulation software like EnergyPlus provides reliable results but requires detailed input parameters and substantial computational power, especially for buildings with multiple zones (USDOE, 2014). This computational intensity makes it challenging to perform rapid comparisons of multiple design schemes (Picco, Lollini, & Marengo, 2014). The Resistance-Capacitance (RC) model, which simulates heat transfer processes through circuit component analogies, offers a promising alternative due to its lower complexity and computational requirements (Hong et al., 2000). Building energy simulation models generally fall into three categories: white-box, black-box, and gray-box models. White-box models, while accurate, require numerous

input parameters and lengthy calculation times (Crawley et al., 2001). Black-box models, though adaptable, demand high-quality training data and lack interpretability. The gray-box RC model combines the advantages of both approaches, offering clearer physical significance than black-box models while maintaining lower computational costs than white-box models when dealing with both building scale (Y. Li et al., 2021) or regional scale building energy modeling (Shen, Wang, & Ji, 2021). While current RC model implementations primarily rely on inverse methods, requiring historical data for parameter identification through various algorithms, the forward RC model approach remains relatively unexplored, particularly for multi-thermal zone applications. The forward method establishes thermal balance models using building parameters like envelope thickness and heat transfer coefficients (Shen, Braham, & Yi, 2018). Although some studies have validated forward RC models (Vivian, Zarrella, Emmi, & Carli, 2017), research on multi-thermal-zone RC models rarely considers coupled heat transfer between zones (Bacher & Madsen, 2011).

This study aims to develop RCBldEng, a fast simulation method for multi-thermal-zone building energy consumption based on a mixed-forward-inverse RC model. The research explores computational costs and accuracy across different model orders, solution methods, and building types while establishing a comprehensive whole-building multi-zone RC energy consumption modeling structure. This approach can provide architects and engineers with a lightweight algorithm for rapid simulation and comparison of building energy consumption, supporting both new construction and renovation projects in achieving sustainable design goals (GhaffarianHoseini et al., 2013).

Methodology

The proposed forward-inverse-mixed RC models

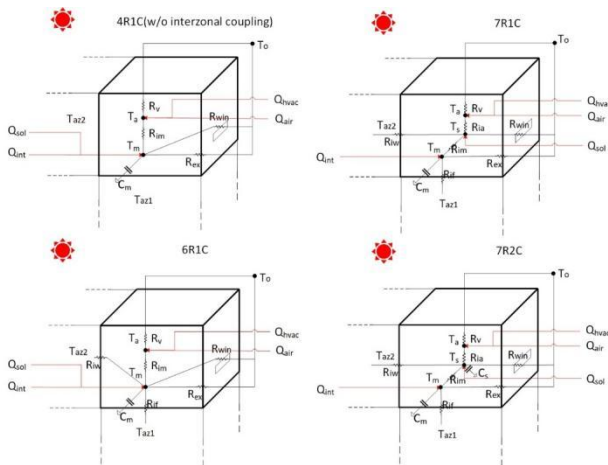


Figure 1: The proposed RC models with different modeling parameters: a) 4R1C w/o coupling; b) 6R1C; c) 7R1C; d) 7R2C

Interzonal thermal coupling can play a critical role in capturing the intricate thermal interactions between different zones within a building. Hence, three distinct RC models—6R1C, 7R1C, and 7R2C—have been proposed to address these complexities. The structures of the three models, including the 4R1C model without interzonal thermal coupling are plotted together in Figure 1.

The 6R1C model

The 6R1C model has two temperature nodes T_a and T_m as well. It takes into account the heat fluxes between the current zone and all the adjacent zones.

$$\frac{T_o - T_a}{R_v} + \frac{T_m - T_a}{R_{im}} + Q_{hvac} + Q_{air} = 0 \quad (3)$$

$$C_m \frac{dT_m}{dt} = \frac{T_o - T_m}{R_{win}} + \frac{T_o - T_m}{R_{ex}} + \sum_i \frac{T_{az,i} - T_m}{R_{if,i}} + \sum_i \frac{T_{az,i}}{R_{iw,i}} + \frac{T_o - T_m + (Q_{hvac} + Q_{air})R_v}{R_{im} + R_v} + Q_{sol} + Q_{int} \quad (4)$$

Where,

$T_{az,i}$: Temperature of i^{th} adjacent zone of the current zone (K);

$R_{if,i}$: Thermal resistance of internal floor of i^{th} adjacent zone (m^2K/W);

$R_{iw,i}$: Thermal resistance of internal wall of i^{th} adjacent zone (m^2K/W);

The 6R1C model employs temperature nodes T_a (representing internal air) and T_m (depicting thermal mass) and is adept at integrating heat fluxes between the current zone and its adjacent zones. Its structure recognizes the importance of the building's internal zones in shaping its thermal behavior, which is essential for larger structures or those with prominent internal heat sources or sinks. By considering both the external environment and neighboring zones, this model offers a more comprehensive thermal view of single-zone behaviors, and their adjacent interactions compared to the 4R1C model.

The 7R1C model

The 7R1C model has three temperature nodes, namely T_a , T_s and T_m , in which T_s represents the central mass node.

$$Q_{hvac} + Q_{air} = \frac{T_a - T_o}{R_v} + \frac{T_a - T_s}{R_{ia}} \quad (5)$$

$$\frac{T_m - T_s}{R_{ia}} + \frac{T_o - T_s}{R_{win}} + \sum_i \frac{T_{az,i} - T_s}{R_{iw,i}} + \frac{T_o - T_s + (Q_{hvac} + Q_{air})R_v}{R_{ia} + R_v} + Q_{int} = 0 \quad (6)$$

$$C_m \frac{dT_m}{dt} + \frac{T_m}{\frac{1}{R_{ia} + R_v} + \frac{1}{R_{win}} + \frac{1}{R_{iw}}} = \frac{T_o - T_m}{R_{ex}} + \frac{T_s - T_m}{R_{im}} + \sum_i \frac{T_{az,i} - T_m}{R_{if,i}} + \sum_i \frac{T_{az,i}}{R_{iw,i}} + Q_{sol} + Q_{int} \quad (7)$$

where,

R_{ia} : Thermal resistance of internal air (m^2K/W);

Advancing from the 6R1C configuration, the 7R1C model introduces an additional node, T_s , to signify the central thermal mass. This central mass is differentiated from the peripheral or envelope mass represented by T_m . The

introduction of T_s can better represent the temperature of interior surfaces within the thermal zone (such as internal walls, floors, and ceilings). The resistances related to internal walls and floors of neighboring zones further detail this interaction. Thus, the 7R1C provides a layered approach to capturing both external influences and intricate interzonal dynamics.

The 7R2C model

$$Q_{hvac} + Q_{air} = \frac{T_a - T_o}{R_v} + \frac{T_a - T_s}{R_{ia}} \quad (8)$$

$$C_s \frac{dT_s}{dt} = \frac{T_m - T_s}{R_{im}} + \frac{T_o - T_s}{R_{win}} + \sum_i \frac{T_{az,i} - T_s}{R_{iw,i}} + \frac{T_o - T_s + (Q_{hvac} + Q_{air})R_v}{R_{ia} + R_v} + Q_{int} \quad (9)$$

$$C_m \frac{dT_m}{dt} + \frac{T_m}{\frac{1}{\frac{1}{R_{ia} + R_v} + \frac{1}{R_{win}} + \frac{1}{R_{iw}}} + R_{im}} = \frac{T_o - T_m}{R_{ex}} + \frac{T_s - T_m}{R_{im}} + \sum_i \frac{T_{az,i} - T_m}{R_{if,i}} + \sum_i \frac{T_{az,i}}{R_{iw,i}} + Q_{sol} + Q_{int} \quad (10)$$

where,

C_s : thermal capacity of central thermal mass node per building area (J/m^2K)

Building upon the foundation of the 7R1C, the 7R2C model introduces the C_s term, capturing the thermal storage capability of the central thermal mass mode T_s . This distinction in capacitance— C_m for peripheral mass and C_s for central mass—gives the 7R2C model a refined representation of energy storage and discharge dynamics. This dual-capacitance mechanism can ensure a more detailed portrayal of how heat ebbs and flows within different building components compared with the 7R1C model, making it especially useful for buildings undergoing pronounced day-night thermal variations.

Parameter Determination in RCBldEng

The RC model parameters in RCBldEng are determined through a systematic approach that distinguishes between new building design applications and existing building analysis. For new building design scenarios, which represent the primary application of this study, all parameters are calculated using forward modeling approaches based on standard building design inputs including geometry, construction assemblies, thermal properties, and operational schedules. The aggregated internal parameters including R_{im} (internal mass resistance), R_{if} (internal floor resistance), R_{iw} (internal wall resistance), and thermal capacitances represent complex interzonal thermal interactions that cannot be directly calculated from individual building components. These parameters can be established through physical relationships and typical ranges documented in building thermal modeling literature or building codes, ensuring that users need only provide conventional building design parameters rather than estimating specialized RC circuit values.

For existing buildings, external thermal resistances such as R_{ex} and R_{win} can be directly input from documented wall and window U-values, while ventilation resistance R_v

can be determined from specified air change rates and building volume. For existing building applications where some building properties may be unknown or uncertain, RCBldEng incorporates an inverse modeling capability that employs a non-dominated sorting evolution algorithm to optimize hard-to-determine parameters such as effective thermal capacitance and interior wall thermal properties. This optimization process uses measured building performance data to calibrate parameters while maintaining physical constraints and relationships between thermal circuit elements.

The developed tool, now publicly available at <https://github.com/andersonspy/RCBldEng>, automates the parameter determination process and includes sample building models in the Projects folder that are more complicated in terms of geometry and thermal zoning, together with their complete model input specifications. In short, users are needed to provide standard architectural and engineering design inputs, and the tool calculates appropriate RC parameters without requiring specialized knowledge of thermal circuit modeling.

Load Calculation

While RC models typically solve for indoor temperature given heating and cooling power inputs, RCBldEng is formulated to calculate the required heating and cooling loads needed to maintain specified indoor temperature setpoints. This is achieved by rearranging the thermal balance equations to solve for Q_{hvac} as the dependent variable rather than T_a . The models enforce indoor temperature constraints by setting T_a equal to the thermostat setpoint temperatures and calculating the necessary HVAC power to satisfy the thermal balance under given outdoor conditions and internal loads. This approach enables direct comparison with EnergyPlus load calculations, which similarly determine the energy required to maintain thermal comfort conditions rather than predicting free-floating temperatures.

Simulation of DOE prototype buildings

Prototype building models

The validation and performance assessment of the developed RC-based simulation engine are grounded on two prototype buildings: a detached house and a medium office building as shown in Figure 2. The case study building is derived from the U.S. Department of Energy (DOE) models, specifically from the commercial prototype model series, ensuring the representation of climate-dominant and internal-load dominant building types (Shen & Wang, 2024). The prototype building adheres to the ASHRAE 90.1-2013 standard, underlining their commitment to energy efficiency and sustainable design. ASHRAE 90.1-2013 is a well-established standard in the building industry, widely adopted for its benchmarks and guidelines on energy-efficient design and practices (Halverson et al., 2014). The occupancy and building use schedule, and the indoor cooling and heating setpoint schedule can be found in ref (Shen et al., 2018).

Adherence to this standard ensures that the case study buildings reflect contemporary building design practices, especially in the context of energy efficiency.

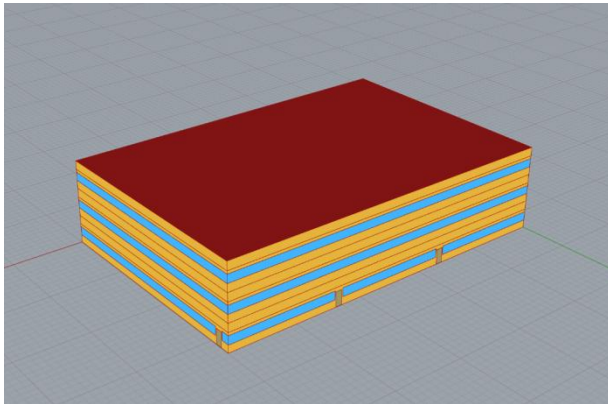


Figure 2: The EnergyPlus model of the DOE prototype medium office building

To comprehensively evaluate the robustness and generalizability of the proposed RC models across diverse climatic conditions, the weather data utilized for building simulations are sourced from typical meteorological year (TMY) datasets for three Chinese cities that have representative climate conditions: Shanghai, Guangzhou, and Shenyang. The locations of the three cities have been plotted in Figure 3.

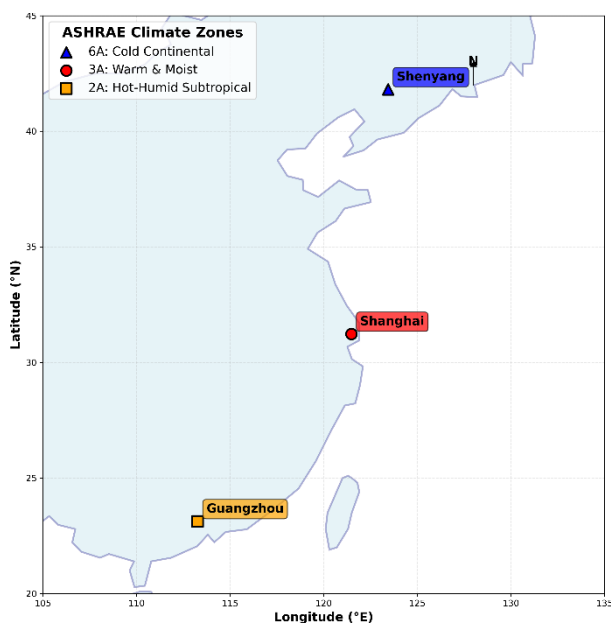


Figure 3: Cities for RC building energy model validation across different climate zones in China

These locations were strategically selected to encompass various thermal challenges and seasonal variations.

Shanghai falls under ASHRAE climate zone 3A, characterized by a warm and moist climate with hot summers and mild winters. Guangzhou represents ASHRAE climate zone 2A, featuring a hot-humid subtropical climate with extended cooling seasons and minimal heating requirements. Shenyang corresponds to ASHRAE climate zone 6A, characterized by a cold continental climate with severe winters and significant heating demands. This multi-climate validation approach ensures that the developed RC model simulation engine is tested across heating-dominated, cooling-dominated, and balanced thermal load conditions, providing a comprehensive assessment of model performance under diverse environmental contexts. For the sake of comparison and to establish a performance baseline, EnergyPlus, a renowned and widely accepted building energy simulation software, is employed as the "benchmark" reference simulation engine. The specific version of EnergyPlus used in this study is 9.5. It serves as a robust yardstick against which the outcomes of the RC-based simulation engine can be gauged. This comparative approach offers a comprehensive understanding of the fidelity and reliability of the developed RC-based engine. For a comprehensive comparison, the proposed four RC model configurations, namely 4R1C, 6R1C, 7R1C, and 7R2C, are considered. These configurations represent different complexities and granularity in modeling, hence providing a spectrum of results. This structured assessment across three distinct climate zones allows for a thorough evaluation of the developed engine's accuracy, robustness, computational cost, and versatility across a range of modeling intricacies and climatic conditions.

Results and Discussions

In Figure 8, the hourly simulation results for the office building using EnergyPlus and the RC models (6R1C, 7R1C, and 7R2C) in Shanghai are plotted. The 7R2C model, with its intricate structure, emerges as the top contender in terms of minimizing biases relative to EnergyPlus. Its prowess in predicting heating and cooling loads is especially conspicuous during transitional seasons. Complementing this observation, Figure 9, the scatter plot reflecting the simulation accuracy of the models for the office buildings in Shanghai, demonstrates hierarchical performance. While both the 4R1C and 6R1C models exhibit less persuasive performance relative to the 7R models for hourly heating and cooling load predictions, the 7R2C model comfortably takes the lead over the 7R1C.

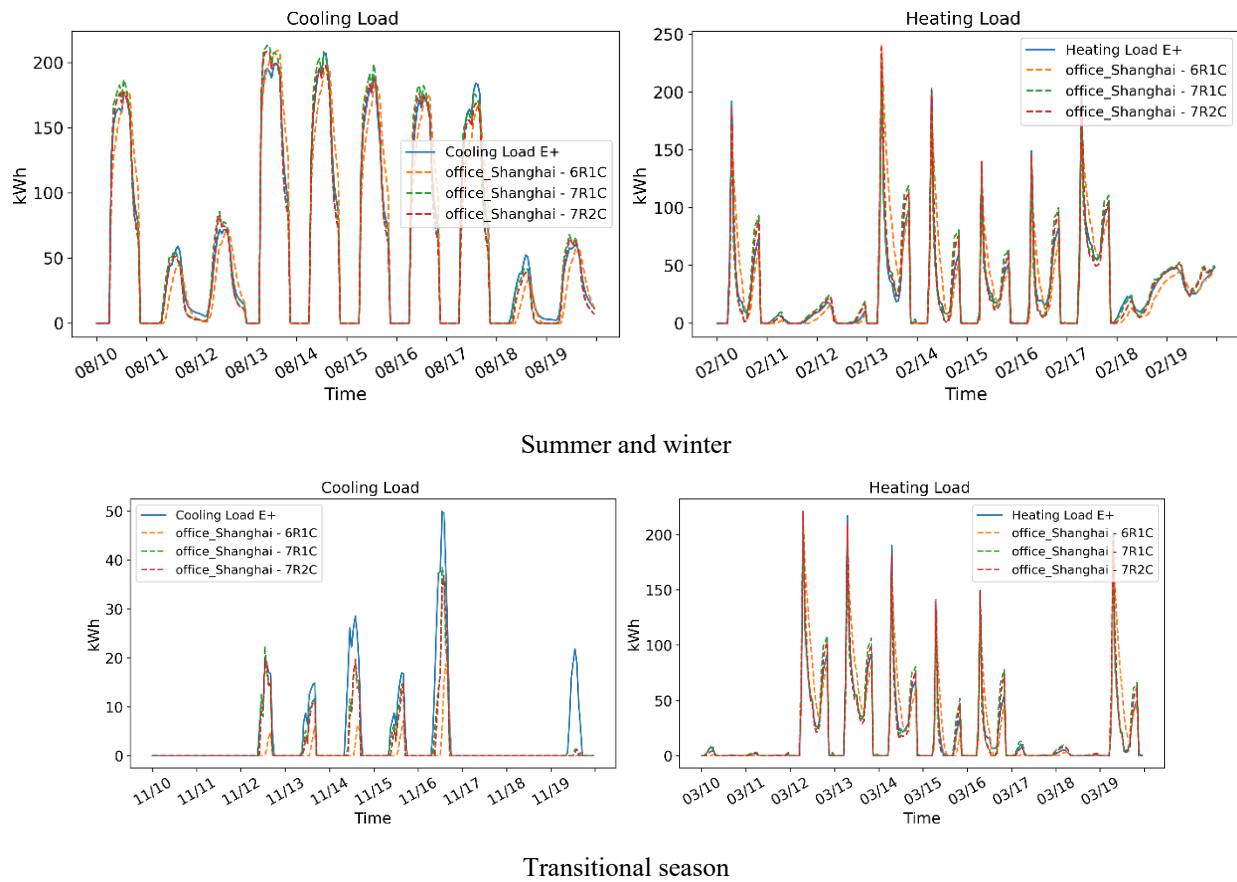
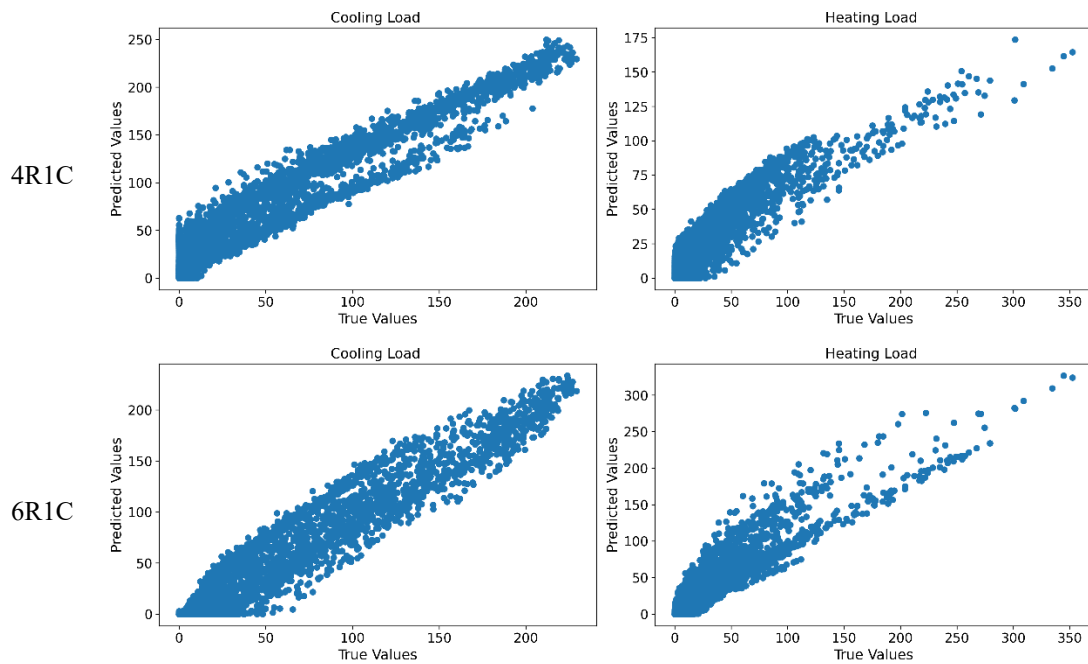


Figure 4: Hourly simulation results of EnergyPlus and the 6R1C, 7R1C, and 7R2C model for the office buildings in Shanghai



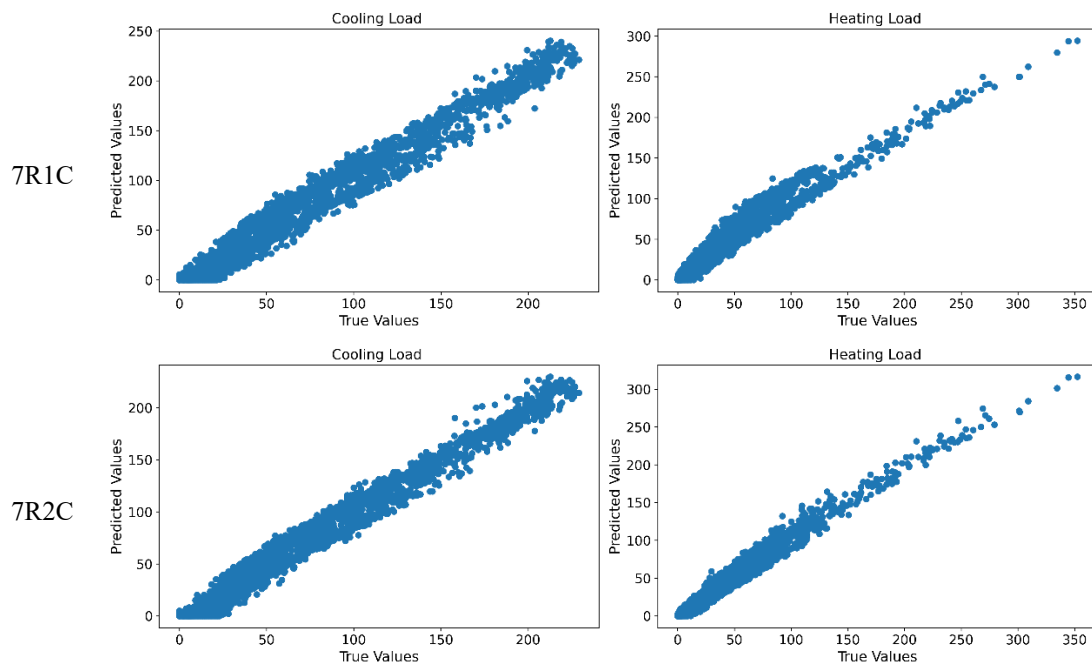


Figure 5: Scatter plot of simulation accuracy of the 4R1C, 6R1C, 7R1C, and 7R2C model for the office buildings in Shanghai (True value: EnergyPlus, Predicted value: RC model)

The cross-climate validation results presented in Table 1 demonstrate the consistent superior performance of the 7R2C model across all three climate zones, reinforcing its robustness under diverse thermal conditions. Notably, the model accuracy remains remarkably stable across different climates, with the 7R2C model achieving cooling load R-squared values of 0.988, 0.989, and 0.981 for Shanghai, Guangzhou, and Shenyang respectively, and heating load R-squared values of 0.983, 0.964, and 0.983.

Interesting climate-specific patterns emerge from this analysis. The Guangzhou results show slightly higher cooling load accuracy ($r^2 = 0.989$) compared to other locations, reflecting the model's effectiveness in capturing the predominantly cooling-dominated thermal behavior characteristic of hot-humid climates. Conversely, Shenyang demonstrates the highest heating load accuracy ($r^2 = 0.983$) and lowest heating NRMSE (1.06%), indicating the model's proficiency in cold climate heating load predictions. Shanghai, with its transitional climate characteristics, shows balanced performance across both heating and cooling predictions.

The NRMSE values for daily peak load predictions show remarkable consistency across climates, with the 7R2C model maintaining peak cooling load errors between 3.61% and 3.75% and peak heating load errors between 1.94% and 2.24% across all three locations. This consistency in peak load prediction accuracy is particularly significant for HVAC system sizing and energy demand planning applications. The progressive improvement from 4R1C to 7R2C models is consistently observed across all climate zones, with the 4R1C model showing notably higher errors in peak load predictions

(ranging from 12.95% to 14.62% for cooling peaks and 13.93% to 14.62% for heating peaks), emphasizing the importance of interzonal thermal coupling regardless of climate conditions.

These cross-climate validation results establish the 7R2C model as a reliable tool for building energy simulation across diverse geographic and climatic contexts, supporting its potential for widespread adoption in international building design and energy analysis applications.

The validation presented in this study represents a forward modeling assessment where RC model predictions are compared against EnergyPlus simulations serving as reference benchmarks. EnergyPlus results were not used to train or calibrate the RC model parameters, ensuring that the accuracy comparisons reflect genuine predictive capability rather than curve-fitting performance. The progressive improvement observed from 4R1C to 7R2C configurations demonstrates the effectiveness of increased thermal coupling complexity in capturing building thermal behavior, with each model using identical parameter determination methodologies but different thermal network structures.

The progression from 4R1C to 7R2C models involves increasing thermal network complexity while maintaining consistent input data requirements from users. All RC model configurations utilize the same fundamental building design inputs including geometry, construction assemblies, thermal properties, HVAC schedules, and occupancy patterns. The key difference lies in the internal thermal coupling complexity rather than additional user-specified parameters. The 4R1C model requires basic zone-level inputs, while the 6R1C, 7R1C, and 7R2C

models automatically incorporate interzonal thermal relationships using the same building geometry and adjacency information already provided.

This represents simplification in model inputs compared to EnergyPlus, which requires detailed specifications for numerous individual building components, surface-by-surface thermal properties, detailed HVAC system configurations, and extensive modeling parameters that can exceed several hundred inputs for complex buildings.

RCBldEng maintains relatively constant input requirements across all model complexities, with the tool automatically determining the appropriate level of thermal coupling based on building geometry and adjacency relationships. The accuracy improvements demonstrated by higher-order models are achieved through enhanced internal thermal network structures rather than increased input burden on users, preserving the tool's objective of providing simplified yet accurate building energy simulation for early design applications.

Table 1: Overall simulation performance of the RC based office building models compared to EnergyPlus

Climate Zone	Model	R ² of CL	R ² of HL	NRMSE of CL	NRMSE of HL	NRMSE of daily peak CL	NRMSE of daily peak HL
Shanghai	4R1C	0.925	0.869	8.41%	3.75%	13.40%	14.20%
	6R1C	0.955	0.893	4.73%	3.21%	4.42%	3.69%
	7R1C	0.985	0.969	2.84%	1.56%	3.92%	3.36%
	7R2C	0.988	0.983	2.48%	1.17%	3.63%	2.09%
Guangzhou	4R1C	0.931	0.852	8.21%	3.82%	12.95%	14.62%
	6R1C	0.962	0.882	4.63%	3.25%	4.36%	3.73%
	7R1C	0.987	0.951	2.75%	1.67%	3.87%	3.45%
	7R2C	0.989	0.964	2.42%	1.39%	3.61%	2.24%
Shenyang	4R1C	0.907	0.883	8.78%	3.84%	14.51%	13.93%
	6R1C	0.943	0.904	4.95%	3.19%	4.62%	3.57%
	7R1C	0.978	0.974	3.02%	1.45%	4.12%	3.21%
	7R2C	0.981	0.983	2.57%	1.06%	3.75%	1.94%

Conclusions

The multi-thermal zone RC models with interzonal thermal coupling evaluated in this study included a comprehensive evaluation across three representative climate zones in China: Shanghai (ASHRAE 3A), Guangzhou (ASHRAE 2A), and Shenyang (ASHRAE 6A), demonstrating their robustness under diverse thermal conditions. The systematic parameter determination methodology enables RCBldEng to serve as an accessible building energy simulation tool that requires only conventional design inputs while maintaining physical interpretability. The publicly available toolkit in Windows platform at <https://github.com/andersonspy/RCBldEng> provides the building simulation community with both the tool and comprehensive documentation for further application across diverse building types and design scenarios. We demonstrated through comprehensive cross-climate comparison of four RC model configurations (4R1C, 6R1C, 7R1C, and 7R2C) against EnergyPlus simulations that the prediction accuracy progressively improves as the model complexity increases across all three climate zones. The office building prototype validation across Shanghai, Guangzhou, and Shenyang showed that the 7R2C model consistently outperformed simpler configurations regardless of

climatic conditions. The model exhibited remarkably stable performance across diverse thermal environments, with cooling load r-squared values of 0.988, 0.989, and 0.981 for Shanghai, Guangzhou, and Shenyang respectively, and heating load r-squared values of 0.983, 0.964, and 0.983. Cross-climate analysis revealed climate-specific strengths: superior cooling load prediction in hot-humid Guangzhou, excellent heating load accuracy in cold Shenyang, and balanced performance in transitional Shanghai climate. It is shown in this research that the interzonal thermal coupling and the addition of additional thermal mass nodes were critical to achieving accurate load predictions especially during the transitional seasons. All interzonal thermally coupled models outperformed the baseline 4R1C model consistently across the three validation climates, but the 7R2C model had the best tradeoff between accuracy and computational efficiency. Through this comprehensive multi-climate validation, we established a valid lightweight alternative to detailed energy simulation software that maintains consistent accuracy in diverse geographic and climatic contexts, providing architects and engineers with a practical fast comparative analysis tool for early design stages suitable for international applications.

References

- Bacher, P., & Madsen, H. (2011). Identifying suitable models for the heat dynamics of buildings. *Energy and Buildings*, 43(7), 1511-1522. doi:<https://doi.org/10.1016/j.enbuild.2011.02.005>
- Crawley, D. B., Lawrie, L. K., Winkelmann, F. C., Buhl, W. F., Huang, Y. J., Pedersen, C. O., . . . Glazer, J. (2001). EnergyPlus: creating a new-generation building energy simulation program. *Energy and Buildings*, 33(4), 319-331. doi:[https://doi.org/10.1016/S0378-7788\(00\)00114-6](https://doi.org/10.1016/S0378-7788(00)00114-6)
- GhaffarianHoseini, A., Dahlan, N. D., Berardi, U., GhaffarianHoseini, A., Makaremi, N., & GhaffarianHoseini, M. (2013). Sustainable energy performances of green buildings: A review of current theories, implementations and challenges. *Renewable and Sustainable Energy Reviews*, 25, 1-17. doi:<https://doi.org/10.1016/j.rser.2013.01.010>
- Halverson, M. A., Rosenberg, M. I., Hart, P. R., Richman, E. E., Athalye, R. A., & Winiarski, D. W. (2014). *ANSI/ASHRAE/IES Standard 90.1-2013 Determination of Energy Savings: Qualitative Analysis*. Retrieved from
- Hong, T., Chou, S. K., & Bong, T. Y. (2000). Building simulation: an overview of developments and information sources. *Building and Environment*, 35(4), 347-361. doi:[https://doi.org/10.1016/S0360-1323\(99\)00023-2](https://doi.org/10.1016/S0360-1323(99)00023-2)
- Li, S., Wang, M., Shen, P., Cui, X., Bu, L., Wei, R., . . . Wu, C. (2022). Energy Saving and Thermal Comfort Performance of Passive Retrofitting Measures for Traditional Rammed Earth House in Lingnan, China. *Buildings*, 12(10), 1716.
- Li, Y., O'Neill, Z., Zhang, L., Chen, J., Im, P., & DeGraw, J. (2021). Grey-box modeling and application for building energy simulations - A critical review. *Renewable and Sustainable Energy Reviews*, 146, 111174. doi:<https://doi.org/10.1016/j.rser.2021.111174>
- Picco, M., Lollini, R., & Marengo, M. (2014). Towards energy performance evaluation in early stage building design: A simplification methodology for commercial building models. *Energy and Buildings*, 76, 497-505.
- Shen, P. (2024). Building retrofit optimization considering future climate and decision-making under various mindsets. *Journal of Building Engineering*, 96, 110422. doi:<https://doi.org/10.1016/j.jobbe.2024.110422>
- Shen, P., Braham, W., & Yi, Y. (2018). Development of a lightweight building simulation tool using simplified zone thermal coupling for fast parametric study. *Applied Energy*, 223, 188-214. doi:<https://doi.org/10.1016/j.apenergy.2018.04.039>
- Shen, P., & Wang, H. (2024). Archetype building energy modeling approaches and applications: A review. *Renewable and Sustainable Energy Reviews*, 199, 114478. doi:<https://doi.org/10.1016/j.rser.2024.114478>
- Shen, P., Wang, Z., & Ji, Y. (2021). Exploring potential for residential energy saving in New York using developed lightweight prototypical building models based on survey data in the past decades. *Sustainable Cities and Society*, 66, 102659. doi:<https://doi.org/10.1016/j.scs.2020.102659>
- Shen, P., & Yang, B. (2020). Projecting Texas energy use for residential sector under future climate and urbanization scenarios: A bottom-up method based on twenty-year regional energy use data. *Energy*, 193, 116694. doi:<https://doi.org/10.1016/j.energy.2019.116694>
- USDOE. (2014). The Encyclopedic Reference to EnergyPlus Input and Output (Version 8.0). Champaign, IL, Univ. of Ill: EnergyPlus Development Team.
- Vivian, J., Zarrella, A., Emmi, G., & Carli, M. d. (2017). *Analysis of simplified lumped-capacitance models to simulate the thermal behaviour of buildings*.
- Weisberg, M. (2012). *Simulation and similarity: Using models to understand the world*: Oxford University Press.
- Wittchen, K. B., Johnsen, K., & Sørensen, K. G. (2007). BSIm: Building Simulation.
- Yan, D., Xia, J., Tang, W., Song, F., Zhang, X., & Jiang, Y. (2008). *DeST—An integrated building simulation toolkit Part I: Fundamentals*. Paper presented at the Building Simulation.