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A system identification of radiant ceiling panels using simplified RC network model for cooling performance prediction under tropical climate in Thailand

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Abstract. Accurate thermal modeling is essential for energy-efficient operation of building cooling systems, particularly in tropical climates where buildings are predominantly cooling-dominated. This study develops a gray-box thermal model for radiant cooling using a Resistance–Capacitance (RC) network with Dynamic Mode Decomposition (DMD) for automated parameter identification. Experiments were conducted in a 27 m² test chamber at King Mongkut's University of Technology Thonburi (KMUTT) in Bangkok, Thailand, during the peak hot season, with outdoor temperatures reaching 35°C and solar radiation up to 1,390 W/m². A four-state RC model representing ceiling panel, indoor air, interior surface, and operative temperatures was developed. Using one week of data at 1-minute intervals, the model achieved 0.34°C RMSE in operative temperature prediction. Identified parameters showed physical consistency, with air time constants of 15–30min and surface time constants of 4–6h. Parameter identification required less than 5s, and forward prediction required less than 0.001s per step, supporting real-time applications. The method combines physical interpretability with computational efficiency, providing a practical tool for sustainable building energy management in tropical climates.

1 Introduction

Buildings in tropical climates are predominantly cooling-dominated, making efficient system design and operation essential for reducing energy consumption and greenhouse gas emissions [1–3]. In Southeast Asia and similar regions, cooling demand can account for a significant share of building electricity consumption, highlighting the need for more energy-efficient cooling technologies and improved control strategies.

Radiant cooling systems, particularly radiant ceiling panels (RCPs), have emerged as an energy-efficient alternative to conventional all-air systems. Unlike traditional air-based cooling that relies mainly on convective heat transfer, radiant systems remove sensible heat

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through cooled surfaces that exchange heat directly with occupants and surrounding surfaces. This approach allows operation with higher chilled-water temperatures and reduced fan energy, and previous studies have reported potential energy savings of 30–50% compared with conventional systems [4]. However, achieving these benefits requires accurate thermal models capable of predicting system behavior and supporting effective control strategies.

Building thermal models are generally categorized as white-box, black-box, and gray-box models. White-box models rely on detailed physical descriptions of building geometry and material properties, but they require extensive input data and computational effort. Black-box models are purely data-driven and can capture system behavior from measurements, but they often lack physical interpretability and may not generalize well. Gray-box models combine simplified physical structures with data-driven parameter estimation, providing a balance between physical meaning and computational efficiency [5–6].

A key challenge in gray-box modeling is identifying the model parameters from measured data. Traditional parameter estimation methods typically rely on nonlinear optimization algorithms that can be computationally expensive and sensitive to initial conditions [5]. Dynamic Mode Decomposition (DMD) [7,8] offers an alternative data-driven system identification approach by estimating discrete-time system matrices directly from time-series data using singular value decomposition (SVD). This approach enables efficient and robust parameter identification without iterative optimization.

Despite the growing interest in radiant cooling systems, limited studies have investigated automated parameter identification for RC models of radiant cooling under tropical climate conditions. Tropical environments such as Bangkok present challenging thermal conditions characterized by high outdoor temperatures, intense solar radiation, and significant humidity variations.

Therefore, this study develops and validates a gray-box RC thermal model for radiant ceiling panel cooling systems using Dynamic Mode Decomposition for automated parameter identification. Experimental data were collected from a radiant-cooled test chamber at King Mongkut's University of Technology Thonburi in Bangkok under tropical climate conditions. The objectives of this study are to: (1) develop a four-state RC network model representing the thermal dynamics of the ceiling panel, indoor air, interior surfaces, and operative temperature; (2) identify model parameters using DMD based on one week of experimental measurements; and (3) evaluate the prediction accuracy, physical interpretability, and computational efficiency of the proposed modeling approach for potential real-time building energy management applications.

2 Experimental facility and RC modeling

2.1 Experimental facility

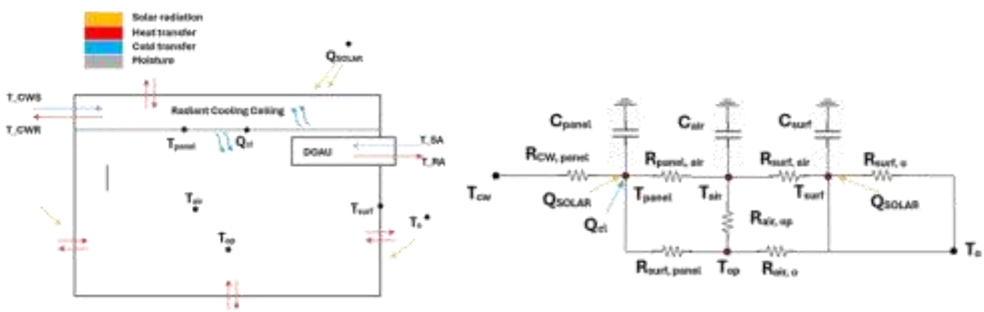
Experiments were conducted in a 27 m² radiant-cooled test chamber at KMUTT, Bangkok (tropical climate). The envelope includes insulated walls and roof (U ≈ 0.32 W/m²K) and low-emissivity double glazing. Ceiling radiant panels (16.9 m²) operate with 15–18°C chilled water, while a dedicated outdoor air unit (DOAU) provides ventilation and latent load control.

Indoor air, surface, panel, and water temperatures, cooling load, outdoor temperature, and solar radiation were recorded at 1-minute intervals. The dataset covers peak tropical conditions with outdoor temperatures up to 35 °C and solar radiation up to 1,390W/m². The pictures of experimental facility and radiant cooling test chamber are available in [4].

2.2 Resistance-Capacitance thermal network model

Resistance–Capacitance (RC) network models represent building thermal behavior using an electrical circuit analogy, where temperature corresponds to voltage and heat flow corresponds to current. Thermal resistances represent heat transfer paths, while thermal capacitances represent heat storage in building components. This formulation produces a set of coupled first-order differential equations describing the dominant thermal dynamics of the building system. [9,10].

Figure 1(a) shows the four-state RC network model of the radiant-cooled test chamber, representing ceiling panel temperature (T_{panel}), indoor air temperature (T_{air}), interior surface temperature (T_{surf}), and operative temperature (T_{op}). Here, C denotes thermal capacitance (J/K), R thermal resistance (K/W), T temperature (°C), Q_{solar} solar heat gain (W), and $Q_{cooling}$ radiant panel cooling (W). The coupled first-order differential equations describe heat transfer among states through the resistance network in Figure 1(b).



(a) Schematic diagram of radiant cooling system with DOAU

(b) Four-state RC network model

Fig. 1. Resistance- Capacitance thermal network model

The thermal dynamics of each state are governed by energy conservation principles, expressed as heat balance equations:

$$C_{surf}\frac{dT_{surf}}{dt} = \frac{T_{air}-T_{surf}}{R_{surf,air}} + \frac{T_{op}-T_{surf}}{R_{surf,op}} + \frac{T_{panel}-T_{surf}}{R_{surf,panel}} + \frac{T_{o}-T_{surf}}{R_{surf,o}} + Q_{solar} \tag{2.1}$$

$$C_{air}\frac{dT_{air}}{dt} = \frac{T_{surf}-T_{air}}{R_{air,surf}} + \frac{T_{op}-T_{air}}{R_{air,op}} + \frac{T_{panel}-T_{air}}{R_{air,panel}} + \frac{T_{o}-T_{air}}{R_{air,o}} \tag{2.2}$$

$$C_{op}\frac{dT_{op}}{dt} = \frac{T_{surf}-T_{op}}{R_{op,surf}} + \frac{T_{air}-T_{op}}{R_{op,air}} + \frac{T_{panel}-T_{op}}{R_{op,panel}} + \frac{T_{o}-T_{op}}{R_{op,o}} \tag{2.3}$$

$$C_{panel}\frac{dT_{panel}}{dt} = \frac{T_{surf}-T_{panel}}{R_{panel,surf}} + \frac{T_{air}-T_{panel}}{R_{panel,air}} + \frac{T_{op}-T_{panel}}{R_{panel,op}} + \frac{T_{cw}-T_{panel}}{R_{panel,cw}} + Q_{solar} + Q_{cooling} \tag{2.4}$$

2.3 DMD-based parameter identification

The RC network model is formulated as a discrete-time linear state-space system:

$$x(k+1) = A\cdot x(k) + B\cdot u(k) + E\cdot d(k) \tag{2.5}$$

where $x = [T_{surf}, T_{air}, T_{op}, T_{panel}]^T$ is the state vector, u represents control inputs (cooling load), d represents disturbances vector (outdoor air temperature, solar radiation). Matrices A,B and E are derived from RC network structure.

Dynamic Mode Decomposition (DMD) identifies matrices A, B and E from time-series data by solving $X_2 \approx A\cdot X_1 + B\cdot U + E\cdot D$, where X_1, X_2 are time-shifted state measurements, U contains inputs and D disturbances. Unlike traditional RC parameter estimation methods based on nonlinear optimization, DMD estimates system matrices through a single singular value decomposition (SVD), reducing computation time to ~5 seconds and avoiding convergence uncertainty. While DMD has been widely applied in fluid dynamics and engineering systems [7,8], its application to RC-based thermal modeling of radiant cooling systems, particularly under tropical climate conditions characterized by high solar radiation and humidity variability has not been reported in the literature.

2.4 Model Identification and Validation Procedure

The overall workflow for model development and validation follows five steps: (1) Data collection —experimental data were recorded at 1-minute intervals over one week under real operating conditions; (2) Data preparation — time-series data were organized into state matrices X_1 and X_2 (time-shifted by one step), along with input matrix U and disturbance matrix D; (3) DMD parameter identification — system matrices A, B, and E were estimated by solving the least-squares problem using SVD, requiring less than 5 seconds; (4) Model validation — identified parameters were used for forward simulation and predicted temperatures were compared against measured values using RMSE; and (5) Physical interpretation — identified parameters were checked for consistency against expected building physics, including thermal time constants and coupling magnitudes.

3 Results and discussion

3.1 Experimental measurements and model variables

Comprehensive experimental data were collected continuously over one week (June 22–28, 2025) during Bangkok's peak hot season, representing challenging tropical cooling conditions and enabling robust model validation. Measurements were recorded at 1-minute intervals, producing 10,080 data points per sensor.

Meteorological conditions exhibited strong diurnal and day-to-day variation. Outdoor dry-bulb temperature ranged from 23.8°C (night) to 35.4°C (afternoon), with a daily average of 30.1°C. Global horizontal solar radiation followed clear-sky patterns, peaking at 1,390 W/m² at solar noon and averaging 211 W/m² over the period. Relative humidity varied from 52.4% (afternoon) to 99% (evening), inversely correlated with temperature. Figure 2 presents the outdoor air temperature and solar radiation profiles over the measurement period, while Figure 3 shows the measured radiant panel cooling load profile.

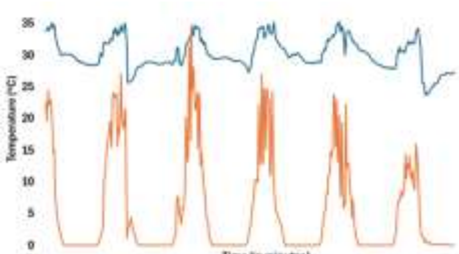


Fig. 2. Outdoor air temperature and solar radiation during the experiment

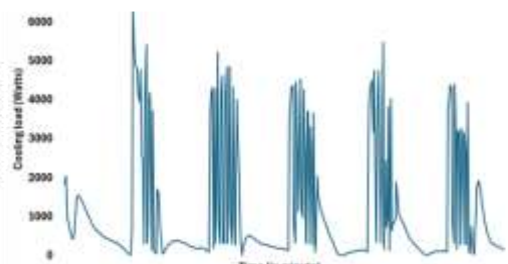


Fig. 3. Measured radiant cooling load profile

Indoor measurements reflected radiant cooling performance. Ceiling panel surface temperature ranged from 18.5–34.4°C (average 26.0°C) under chilled-water control. Indoor air temperature varied between 24.7–35.4°C (average 28.4°C), responding rapidly to control actions due to low thermal capacity. Interior surface temperatures varied more slowly, from 23.5–34.2°C (average 27.1°C), reflecting building thermal mass. Operative temperature ranged from 24.1–34.7°C (average 27.7°C). Radiant panel cooling load ranged from 0.7 W to 6,413 W, with an average of 1,084 W (~40 W/m² floor area).

3.2 Physical interpretation of parameters

The identified parameters show physically consistent behavior. The indoor air time constants range between 15–30 minutes, reflecting the relatively fast response of air temperature to cooling inputs. In contrast, interior surfaces exhibit longer time constants of approximately 4–6 hours due to their higher thermal mass. These results are consistent with expected building thermal dynamics reported in previous studies.

3.2.1 System dynamics matrix

The identified system matrix A_c (4×4) shows the following structure:

$$[A_c] = \begin{bmatrix} 1.0396783 & -0.7754020 & 0.5247959 & 0.1485396 \\ 0.2294213 & 0.0420675 & 0.4759257 & 0.1934173 \\ 0.5811996 & -0.4190550 & 0.6042213 & 0.1722486 \\ 0.8188486 & -0.6117392 & -0.2920355 & 1.0079436 \end{bmatrix} \tag{3.1}$$

The rows and columns correspond to the state variables [T_{surf}, T_{air}, T_{op}, T_{panel}]. Diagonal elements represent state persistence and thermal response. Interior surface temperature (a_{11} = 1.040) shows strong persistence due to the high thermal mass of the building envelope, while ceiling panel temperature (a_{44} = 1.008) reflects moderate thermal inertia. Indoor air temperature (a_{22} = 0.042) exhibits very low persistence, indicating rapid response due to its low thermal capacity. Operative temperature (a_{33} = 0.604) shows intermediate persistence as it depends on both air and radiant temperatures.

Off-diagonal elements represent thermal coupling between states. Strong interaction between indoor air and interior surfaces (a_{12} = –0.775) indicates significant convective heat transfer. Radiative exchange between interior surfaces and the ceiling panel is reflected by a_{41} = 0.819 , while the cooling influence of the panel on indoor air is captured by a_{42} = -0.612. The relatively large off-diagonal values indicate strong thermal coupling, emphasizing the importance of modeling the coupled dynamics of radiant cooling systems.

3.2.2 Disturbance and control matrices

The disturbance influence matrix D_c (4×2) characterizes how external factors affect thermal states:

$$[D_c] = \begin{bmatrix} 0.0902654 & -0.0004904 \\ 0.0972787 & -0.0005449 \\ 0.0935474 & -0.0005113 \\ 0.1098221 & -0.0025770 \end{bmatrix} \tag{3.2}$$

The first column represents the influence of outdoor temperature (T_o) in °C/°C, while the second column represents the effect of solar radiation (Q_{solar}) in °C/W. Positive T_o coefficients (0.090–0.110) indicate that a 1 °C increase in outdoor temperature raises indoor states by approximately ~0.09–0.11 °C through envelope heat transfer. Solar radiation coefficients are small and negative (10^{-4}–10^{-3} °C/W), reflecting the short 1-minute timestep and distributed heat gains, with the ceiling panel showing the strongest response (–0.0026).

The control input matrix B_c (4×1) reveals cooling effectiveness:

$$[B_c] = \begin{bmatrix} -0.0000972 \\ -0.0000680 \\ -0.0000815 \\ 0.0002701 \end{bmatrix} \tag{3.3}$$

The control input is ceiling panel cooling power ($Q_{cooling}$, W). Negative coefficients for T_{surf}, T_{air}, and T_{op} indicate that increasing cooling reduces these temperatures, with magnitudes consistent with the timestep (about 0.07–0.10 °C decrease per 1000 W per minute). The positive coefficient for T_{panel} shows that reducing cooling (warmer chilled water) increases panel temperature. Its larger value highlights that chilled water temperature has the strongest direct influence on panel dynamics. These physically consistent results demonstrate the interpretability advantage of gray-box modeling [11–13].

3.3 Model accuracy and validation

The four-state RC model was identified using DMD applied to the week-long dataset and validated through forward simulation with measured inputs and disturbances. The gray-box model achieved high prediction accuracy across all thermal states, as shown in Table 1.

Table 1. Model prediction accuracy (RMSE) compared to representative studies in the literature

Study	Climate	Method	RMSE (°C)
Present study	**Tropical (Bangkok)**	**DMD + (Gray-box)**	**0.34 (T_{op})**
Bacher & Madsen [10]	Temperate (Denmark)	RC + MLE	0.40–0.60
Jiménez & Madsen [5]	Temperate (Europe)	RC + parameter ID	0.30–0.50
Ramallo-González et al. [9]	Temperate (UK)	Lumped RC model	0.40–0.80
Širokỳ et al. [11]	Central Europe	Gray-box MPC	~0.50 (zone)

The achieved accuracy compares favorably with RC-based building models reported in the literature. Bacher and Madsen [10] obtained RMSE values of 0.40–0.60°C for RC models identified using maximum likelihood estimation in a Danish climate, while Jiménez and Madsen [5] reported 0.30–0.50°C for European buildings. Ramallo-González et al. [9] achieved 0.40–0.80°C for lumped RC models in the UK. The present study therefore achieves comparable or better accuracy under tropical conditions with higher temperature and solar radiation variability, while using a significantly faster identification method (DMD in <5 s compared with hours for nonlinear optimization). The model also satisfies the ±0.5°C operative temperature accuracy recommended by ASHRAE [14] and advanced control design guidelines [11–13].

Figure 4 presents validation results comparing predicted and measured temperatures for all four states over the week. The model shows strong tracking performance, accurately capturing diurnal and day–night temperature patterns. Close agreement is observed for interior surface temperature (T_{surf}), indoor air temperature (T_{air}), and operative temperature (T_{op}). Ceiling panel temperature (T_{panel}) shows larger variations due to the direct influence of chilled water control actions.

Operative temperature prediction achieved an RMSE of 0.34°C, representing the primary thermal comfort indicator. Similar accuracy for T_{surf} and T_{air} (RMSE ≈ 0.34–0.35°C) indicates robust performance across comfort-related states. The higher error for T_{panel} (RMSE = 1.18°C) reflects its direct exposure to control dynamics and wider operating range (18.5–34.4°C), but remains acceptable under active control conditions.

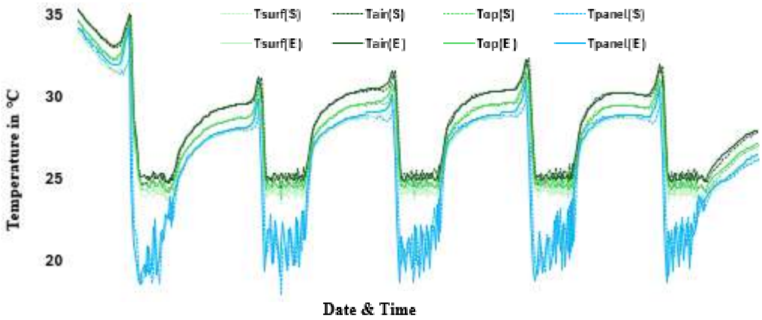


Fig. 4. Comparison of measured and predicted temperatures for model validation.

4 Conclusions

This study developed a gray-box RC thermal model for radiant ceiling panel cooling systems in tropical climates using Dynamic Mode Decomposition (DMD) for parameter identification. The model accurately captured the test chamber's thermal dynamics, achieving an RMSE of 0.34 °C in operative temperature prediction, with parameters consistent with expected building thermal behavior. The DMD-based method required less than 5 seconds, demonstrating its potential for real-time building energy management. Results show that gray-box modeling with data-driven identification can provide accurate and computationally efficient thermal models for radiant cooling systems in tropical climates.

Future work will integrate the identified RC model into a Model Predictive Control (MPC) framework to optimize chilled-water scheduling and quantify long-term energy savings under real tropical operating conditions. The approach should further be extended to multi-zone buildings, incorporate latent load and humidity dynamics, and validated across different climate zones to assess broader applicability.

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