Model Predictive Control Strategy for a Radiant Cooling System Coupled with a Fresh Air System Based on Deep Learning

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Abstract. This paper proposes a prediction method for indoor temperature and humidity parameter changes in a radiant cooling system coupled with fresh air system based on One-Dimensional Convolution coupled Long Short-Term Memory neural network is proposed, and a model prediction control strategy for the radiant cooling system coupled with fresh air system is designed based on this method. The simulation experimental results demonstrate that the model predictive control strategy exhibits enhanced stability in maintaining indoor thermal comfort and reduces the risk of condensation in comparison to the rule-based control strategy. Additionally, the model predictive control strategy was observed to reduce energy consumption by 16% over the entire cooling period in comparison to the rule-based control strategy.

Keywords: Radiant cooling system, Artificial neural network, Model predictive control

1 Introduction

The radiant cooling system represents a novel approach to air conditioning that has garnered significant interest and adoption due to its ability to provide superior indoor thermal comfort and energy efficiency[1]. Radiant cooling systems are often used in conjunction with fresh air systems to prevent condensation[2, 3], where the radiant cooling system takes over the indoor sensible heat loads and the fresh air system takes over the indoor latent heat loads and part of the indoor sensible heat loads. Rule-based control(RBC) strategies such as on-off control and PID control are difficult to deal with the thermal inertia of the radiant cooling system in exchanging heat with the indoor environment, and some researchers have proposed the use of intermittent cooling control strategies to achieve a more stable indoor temperature, reduced risk of condensation and lower energy consumption[4].

In order to improve the hysteresis of the control and increase the energy efficiency of the radiant cooling system and the comfort of the indoor environment, a predictive control strategy that can make corrections to the control signals based on the prediction

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of the future information of the system is needed[5]. Among the predictive control strategies, model predictive control(MPC) makes optimal control operations by predicting the system state through the future state of the indoor environment, combined with constraints and optimal algorithms, which can well meet the requirements of radiant cooling system, and at the same time shows great potential for energy saving[6]. Zhao et al[7] proposed a MPC dynamic model to address energy supply-demand mismatch in the radiant cooling system resulting from time lag and lack of precise control, they simulated this model achieving an 8.51% energy saving over PID control by using TRNSYS software.

In general, the majority of MPC strategy studies for radiant cooling systems are combined with artificial neural networks with the objective of optimizing the energy consumption and indoor thermal comfort of the radiant cooling system[8]. The issue of condensation in such systems is either overlooked or addressed through the study of optimal control strategies for energy consumption and condensation prevention. However, there is a notable absence of integrated control strategies that would encompass both aspects.

This paper presents a model predictive control strategy for radiant air conditioning coupled with a fresh air system. The MPC strategy addresses two key issues: delayed heat exchange between the system and the indoor environment and surface condensation at the terminal of the system. A neural network called One-Dimensional Convolution coupled Long Short-Term Memory neural network(1DCNN-LSTM) for predicting indoor heat and humidity parameters is proposed. The MPC strategy has been demonstrated to provide more stable and comfortable indoor temperatures than existing rule-based control strategies. Furthermore, it effectively avoids the risk of condensation and reduces the energy consumption of the system by 16% with the help of planning algorithms.

2 Model Predictive Control

2.1 Predictive Model

The predictive model used is a 1DCNN-LSTM neural network, which couples a 1×1 convolution layer with a Long Short-Term Memory layer. One-Dimensional Convolution neural network (1DCNN) as a 1×1 convolution layer is commonly used to adjust the number of channels in the network layer and control the complexity of the model. Long Short-Term Memory(LSTM) neural network is used to deal with complex problems involving time-series data by learning the long-term dependencies retained between time steps.

The following parameters are selected as input variables: room temperatureT_{indoor}, room dew point temperatureT_{dp}, wall surface temperatureT_{wall}, ceiling surface temperature$T_{ceiling}$, and control signal$[u_{radiant}, u_{air}]$. The model utilizes the indoor environmental state parameters and the system state at the current moment$[u_{radiant}, u_{air}]$ as inputs, and the indoor environmental state parameters at the next moment$T(t+1)$ as outputs. The prediction time interval is determined as 30 minutes. The trained model is validated on a previously segmented test set and the Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination R^2 are used to compare and analyse the prediction results with the actual values.

2.2 MPC Controller

The control objective of the MPC designed in this paper is to ensure stable indoor temperature while satisfying the constraints of preventing condensation on the end surface of the radiant terminal and minimizing energy consumption. The target indoor temperature objective is set to 26°C. Since the condensation problem is an important influencing factor that restricts the application of the radiant cooling system, the prevention of condensation on the terminal surface of the radiant system is set as a hard constraint, and the operation of reducing the energy consumption is usually the opposite of the operation of maintaining the stable indoor temperature, i.e., the system starts and stops, so the constraint of reducing the energy consumption is set as a soft constraint, which is written into the objective function.The control problem is defined in Eq(1)-Eq(5):

$$J(k) = \min \sum_{k}^{k+N-1} [(T_{indoor}(k) - 26)^2 + \rho[E_{radiant}(k) + E_{air}(k)]] \tag{1}$$

$$T_n(k+1) = \mathrm{Model}[T_n(k), u_{radiant}(k), u_{air}(k)] \tag{2}$$

$$E_{radiant}(k) = \int_0^{\Delta t} P_{radiant} * u_{radiant}(k)dt \tag{3}$$

$$E_{air}(k) = \int_0^{\Delta t} P_{air} * u_{radiant}(k)dt \tag{4}$$

$$\text{subject to} \begin{cases} T_{dp}(k) \le T_{wall}(k) \\ T_{dp}(k) \le T_{ceiling}(k) \\ u_{radiant} \in \{0,1\} \\ u_{air} \in \{0,1\} \end{cases} \tag{5}$$

where ρ is the weight to adjust between indoor temperature and energy consumption,$P_{radiant}(t)$ and $P_{air}(t)$ are the power of the radiant system and the fresh air system, T_n contains the parametersT_{indoor}, T_{dp}, T_{wall}, $T_{ceiling}$, Δt is control horizon, N is control step.

A quadratic programming algorithm is used in the rolling optimal process to compute the current optimal control operation at each step of the control interval, and ultimately to output the optimal control sequence over the entire prediction interval and the first step control signal$[u_{radiant}(k), u_{air}(k)]$.

3 Case Study

3.1 Building Overview

The office studied in this paper is located in Nanjing, China, with room dimensions of 13.3m×8.3m×3.0m. The radiant system is set to switch on at 8:00 daily, and to prevent condensation problems during the start-up phase, the fresh air system is set to switch on at 7:30 daily. The data collector recorded the ambient indoor heat and humidity data from 1 July to 31 August 2022, which constituted the data-set employed for the training of the neural network model.

3.2 TRNSYS Model

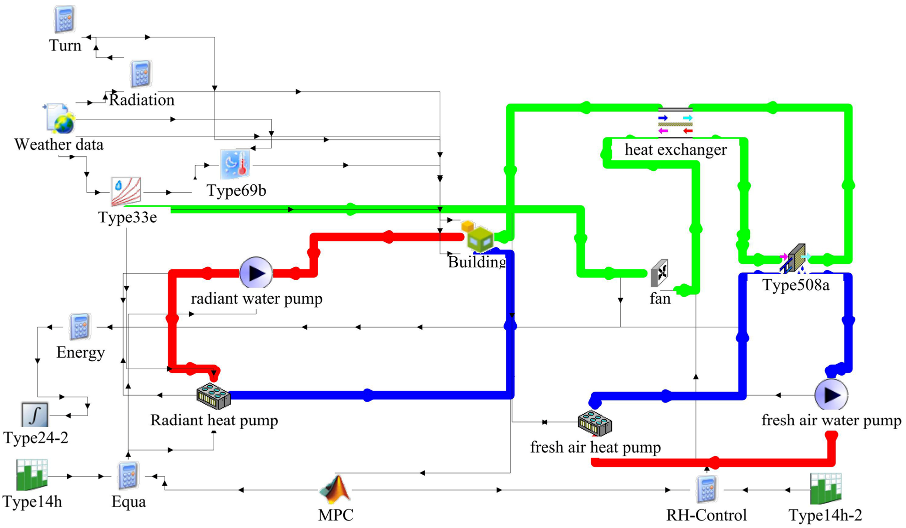


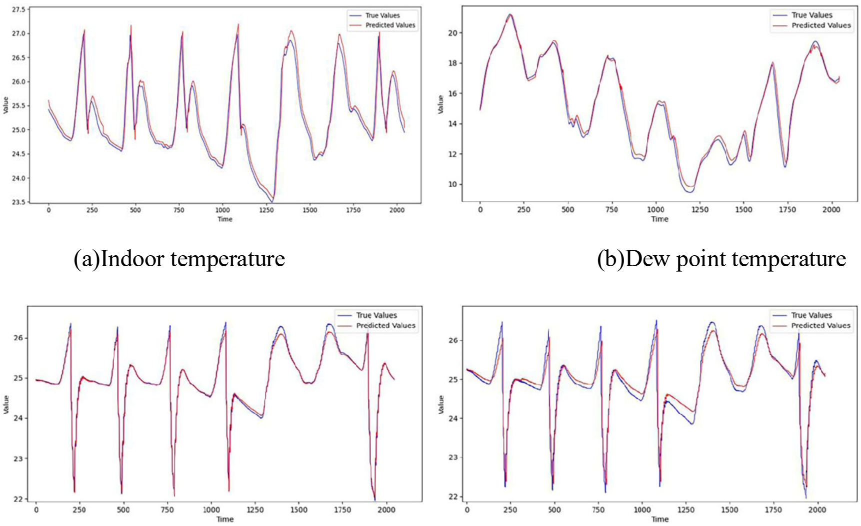
Fig. 1. TRNSYS Model

Fig. 1 shows the TRNSYS model built based on the above mentioned buildings. The indoor environment model is built with the thermal parameters of the actual building as a reference, which is entered into the TRNSYS via TRNBuilding. The capillary network of the radiant system is embedded in the building envelope in the form of an active layer and finally imported into the system model via the Type56a module. The radiant system heat pump and the fresh air system heat pump are represented by the Type655 module, and the water pump is represented by the Type3 module. The outdoor meteorological parameters are read from the typical annual meteorological data of Nanjing, China by Type109-TMY2.

Simulation experiments of model predictive control strategy and rule-based control strategy based on TRNSYS model will be carried out to evaluate the performance of model predictive control strategy in maintaining stable room temperature, preventing condensation, and saving energy.

4 Results and Discussion

4.1 Prediction Performance



(a)Indoor temperature

(b)Dew point temperature

(c)Wall temperature

(d)Ceiling temperature

Fig. 2. 1DCNN-LSTM prediction performance

Table 1. Validation results

Output	RMSE	MAE	R^2
T_{indoor}	0.0269	0.0213	0.9525
T_{dp}	0.0015	0.0086	0.9879
T_{wall}	0.0368	0.0607	0.9684
$T_{ceiling}$	0.0467	0.0792	0.9206

The trained neural networks are applied to the test set data to verify their prediction accuracy, and **Fig. 2** shows the prediction performance of the four neural networks on the test set. Evaluation of the prediction accuracy of the four 1DCNN-LSTM neural networks computed on the test set is recorded in Table 1. From the data, 1DCNN-LSTM is fully applicable to the prediction of indoor thermal and humidity environment parameters, and it performs best in predicting indoor dew point temperature, and the prediction accuracy is still lacking in predicting ceiling temperature despite several adjustments to the model structure.

4.2 Indoor Thermal Environment and Condensation Prevention

The existing rule-base control(RBC) strategy is to control the room temperature to 26℃ and the room relative humidity to 60%. The RBC and MPC strategies are employed to regulate the radiant cooling system on a typical cooling day and week, respectively. As illustrated in **Fig. 3** and **Fig. 4**, the MPC control strategy exhibits enhanced flexibility, enabling the stabilization of the indoor temperature at 26℃ during the occupancy period without significant temperature fluctuations.

Fig. 5 shows the variation curves of wall temperature, ceiling temperature and indoor dew point temperature during the cooling week. It can be seen that the radiant cooling system with the rule-based control strategy still has a condensation risk, while the system with the model predictive control strategy has no condensation risk.

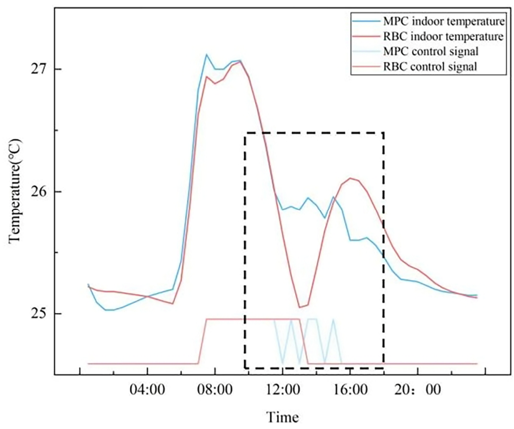


Fig. 3. Temperature comparison on a typical cooling day

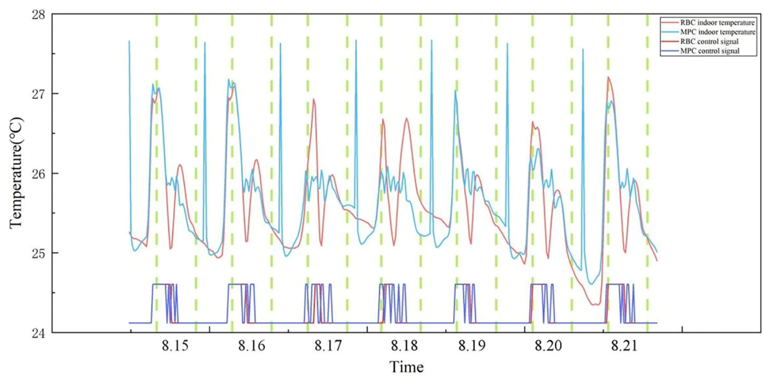
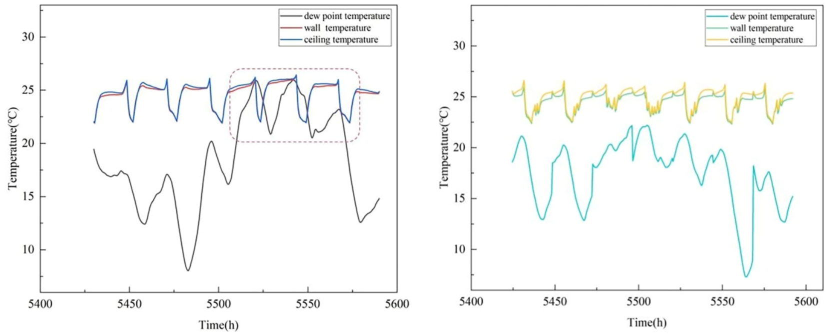


Fig. 4. Temperature Comparison for a Typical Cooling Week



(a)Rule-based control (b)Model predictive control

Fig. 5. Risk of condensation

4.3 Energy Consumption

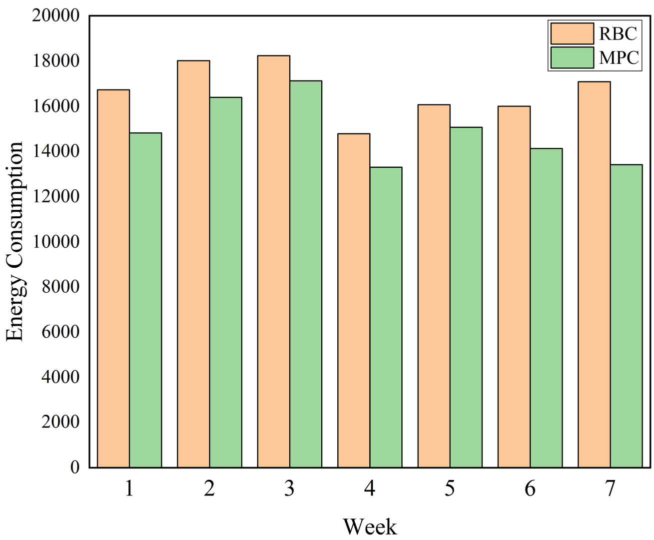


Fig. 6. Energy consumption

As shown in **Fig. 6**, the period from 8 July to 25 August is divided into seven cooling weeks to compare the energy consumption of the radiant cooling system. Using the MPC strategy will save 16% of the energy consumption for the radiant cooling system than using the RBC strategy for the whole cooling period. This is because MPC can accurately predict the future state of the system and the environment, avoiding the waste of energy caused by the system being on for too long, and also avoiding the situation where the indoor thermal comfort is briefly achieved but not maintained.

5 Conclusion

The 1DCNN-LSTM neural network established in this paper improves the feature extraction ability of the prediction model on the input data, and reflects good accuracy in the prediction tasks of indoor dew point temperature, indoor temperature, and the ceiling temperature prediction is not accurate enough, but does not affect the anti-condensation control effect. The MPC strategy can well achieve the control objectives of maintaining a stable indoor thermal environment and preventing condensation on the terminal surface of the system, providing a better thermal environment for the office. MPC benefits from accurate prediction of the future state of the system and the environment, and can switch the system on or off in a timely manner, reducing unnecessary energy consumption for the system while meeting its own control objectives. MPC can save up to 16% of energy consumption for radiant cooling systems compared to rule-based control strategies.

The MPC strategy devised in this paper is highly effective in meeting the requirements of the existing radiant cooling system for the control strategy. In subsequent research, there will be a continued effort to enhance the integration of deep learning technology and control algorithms, thereby expanding the actual operational data of the radiant cooling system. This will enable the radiant cooling system to demonstrate enhanced flexibility in coping with the complexities inherent in evolving application scenarios.

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