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[PO-07] Fast Prediction of Indoor Heat Transfer Based on Convolutional Autoencoder with ResNet

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Keywords: Reduced order modeling, Data-driven model, Convolutional neural network, CFD simulation, Indoor heat transfer prediction

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Fast Prediction of Indoor Heat Transfer based on Convolutional Autoencoder with ResNet

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Abstract: Conventional computational fluid dynamics (CFD) simulation based on solving partial differential governing equations requires high computation ability and long solving time. Besides, CFD modeling demands specialized knowledge, such as numerical methods and mesh drawing skills. These are the critical barriers for integrating CFD simulation into the building design process to enable the designers to get real-time analysis of indoor environments to support decision making. Considering a design space combining different variations, data-driven surrogate modelling is required to be developed to assist the design phase of building. In order to achieve the fast prediction of the indoor environment for the design phase, a CAERes-NN approach integrating convolutional autoencoder (CAE), Residual networks (ResNet), and Predictive neural networks (NN) is employed in this study to do fast reconstruction and prediction of the temperature and heat transfer in the room with different inlet positions in a 2-dimension (2D) space. Besides, unlike previous studies, this study only takes a sparse training dataset to reduce the computational effort. Lastly, the comparison between CFD results and CAERes-NN predictions is implemented and analyzed in the form of 2D temperature fields, box plots of relative errors and correlation figures. The final results prove that the CAERes-NN surrogate model is able to predict the temperature of the main area of the room accurately with a relative low error of 2% in testing dataset, but the air inlet position prediction is somewhat misplaced. Last but not least, the prediction time of CAERes-NN is been shortened to within one second per scenario, which is a great improvement on time-consuming problem compared with CFD simulation.

Keywords: Reduced order modeling, Data-driven method, Convolutional neural networks, CFD simulation, Indoor heat transfer prediction.

1 Introduction

Indoor environment and thermal comfort are both of importance to human daily life as the development of indoor living, working and production behaviors. The room temperature is one of the most critical indexes for thermal comfort evaluation [1]. The premise of achieving a satisfied indoor environment and thermal comfort is the accurate prediction of indoor temperature and appropriate conditioning. CFD simulations are prevalently employed to predict and forecast indoor temperature dependent on air flow in the past decades [2], including modeling of air flow patterns, temperature and heat transfer inside the room [3]. However, the conventional CFD simulation cannot meet the requirement of fast prediction and control of indoor temperature, because of the heavy computational efforts demand [4]. Besides, establishing a CFD model necessitates specialized knowledge which building engineers and designers typically lack, leading to the potential for poorly defined models. Therefore, a key objective in using CFD simulations for predicting indoor environments is to develop a system that is design-integrated, quick, low-effort, requires, intuitive, minimal specialized knowledge and highly reliable. For this aim, some methods are proposed based on the original CFD foundation. For instance, researchers have developed advanced algorithms that optimize computational efficiency, such as adaptive mesh refinement, which dynamically adjusts the mesh density in areas requiring higher resolution [5]. Besides, some simplified numerical schemes are studied, such as coarse-grid [6] and fast fluid dynamics (FFD) [4]. Despite a certain compromise in accuracy, the computation speed still needs further enhancement.

In this regard, various attempts have been conducted to further accelerate the calculation speed based on data science and reduced order modeling (ROM) approaches including linear and non-linear reduction methods [7]. Several linear projection-based methods have been explored, including proper orthogonal decomposition (POD) [8], dynamic mode decomposition (DMD) [9], and the Karhunen-Loeve expansion. Additionally, methods like principal component analysis (PCA), which transforms the data to a set of linearly uncorrelated variables called principal components, and independent component analysis (ICA), which separates a multivariate signal into additive, independent non-Gaussian signals, have been considered. However, the inherent linear nature of these low-rank approximations limits their ability to accurately reconstruct airflow distributions with high levels of nonlinearity [10]. To address this issue, various nonlinear reduction techniques have been developed to predict and reconstruct the indoor environment. Neural networks are employed to reproduce CFD simulations of non-isothermal indoor airflow distribution, which concludes that optimal preprocessing is crucial for improving the predictive capabilities of neural networks in complex airflow simulations, but the large amount of CFD simulation data used as input for neural networks results in a computationally intensive training process [11]. A hybrid method combining autoencoder (AE) and neural network (NN) is implemented on a 2D room airflow prediction with varying inlet velocities and demonstrates rapid and accurate predictions at high inlet velocities, but the temperature profile is not studied [10].

This study predicts the temperature profile and indoor heat transfer performance of a 2D room with varying inlet positions using a hybrid approach that combines order reduction with a predictive neural network. This method employs a CAE with ResNet and a predictive NN. CAE is able to effectively compress input data into a lower-dimensional latent space reducing computational complexity while preserving essential temperature patterns [12]. Besides, its convolutional architecture, which adeptly captures local features in images or data, CAE can effectively identify and reconstruct local flow patterns and thermal boundary layers within indoor environments. Incorporating ResNet into CAE allows for direct learning of residuals between inputs and outputs. This integration effectively mitigates issues like vanishing gradients and enhances CAE's capability to recognize features more effectively [13]. The benchmark employed in this paper is a 2D rectangular room, where the variable is inlet position and the output is the indoor temperature distributions and heat transfer behaviors.

The remainder of this paper is structured as follows: firstly, introduce the engineering constraints and research context. Then in the second section, description of the methodologies encompassing CFD simulation and surrogate modeling process, which includes a comprehensive elucidation of CAE, ResNet, and NN. In the third part, results and discussion will be presented and explained. Last but not least, the primary conclusions and future prospects are extracted.

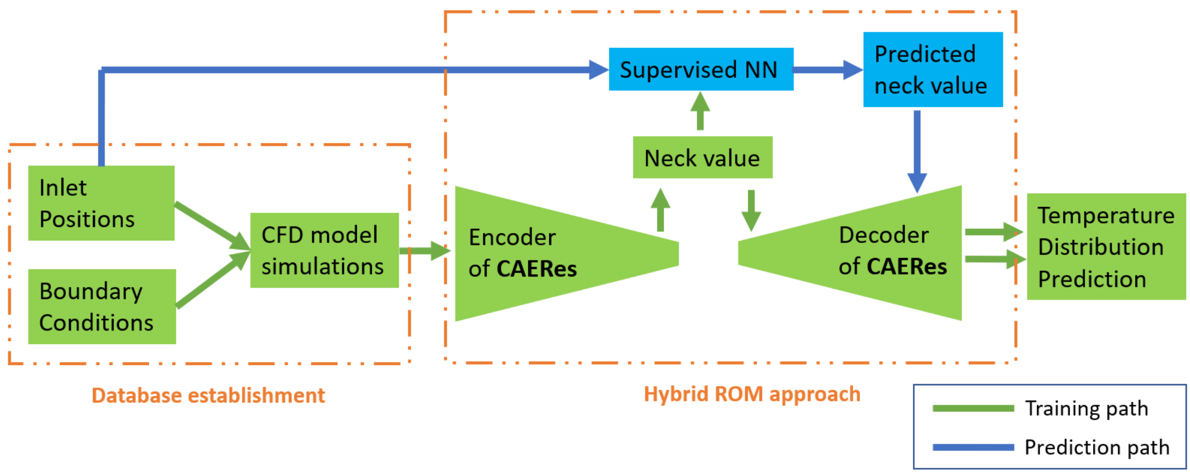


Fig. 1. Workflow

2 Methodology

In this study, the training and testing processes are integrated and shown in Fig. 1. Firstly, a dataset composed of training data and testing data is established with different inlet positions as the label. The proportion of training data and testing data is 8:5 according to temperature characters. Then, as for the training stage which contains two parts, the CAERes training process and the NN training process. During the training process, the prepared training datasets are first imported into CAERes, where the encoder and decoder are trained simultaneously. Subsequently, the bottleneck representations from the well-trained CAERes are transferred into a supervised NN for further training with labels of various inlet positions. Once these networks are well-trained, the testing procedure begins by using the NN to predict the low-rank latent representations for different air inlet heights. These representations are directly fed into the decoder, bypassing the encoder, to reconstruct the original airflow patterns. The details of the benchmark case, CFD simulation setup and database establishment are depicted in section 2.1. The structure and hyperparameters of CAERes and NN are introduced in section 2.2.

2.1 CFD simulation and database

Regarding the CFD model settings, a 2D room is utilized for simplification purposes, as illustrated in Fig. 2. The room has dimensions of 1.5 meters in the x direction and 1 meter in the y direction. Within this room, two windows are present, each measuring 0.9 meters, located on the left and right walls. Additionally, there is an air outlet situated at the bottom of the right wall. To simulate high outdoor temperatures during summer, the windows and inlet air are set to temperatures of 35 °C and 10 °C, respectively. All other walls, except for the windows, have adiabatic boundary conditions applied. There are no additional heat sources in the room, meaning that the indoor environment is influenced solely by the windows and the air inlet/outlet. To study the impact of different air inlet positions, the height of the air inlet along the left wall is varied, ranging from the bottom to the top.

The governing equations are Reynolds-Averaged Navier-Stokes (RANS) equations coupled with the k-ε turbulence model, achieving a balance between accuracy and computational efficiency. The simulations are conducted on a virtual Linux system using OpenFOAM, powered by an Intel Core i7-1265U 1.80 GHz processor. The Finite Volume Method (FVM) is utilized for discretizing the computational domain. The buoyancy term in the momentum equation is modeled using the Boussinesq approximation. To enhance edge accuracy, wall functions are applied to all walls and windows, which is specifically used to handle the boundary conditions of turbulent kinetic energy and Reynolds stress near the wall in turbulence models. This function aids in the more accurate calculation of turbulence parameters in the flow region near the wall, thereby improving the accuracy of the simulation results. Thirteen datasets were compiled for training and testing, focusing on the inlet height ranging from 0.05 meters to 1.0 meters, which corresponds to the upper edge of the air intake. These datasets specifically explore the indoor temperature contour as the dependent parameter. The selection of datasets detailed in Table 1 was based on the distinct characteristics of flow fields and critical flow modes, as discussed in the results and discussion section. Although larger amounts of data generally improve model performance, this also implies longer training times and greater data requirements. To minimize computational load and train the model to adapt to sparse data, only 8 sets of training data were selected here.

Table 1: Training and testing dataset

	Inlet height (m)		
Categories	High temperature	Medium temperature	Low temperature
Training dataset	0.05, 0.20	0.35, 0.50, 0.70	0.80, 0.90, 1.00
Testing dataset	0.15, 0.25, 0.40, 0.60, 0.85		

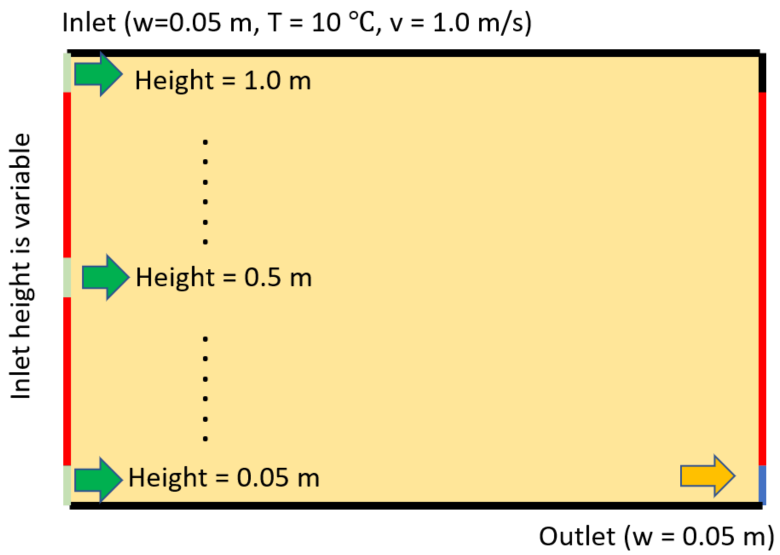


Fig. 2. Benchmark case

2.2 CAERes and NN

CAERes is a combined structure of two parts: CAE and ResNet, with ResNet embedded into each layer of the CAE. CAE is a type of unsupervised neural network that uses convolutional operations and is composed of an encoder and a decoder. Convolution involves sliding a kernel over the input signal, performing weighted summations of overlapping portions to obtain the output signal. The encoder extracts feature maps from the input data, reducing dimensions while increasing the number of channels, producing latent low-rank features that are passed to the decoder, which reconstructs the data to its original dimensions. ResNet enhances the model's performance and generalization by preserving important input features and enabling the network to learn more effective feature representations through residual learning. In CAERes, the encoder consists of three steps, each with a convolutional part, a max pooling downsampling layer, and a ResNet layer. During convolution and downsampling, the channel number expands from 1 to 32, and feature map dimensions decrease from 100×150 to 2×3. In the ResNet layer, dimensions and channels remain unchanged, but residuals from training are introduced to subsequent steps to capture additional information. The decoder mirrors the encoder, completing the CAERes architecture. The final configuration includes using mean squared error (MSE) as the loss function, setting the learning rate to 10^{-4}, utilizing the Adam optimizer with a decay rate of 10^{-7} (a popular variant of stochastic gradient descent), and employing the sigmoid function as the activation function before the output. A structural depiction of CAER is provided in Fig. 3.

The theory of autoencoder is shown in equations (1), (2) and (3). The goal of this process is to produce an output that closely mirrors the input. Initially, the encoder, denoted as ϕ , transforms the original data $\boldsymbol{X}$ into a latent space $\boldsymbol{F}$ situated at the bottleneck. Subsequently, the decoder, denoted as ψ, maps this latent space $\boldsymbol{F}$ back to the input space, generating an output that replicates the original data. The network is trained by optimizing a loss function L, which is minimized through the standard backpropagation method.

$$\phi: \boldsymbol{X} \rightarrow \boldsymbol{F} \quad (1)$$

$$\psi: \boldsymbol{F} \rightarrow \boldsymbol{X} \quad (2)$$

$$\phi, \psi = arg\,min_{\phi,\psi} ||\boldsymbol{X} - (\phi \circ \psi)\boldsymbol{X}||^2 \quad (3)$$

The theory of ResNet is described as equation (4), which is a step in the equation (1) and (2) The output of block $\boldsymbol{Y}$ is calculated by addition of input $\boldsymbol{p}$ and residual function $Z(\boldsymbol{p})$.

$$\boldsymbol{Y} = \boldsymbol{p} + Z(\boldsymbol{p}) \quad (4)$$

Finally, the loss function L is used to train the network through the standard backpropagation procedure.

$$L(\boldsymbol{x}, \boldsymbol{x}') = ||\boldsymbol{x} - \boldsymbol{x}'||^2 \quad (5)$$

$$= ||\boldsymbol{x} - \sigma'(\mathrm{W}'(\sigma(\mathrm{W}\boldsymbol{x} + \mathrm{b})) + \mathrm{b}')||^2 \quad (6)$$

A three-layer fully connected neural network (NN) serves as the predictive model to establish mappings between the air inlet heights and the compressed outputs generated by either CAERes. Each hidden layer in the network comprises 512 neurons, utilizing rectified linear unit (ReLU) activation functions between consecutive layers. The neural network's configuration mirrors that of CAERes.

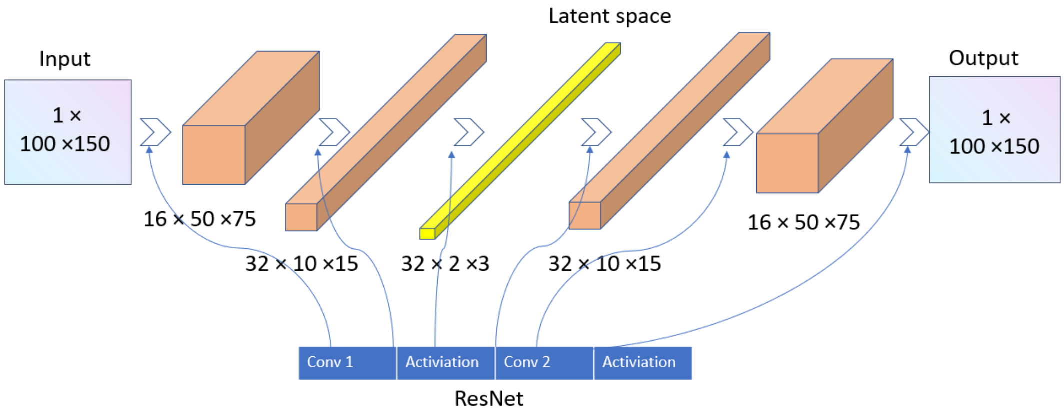
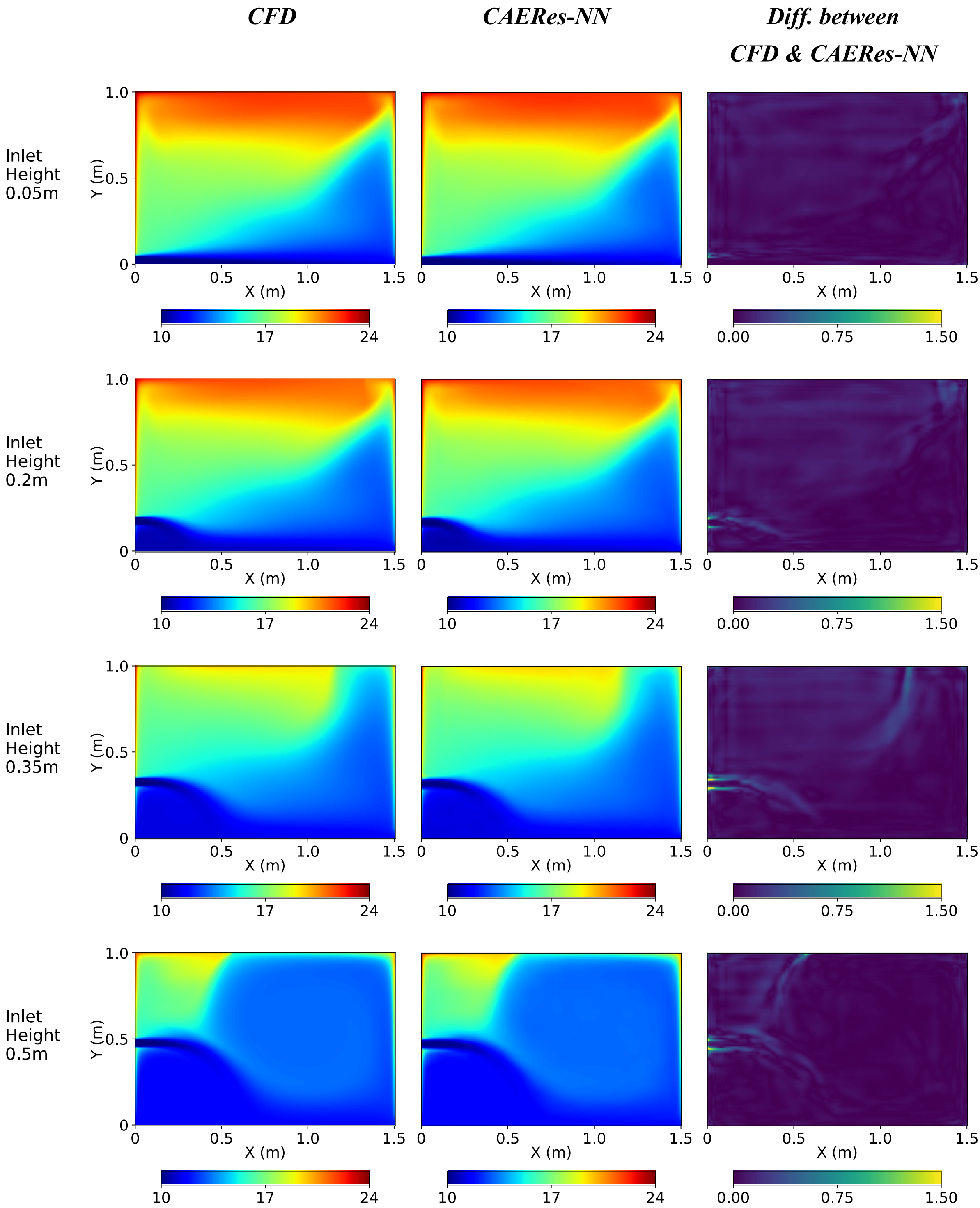


Fig. 3. CAERes structure

3 Results and discussion

In this section, the results and performance of CAERes-NN are presented and compared with CFD simulation results. Figures 4 and 5 depict the indoor temperature contours for different inlet positions, showing both CFD simulation results and CAERes-NN predictions, along with the absolute errors between them. The inlet is located on the left wall, and its height changes from the floor to the ceiling. As the inlet position moves from bottom to top, the temperature field can be roughly divided into three main categories. When the inlet height ranges from 0.05 m to 0.35 m, most of the air injected from the inlet exits the room directly through the outlet in the lower left corner, with only a small portion flowing upwards along the right wall. Obviously, this type of airflow cannot satisfy indoor cooling requirements, as the temperature in most regions remains high. The second type of situation occurs when the inlet height is between 0.35 m and 0.7 m. Here, the cooled air flows into the room and descends into the main area, forming a counter-clockwise circulation. This type is efficient for indoor air conditioning, as the inlet air reaches the personal activity area immediately after flow into the room, maintaining a proper temperature. When the inlet height ranges from 0.7 m to 1.0 m, the Coanda effect causes the air to form an attached jet. As the air flows into the room, it clings to the ceiling and moves forward without descending. Upon reaching the right wall, the air flows downward along the wall, creating a clockwise circulation. The Coanda effect is also used in various nozzle designs, allowing precise control of jet direction and flow by managing airflow attachment. The Fig. 6 and Fig. 7 illustrate the relative error and correlations between CFD and CAERes-NN, respectively without the top 0.5% outliers. The box plot is employed in Fig. 6 where the the five key summary statistics are minimum, first quartile, median, third quartile and maximum.


CFD
CAERes-NN
Diff. between
CFD & CAERes-NN
Inlet
Height
0.05m
Inlet
Height
0.2m
Inlet
Height
0.35m
Inlet
Height
0.5m
Y (m)
X (m)
0
0.5
1.0
1.5
10
17
24
0.00
0.75
1.50

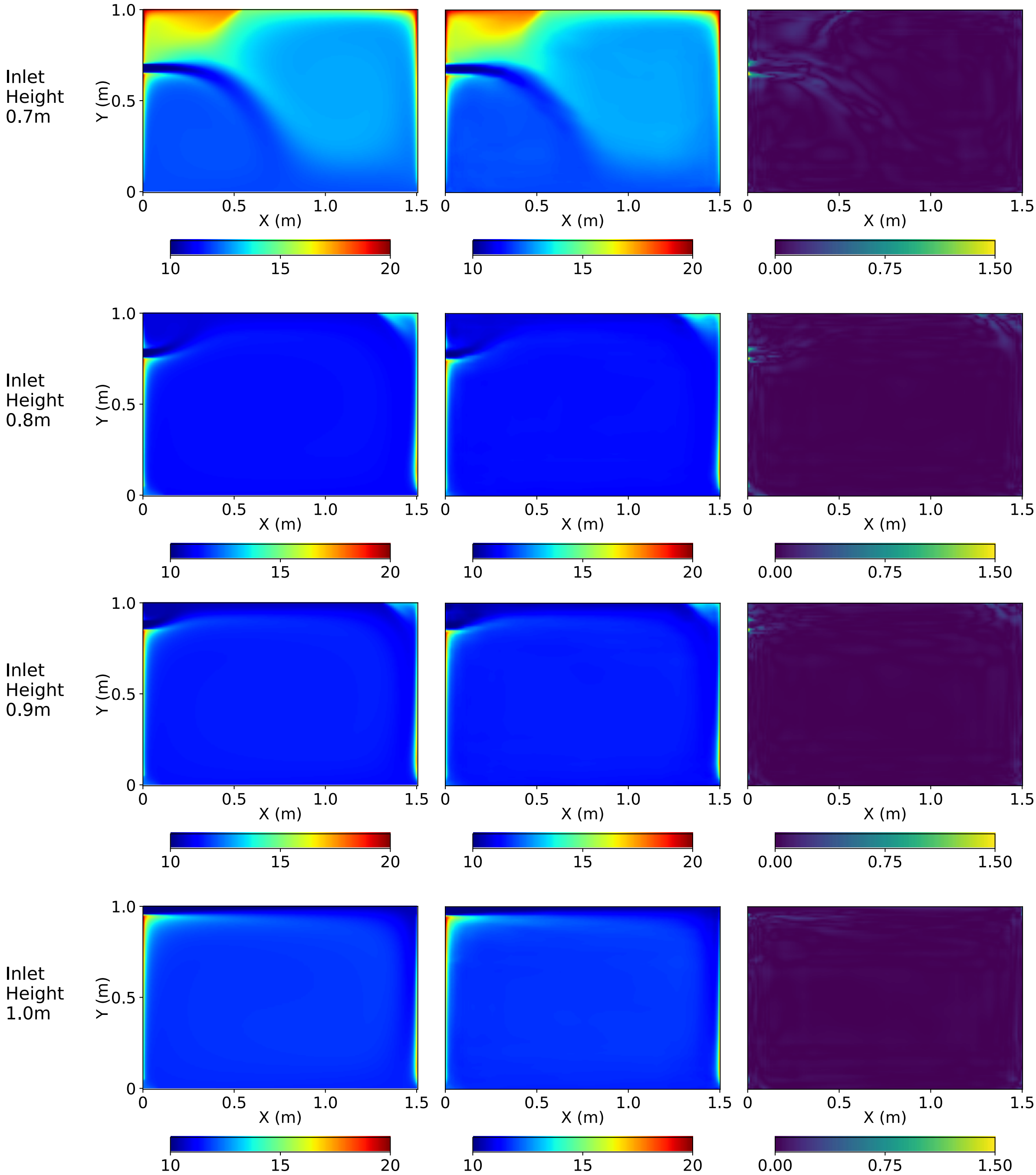
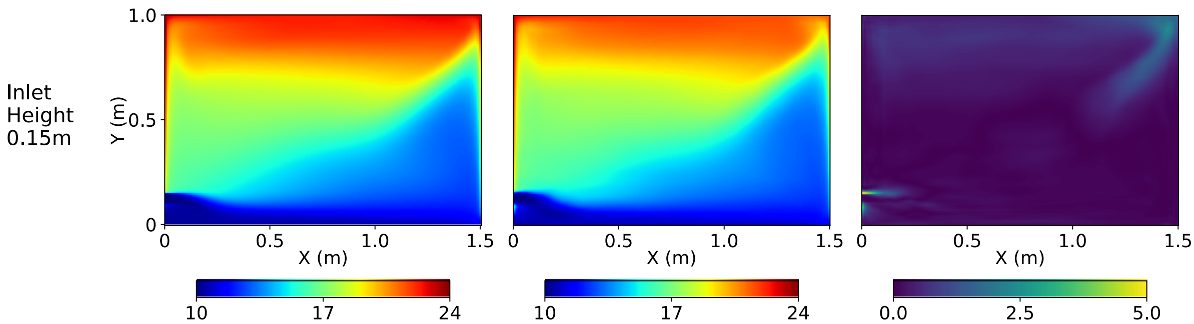


Fig. 4. Training dataset (℃)



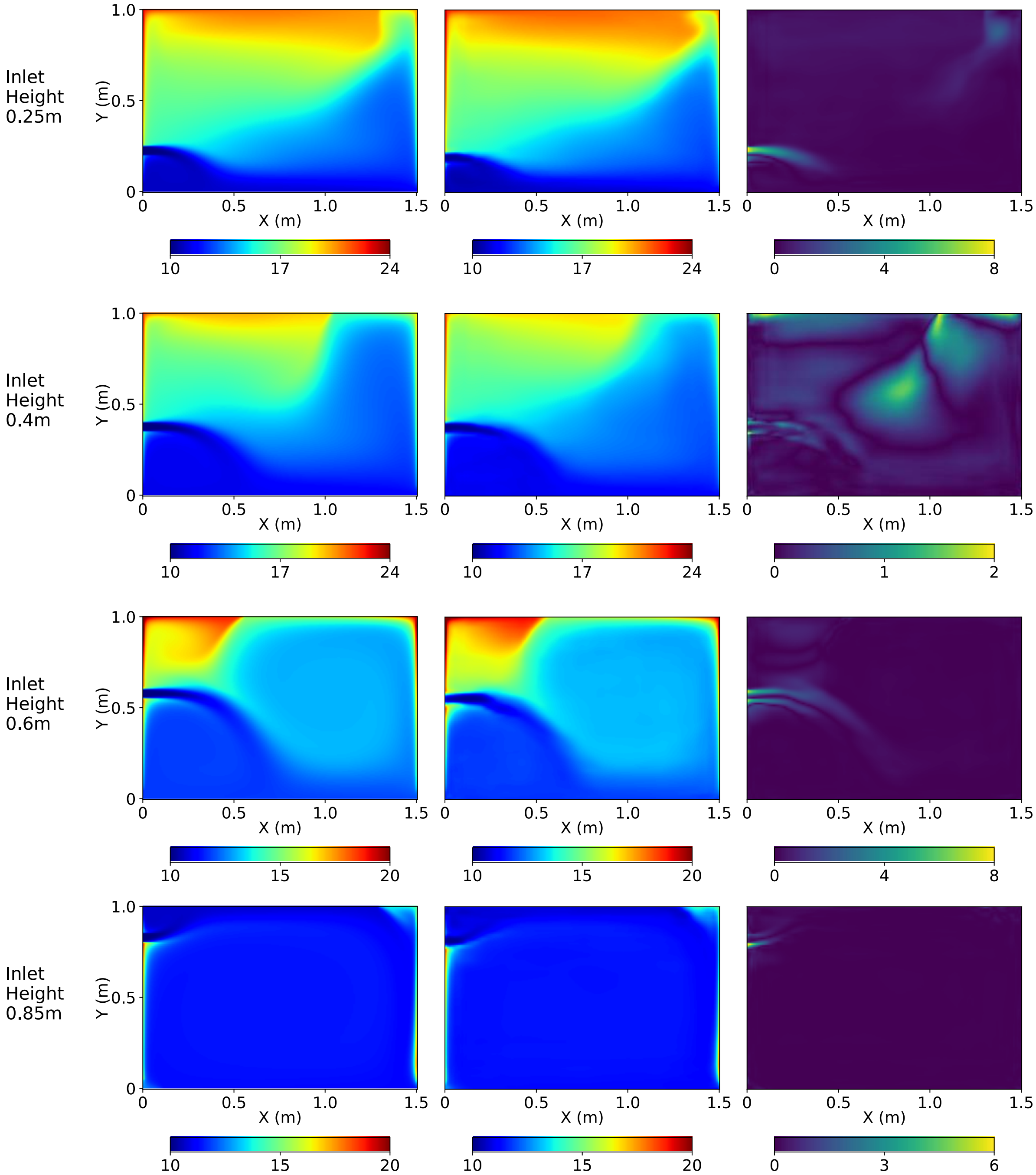


Fig. 5. Testing dataset (℃)

3.1 Training dataset

The training dataset results are shown in the Fig. 4 indicating that indoor temperature fields of CAERes-NN are similar to that of CFD simulations in both three categories. With the inlet height increase, the indoor temperature decreases as the ventilation efficiency improves. This trend was successfully captured and learned by the CAERes-NN surrogate model and has a strong agreement with the CFD simulation results. Besides, in the training datasets, the error between CAERes-NN and CFD in most of the area of the room is little than 0.25℃, which means the predicted indoor temperatures are reliable. However, Fig. 4 indicates that there are some highlighted regions in the air inlet area. These regions correspond to negligible errors, suggesting a slight misalignment in the surrogate model's prediction of the inlet position. Fig. 6 (a) presented the maximum relative error increase and reaching around 1.8%, when the inlet height rises from 0.05 m to 0.35m. Then the relative error decreases to about 0.9% until the inlet height is 1.0 m. The reason of this trend is caused by complexity of temperature distribution of indoor temperature considering the Fig. 4 and Fig. 6 together. It is easily to find that when the inlet height is at lower height, the indoor temperature shows larger temperature difference than that at higher inlet height. As the relatively high errors of height 0.2 m and 0.35 m, Fig. 7 exhibits the correlations between CFD simulated results and CAERes-NN predictions without 0.5% outliers, which prove that the model's predictions align closely with the actual observations, indicating that CAERes-NN's predictions are reliable on the training set.

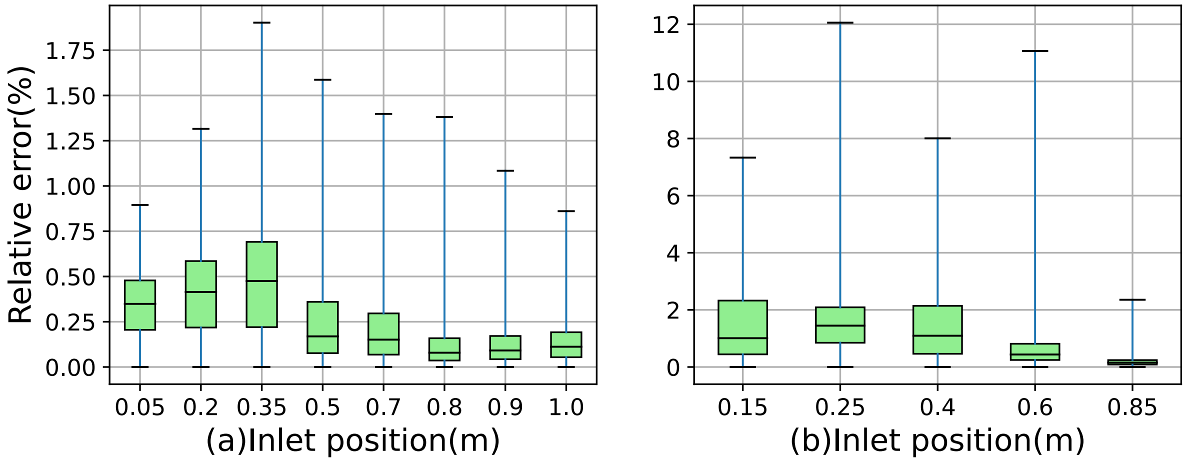


Fig. 6. Relative error of (a) CAERes-NN training data; (b) CAERes-NN testing data

3.2 Testing dataset

In the test dataset, the performance comparison of CFD and CAERes-NN is shown in Fig. 5, which indicates that the predicted temperature profile of CAERes-NN is similar to CFD results visually. The surrogate model describes not only the accurate temperature of the main area for indoor activities, but also the thermal boundary layer of windows. The thickness of boundary layer and the temperature gradient are almost same of CFD and CAERes-NN approaches. Besides, the evaluation of dimensionless numbers such as the Reynolds number and Prandtl number demonstrates CAERes-NN's reliable mastery of heat transfer mechanisms, but because of space limitation, this part is not shown in this paper in detail. However, the out-of-position of air inlet is more serious. Fig. 6 (b) reveals that the maximum relative errors are 12% and 11% when the inlet position is at 0.25 m and 0.6 m, respectively, as these two positions is close to the transition point between the three categories. The maximum value is significantly high, indicating the presence of some extremely high values or outliers. Nevertheless, the third quartile is relatively low, suggesting that the majority of the data is concentrated in the lower range. Considering Fig. 5, the high error area is small and occurs in a very limited volume due to a slight misplacement of flow, so these high errors are not significant. The box plot shows that the third quartile of position 0.15 m and 0.4 m are the two largest values, which means extremely high error values or outliers are minimal, but the errors are consistently concentrated in a higher range. Therefore, correlation plots were examined in Fig. 7 (c) (d) to check the prediction performance. It illustrates a strong linear correlation between the predicted values and CFD values, demonstrating the high accuracy and reliability of the prediction model as the R^2 of positions 0.15 and 0.4 are around 0.98 and 0.97.

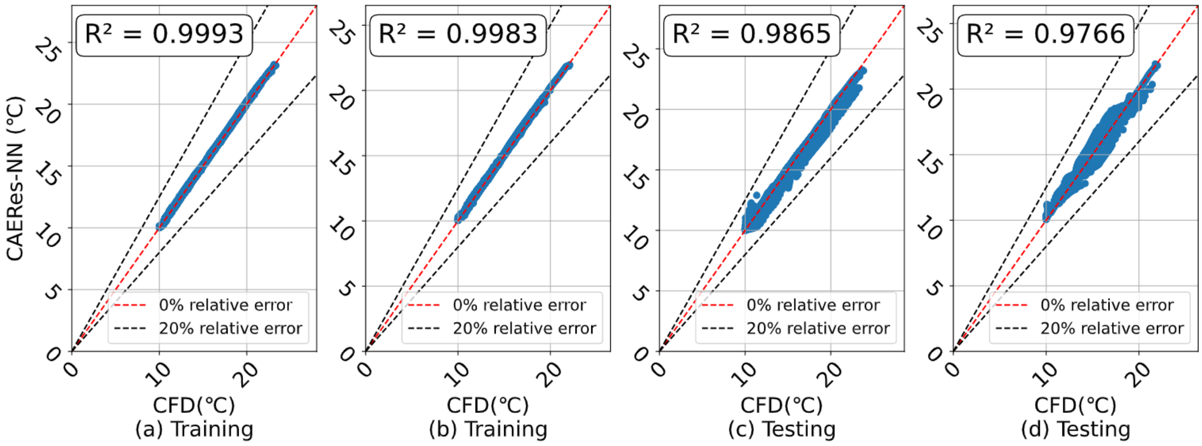


Fig. 7. Correlations between CFD results and CAERes-NN predictions of (a) Position = 0.2 m; (b) Position = 0.35 m; (c) Position = 0.15 m; (d) Position = 0.4 m

4 Conclusion

This paper applied a CAERes-NN surrogate model integrating CAE and ResNet to predict the indoor temperature distribution based on the CFD simulation database with various heights of various scenarios of inlet height variations in a 2D room benchmark. Overall, these results demonstrate the strong performance of the CAERes-NN model on both training and testing data, indicating that the neural network has effectively learned the fundamental patterns and mechanism of indoor heat transfer processes. Firstly, the model accurately captured the trend of indoor temperature decrease with increasing inlet height, reflecting improved ventilation efficiency. Then, the training dataset revealed that CAERes-NN achieved a high level of agreement with CFD results, with relative error mostly below 1.75% in most areas of the room, indicating reliable temperature predictions, but the deviation of air inlet position prediction should not be ignored. Thirdly, in the testing dataset, the maximum relative error is around 9 times of that in the training dataset on account of more serious misalignment of air inlet position. However, the maximum third quartile of relative error is 2.1%, only around 3 times of that in the training dataset. This states that in the majority of cases, the accuracy of the predictions is high, with errors controlled within a small range, which means the temperature of most of the area inside the room is predicted reliably. Last but not least, in the field of indoor temperature field prediction, relying solely on parameters like relative error to assess surrogate model performance is inadequate. Therefore, it is more accurate to evaluate the performance of the surrogate model by considering the stability of error distribution, the impact of extreme values, and the tolerance in practical applications, in conjunction with the structure and rationality of the predicted temperature field.

In summary, this suggests that the CAERes-NN holds promise for understanding and predicting indoor heat transfer behavior and temperature field, offering valuable tools for fast indoor temperature prediction which benefits to the design and optimization of building and air conditioning design and optimization. However, further research could explore methods to enhance the model's accuracy and generalization capabilities, particularly in complex indoor environments and broader parameter spaces.

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