Spatio-Temporal Thermal Condition Prediction System Utilizing Surrogate Model for Fluid Simulation in Indoor Environments

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***Abstract*—In recent years, the rising air temperature associated with climate change is increasing the demand for accurate and efficient methods to predict indoor thermal conditions in buildings. Conventional computational fluid dynamics (CFD) simulations provide high accuracy in analyzing indoor temperature distributions. However, they require substantial computational resources and processing time, which limits their applicability in real-time operations. To address this issue, this study proposes a recurrent surrogate model that employs a convolutional long short-term memory (ConvLSTM) architecture trained with unsteady CFD results to predict future indoor temperature distributions, thereby achieving a balance between accuracy and computational efficiency. The proposed model takes temperature distribution maps generated from measured environmental sensor data as input, and sequentially predicts future distributions of environmental indicators based on historical time-series data. Experimental environment is conducted in an actual university campus environment to demonstrate that the proposed approach achieves a significant reduction in computational time while maintaining high prediction accuracy compared to CFD simulations. The results highlight the potential of integrating measured sensor data with machine learning techniques to establish a practical alternative to traditional CFD-based analysis, with promising applications in heating, ventilation, and air conditioning (HVAC) control optimization and building environmental design support.**

***Index Terms*—Surrogate model, CFD, ConvLSTM, indoor environment prediction, RBF interpolation**

I. INTRODUCTION

Climate change–induced temperature rising the risk of adverse health effects and strengthens the importance of automated control of indoor thermal environments [1]. The building sector accounts for a large portion of energy consumption, and HVAC systems are the major energy consumers, representing approximately 30–50% of the total energy use in residential and non-residential buildings [2]. Accordingly, real-time prediction of environmental indicators inside buildings is essential for the proper operation of the HVAC systems.

For the prediction of environmental indicators in the assumed environment, simulation results from CFD are widely employed. The CFD numerically solves physical equations to analyze and predict the state of the target space. However, high-accuracy CFD simulations demand enormous computational costs [3].

To address this issue, surrogate models based on machine learning are recently attracting attention as an alternative to CFD simulations. In existing studies on the surrogate models for CFD, machine learning–based surrogate models are proposed to reproduce CFD results for indoor airflow distributions [4] [5]. These models achieve fast and accurate estimation of airflow distributions compared with CFD simulations. Nevertheless, the target spaces are restricted to simple cuboid structures, which do not reflect realistic living environments. Moreover, their prediction targets are limited to steady-state conditions and cannot accommodate unsteady variations caused by HVAC operations.

Therefore, this study proposes a surrogate model-based system for predicting indoor temperature distributions in actual building spaces. By employing results from unsteady CFD simulations as training data and adopting ConvLSTM, which is effective for predicting spatiotemporal phenomena, the proposed system enables prediction of time-series of indoor temperature distributions.

II. RELATED WORKS AND OBJECTIVES OF OUR STUDY

A. Research on Surrogate Models for Indoor Environment Prediction

Zhang et al. propose a surrogate model based on an artificial neural network (ANN), trained on CFD simulation results, to rapidly predict indoor air velocity vector distributions [4]. In this approach, multiple CFD simulations are conducted by changing the boundary with the external environment such as inlet location, size, and fluid velocity. These results are then used to train the ANN, which generates images of steady-state velocity distributions. This method significantly reduces computational time compared with CFD while efficiently reproducing airflow patterns throughout indoor spaces.

Similarly, Zhou et al. investigate the prediction of indoor airflow under isothermal conditions by comparing multiple ANN architectures [5]. Their study employs a building model with multiple inlets, demonstrating applicability to more realistic indoor geometries.

However, both of these existing studies restrict the target spaces to simple cuboid structures, which cannot sufficiently represent the complex geometries observed in actual living environments. Furthermore, their predictions are limited to steady-state conditions and cannot capture unsteady variations induced by HVAC operation, occupant movement, or outdoor air changes.

B. Research on Next Frame Prediction of Color Maps Using ConvLSTM

Lu et al. employ a ConvLSTM model to predict the future spatial distribution of radar echo intensity observed by weather radars [6]. The proposed model takes past radar image sequences as input, and by simultaneously learning spatial and temporal patterns through ConvLSTM, it accurately captures the movement of precipitation regions.

The ConvLSTM integrates convolutional neural networks (CNNs) for extracting spatial features with long short-term memory (LSTM) networks for modeling temporal dependencies, thereby preserving spatial locality while learning temporal dynamics. This property is particularly effective for predicting phenomena with spatiotemporal continuity.

The usefulness of ConvLSTM is also demonstrated in other fields. For example, Wang et al. apply ConvLSTM to the prediction of the El Niño–Southern Oscillation (ENSO), using time-series images of sea surface temperature and wind speed to capture spatiotemporal variations in ocean phenomena and improve prediction accuracy [7]. Similarly, Pan et al. utilize ConvLSTM for global sea surface temperature prediction [8].

These studies collectively highlight that ConvLSTM is effective for prediction tasks involving spatiotemporal variations and is applied in diverse domains. ConvLSTM is increasingly positioned as a general and powerful method for spatiotemporal prediction.

C. Objective Our Research

High-accuracy simulation results of indoor environments obtained through CFD are effective for air conditioning control and design, but they involve significant computational cost and time constraints. As a solution, surrogate models trained on CFD simulation results are proposed. However, they do not address predictions for complex geometries found in actual buildings or unsteady environments with temporal variations. In contrast, ConvLSTM, a spatiotemporal sequence prediction model, can simultaneously learn spatial structures and temporal dependencies, making it suitable for predicting dynamically varying two-dimensional distributions.

Therefore, this study proposes a system that integrates a surrogate model based on ConvLSTM to predict temporal variations in temperature distributions. The system uses unsteady CFD simulation results of indoor temperature distributions in real building spaces as training data. With this approach, future temperature fields influenced by HVAC operations and external condition changes can be rapidly and efficiently estimated in realistic architectural environments.

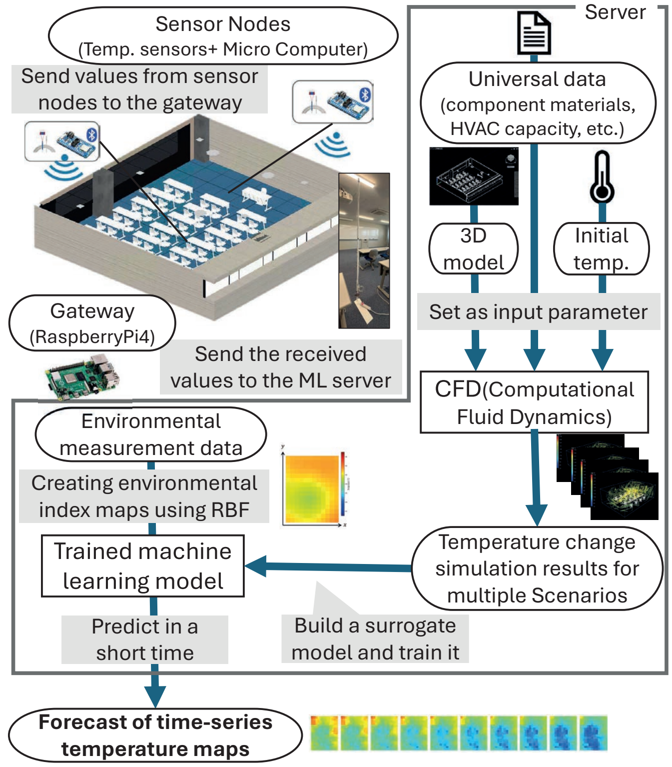


Fig. 1: Overview of the Proposed System.

III. Proposed Environmental Prediction System Using Surrogate Model

Figure 1 illustrates the overall configuration of the system proposed in this study. The system consists of multiple sensor nodes, a gateway, and a server. The sensor nodes are deployed on various places to monitor the three-dimensional environmental distribution, including room temperature, within the target space. To ensure the convenience of the occupants, the nodes are installed near walls, ceilings, or floors, avoiding the central area of the space. A single gateway is placed near the center of the target space.

Each sensor node transmits the measurements obtained from environmental sensors installed at multiple heights, along with identifiers for each sensor, to the gateway via BLE (Bluetooth Low Energy) communication. The gateway collects the measurements from the sensor nodes and periodically aggregates the observed environmental data, such as room temperature, from multiple nodes and transmits them to the server via the Internet. Figure 2 shows an example of the sensor nodes and the gateway, as well as the details of the equipment used.

The surrogate model on the server predicts the environmental conditions on a two-dimensional plane at a floor height of approximately 1.25 meter using the measured environmental data. It is known that human thermal perception and comfort vary depending on the body region, with the facial area being particularly sensitive to temperature changes and an important indicator in indoor environment evaluation [9]. Therefore, the

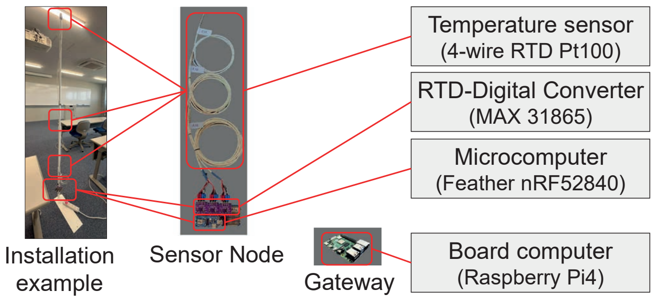


Fig. 2: Details of the Observation Equipment.

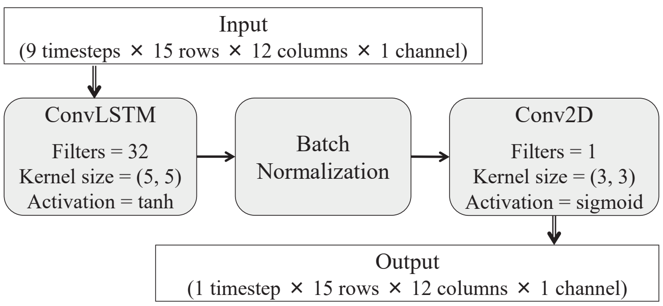


Fig. 3: Configuration of the Surrogate Model.

model targets the prediction of environmental conditions on a two-dimensional plane corresponding to the facial area of a seated occupant at a floor height of approximately 1.25 meter.

IV. Construction of a Surrogate Model Using ConvLSTM

A. Structure of the Surrogate Model

The surrogate model constructed in this study receives spatial distribution of temperature at multiple consecutive time steps as input and outputs the temperature field at the next time step [10]. Its configuration is shown in Fig. 3. The model used in this study consists of a single ConvLSTM layer followed by a Batch Normalization layer and a two-dimensional convolutional layer (Conv2D). The ConvLSTM layer employs a kernel size of 5×5, 32 output channels, and the hyperbolic tangent (tanh) activation function, enabling the simultaneous learning of spatial features and temporal dependencies. The Conv2D layer uses a kernel size of 3×3, a single output channel, and the sigmoid activation function to produce a normalized temperature output. The model is trained using the Adam optimizer with the mean squared error (MSE) as the loss function.

B. Input Environmental Data to the Surrogate Model

The input to the surrogate model in the proposed system is the spatial distribution of the measured environmental data on a two-dimensional plane at a floor height of 1.25 meter. To this end, data obtained from environmental sensors within the target space are interpolated in three dimensions on the server using Radial Basis Function (RBF) interpolation [11]. RBF interpolation is a method capable of smoothly estimating data at scattered observation points and can handle nonlinear and multidimensional spatial distributions, making it suitable for reproducing continuous environmental fields from a limited sensor deployment. This approach enables the filling of spatial gaps between sensors. Moreover, the grid points corresponding to the sensor installation positions retain values identical to the measured data after interpolation. An example of applying RBF interpolation to the measured data is shown in Fig. 4. Multiple datasets are generated at 10-second intervals, including nine consecutive time steps provided as input to the surrogate model.

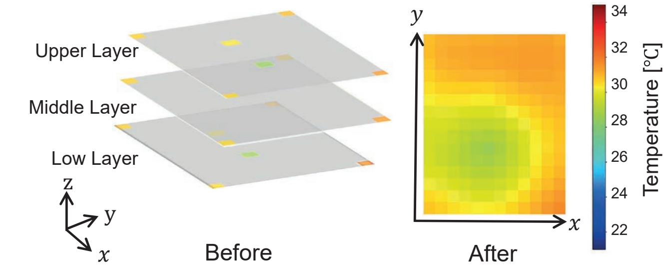


Fig. 4: Example of Interpolated Real-World Data Using RBF.

C. Recursive Prediction

For the prediction of temperature distribution using the surrogate model explained in Section IV-A, a recursive prediction approach is applied. In this approach, the model is provided with temperature distributions over multiple time steps, and its outputs are sequentially used as inputs for subsequent steps, enabling continuous prediction of temperature changes at arbitrary future times.

V. Experimental Evaluation

A. Experimental Setup

The space under analysis is a classroom within the university campus. The dimensions of the space are approximately 14.4 meter in width, 15.33 meter in depth, and 2.7 meter in height, including projections to the outdoors and a raised floor structure. Additionally, four air conditioners and three total heat exchangers are installed as HVAC equipment, and desks, chairs, and other equipment are permanently installed. This study defines a dimensional grid by dividing the space into 16 cells in the X direction, 17 cells in the Y direction, and 3 cells in the Z direction at 0.9 meter intervals as shown in Fig. 5. The temperature at each cell is taken as the value at the cell's center coordinates.

The ConvLSTM-based surrogate model predicts a two-dimensional plane at a floor height of 1.25 meter, specifically the region within 12 cells in the X-direction and 15 cells in the Y-direction that does not contact walls or the outdoors. Fig. 2 shows an outline of the target area. Grid lines are shown in red, and the area predicted by the surrogate model is outlined in blue.

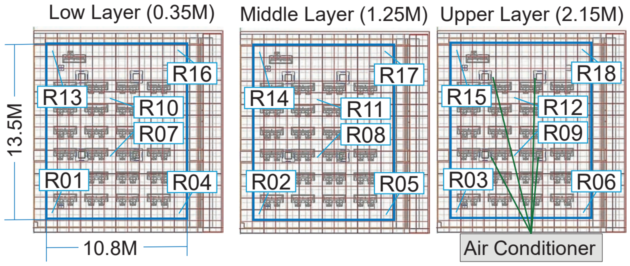


Fig. 5: Surrogate Model Prediction Target Area and Temperature Sensor Installation Location.

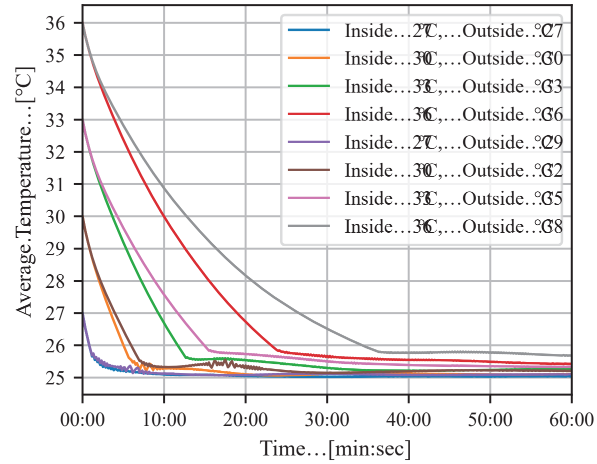


Fig. 6: Time-series Temperature Changes in Training Data Created Via CFD.

The 3D model of the space is created using AutoCAD based on multiple types of design drawings and reflects the actual environment, including furniture and equipment.

The positions of the temperature sensors are shown in Fig. 5. The sensors are installed at three horizontal planes corresponding to floor heights of 0.35 meter, 1.25 meter, and 2.15 meter, with six sensors on each plane, totaling 18 units, such that they correspond to the center coordinates of the pseudo-cells. On each plane, one sensor is placed at each of the four corners of the space, while two sensors are positioned near the center: one between two air conditioners and the other at a location away from the air conditioners. The two sensors located near the center at a floor height of 1.25 meter are not used in the proposed method but are installed obtaining reference data for experimental validation.

CFD simulations are conducted using FlowDesigner (2024 Update3), and an orthogonal structured mesh is applied to the constructed three-dimensional model to divide the space into multiple rectangular cells [12].

The mesh resolution was investigated with three total mesh counts of 499,800, 598,752, and 696,464. Considering the trade-off between computational cost and accuracy, a mesh of 598,752 cells is adopted.

The surrogate model in this study is executed on a Windows OS (64-bit) environment equipped with a 12th-generation Intel Core i9-12900K CPU (3.19 GHz), an NVIDIA RTX 3060 Ti GPU, and 32 GB of RAM.

B. Training Data Used for Model Learning

For training data generation, unsteady CFD simulations of three-dimensional indoor temperature and airflow distributions are performed for one hour after the start of air-conditioning. The time step is 10 seconds, with four initial indoor temperatures (27°C, 30°C, 33°C, 36°C) and two outdoor temperature settings (equal or +2°C), resulting in eight cases. The setpoint of the air-conditioning units is fixed at 25°C. Fig. 6 shows the time-series variation of the average temperature in the target region obtained from CFD.

From the beginning of each time-series data, consecutive 10-step segments are extracted as individual datasets. The dataset is continuously extracted by shifting the start point each time. As a result, 2,672 datasets are prepared, and the first nine steps are served as input and the late step is the target data. These datasets are randomly divided into training (1,864 sets, 70%), validation (392 sets, 15%), and testing (416 sets, 15%). The testing data are further divided into initial (0–20 minutes, 136 sets), middle (20–40 minutes, 136 sets), and late (40–60 minutes, 144 sets) periods to evaluate temporal variations.

C. Actual Measurement Data Used for Verification

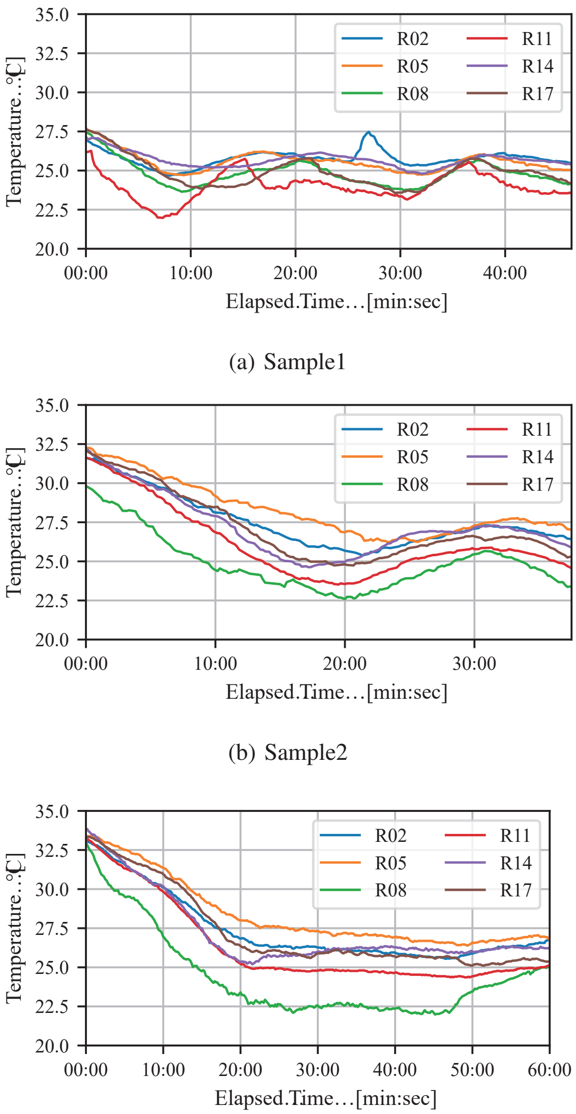
Measured data are acquired every 10 seconds from the 18 sensors shown in Section V-A. Observations are conducted from the start of HVAC operation until a predetermined elapsed time. The set temperature of the air conditioners is fixed at 25°C in all cases. Fig. 7 shows the temperature variations on the middle layer plane for three trials. From the beginning of each time-series data, consecutive 10-step segments are extracted as individual datasets. The dataset is continuously extracted by shifting the start point each time. As a result, nine steps are served as input and the following 18 steps are the test data.

D. Evaluation of the Surrogate Model Accuracy for Simulation Results

The prediction accuracy of the surrogate model constructed in this study is evaluated using the dataset for testing. The model takes the temperature distributions of the past nine time steps as input and sequentially predicts the next 18 time steps recursively, which inherently leads to error accumulation as the number of prediction steps increases.

The evaluation metrics are the root mean square error (RMSE) and mean absolute error (MAE) for average value across all locations and all times. The analysis is conducted by dividing the elapsed time after HVAC operation into three intervals: initial (0–20 minutes), middle (20–40 minutes), and late (40–60 minutes). The RMSE and MAE at each time step are presented in Fig. 8.

The results indicate that the initial interval exhibits slightly higher RMSE and MAE due to large temperature fluctuations.



(a) Sample1

(b) Sample2

(c) Sample3

Fig. 7: Experimental Data.

However, the errors remain sufficiently small, maintaining high overall prediction accuracy. During the middle and late intervals, errors decrease further due to smaller changes in room temperature. Although errors tend to gradually increase with the number of prediction time steps in all intervals, the rate of increase is limited, and accuracy degradation is effectively suppressed even for long-term predictions.

E. Evaluation of the Surrogate Model Accuracy for Actual Measurement Data

Using the proposed surrogate model, temperature distribution predictions are performed based on measured data, and their accuracy is evaluated. The measured data are obtained from 16 temperature sensors installed in the target space and processed as two-dimensional temperature distributions using

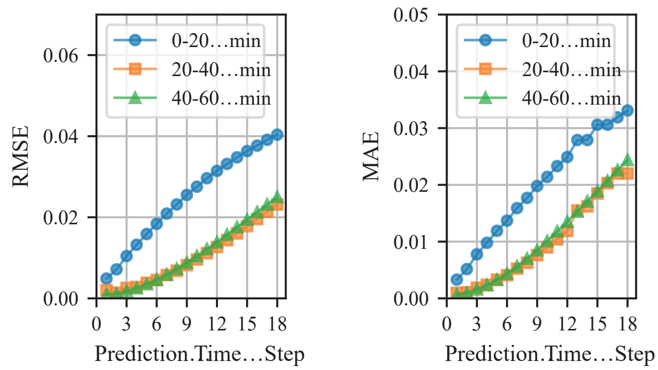


Fig. 8: Evaluation Using the Evaluation Dataset.

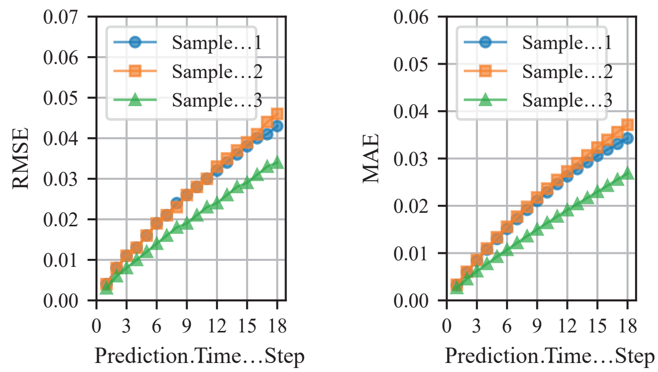


Fig. 9: Evaluation Based on Actual Measurement Data.

the RBF interpolation described in Section IV-B, which differs from the CFD-generated training data. The model takes the past nine time steps of measured data as input and recursively predicts the temperature for the next 18 time steps. Prediction errors are evaluated using RMSE and MAE at each time step. Fig. 9 shows the time series of RMSE and MAE for three measured data samples explained in Section V-D.

Examining the differences among samples, Sample 3, in which the temperature decreases over a certain period and then remains relatively stable, exhibits the highest prediction accuracy. In contrast, Sample 1, which shows little overall temperature decrease or increase across all locations, and Sample 2, which includes a period of temperature rise, show slightly lower prediction accuracy. Nonetheless, the surrogate model maintains high predictive performance overall even for measured data.

In addition, the observed data at the points of R08 and R11 are not incorporated into the two-dimensional temperature distribution maps used as inputs to the surrogate model. In this validation, the prediction errors of the surrogate model are compared with the measured values at these locations. Fig. 10 and 11 illustrate the variations in RMSE between the measured and predicted data at R08 and R11 for Sample 2, with respect to elapsed time and the number of prediction steps. R08 is

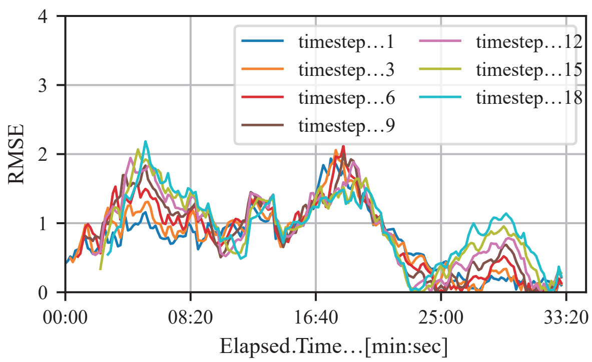


Fig. 10: RMSE Relative to Measured Data with Sample 2 at Point R08.

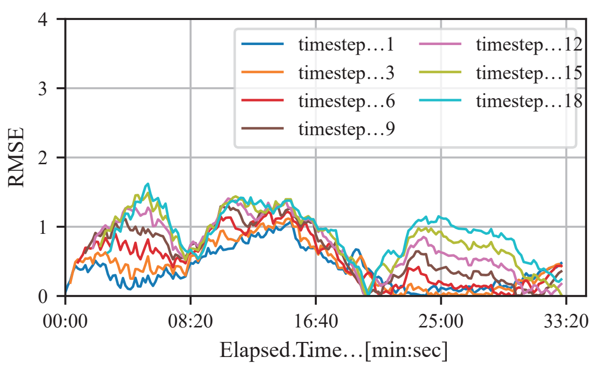


Fig. 11: RMSE Relative to Measured Data with Sample 2 at Point R11.

located between two air-conditioning units, making it susceptible to rapid temperature fluctuations and airflow disturbances. Consequently, the RBF-interpolated values at R08 tend to include larger errors, leading to reduced input accuracy for the surrogate model. This tendency is reflected in the relatively large prediction error observed from the initial time step t_1. In contrast, R11 is located away from all air-conditioning units and is less affected by sudden operational changes. Although error accumulation is observed as the prediction proceeds over time steps, the overall error at R11 remains relatively small.

These results suggest that variations in prediction accuracy arise from both the precision of the RBF-based input maps and the influence of the air-conditioning environment at the observation locations.

F. Comparison of Execution Time Between Surrogate Model and CFD

Using measured data, three-dimensional indoor temperature distributions are generated with the RBF interpolation method described in Section IV-B, and, for only processing CFD simulation, the observed outdoor temperature at the Osaka Meteorological Observatory is also set as the initial condition for the corresponding time. Based on this initial condition, future indoor temperature distributions are recursively predicted over multiple steps using both CFD and the proposed surrogate model, and the required computation times for the two methods are compared. The results show that CFD requires an average of 0.792 seconds each per prediction step, whereas the surrogate model completes the same step in an average of 0.057 seconds, demonstrating a substantial acceleration in environmental prediction.

VI. Conclusion and Future Work

In this study, a recursive surrogate model based on ConvLSTM is developed using unsteady CFD-derived temperature distributions. The model inputs two-dimensional temperature maps generated by RBF interpolation from sensor data and recursively predicts future conditions. The model achieves high accuracy with mitigating error growth, while markedly reducing computation time compared to conventional CFD.

Future work includes to predict for the more distant future, improving generalization through expanded training data and fine tuning, and incorporating human-related factors to enable practical applications in HVAC control and thermal comfort assessment.

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