Research on an AI-based Prediction Model for the Temperature Field of a Nuclear Power Plant Cable Fire Driven by Simulation Data

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Abstract: Nuclear power plants are a high-risk, high-safety requirement field. Once a fire occurs, it can lead to the failure of critical equipment, affecting the safety systems of nuclear power plants and increasing the risk of nuclear leakage. Fires in nuclear power plants are extremely rare events; therefore, the lack of training data sets has been a major obstacle in the development of artificial neural network prediction models in traditional research. Focusing on fire safety in nuclear reactor buildings, this study employs an integrated approach of numerical simulation and artificial intelligence. Specifically, numerical simulations of cable fires in a Chinese nuclear reactor building model are performed utilizing the Fire Dynamics Simulator (FDS).The study covers various fire scenarios and generates extensive three-dimensional spatial fire fields, providing a data foundation for effectively training deep neural network prediction models. On this basis, a fire temperature field prediction model based on CNN-Bi-LSTM is designed, which can significantly improve the accuracy and computational efficiency of fire temperature field analysis and prediction in nuclear reactor buildings, offering an important new approach for fire safety design in nuclear power plants.

Keywords: Nuclear Power Plant; Cable Fire; Numerical Simulation; FDS; Deep Learning Network; Artificial Intelligence

1. State of Research at Home and Abroad

The advancement of China's indigenous new nuclear power technologies has brought the issue of fire safety into sharp focus as a critical concern. This is underscored by statistical evidence, which indicates an annual fire occurrence probability of approximately 0.28 per reactor in nuclear power plants, and the probability of a nuclear safety-related accident caused by fire is 0.44, indicating that fire is currently one of the main risks faced by nuclear power plants and the most direct and realistic threat to nuclear safety [1-2]. Given that the reactor building houses the critical infrastructure of a nuclear power plant, any fire incident poses the risk of severe outcomes. Traditional fire dynamics numerical simulation methods have problems such as slow calculation speed and high computational cost, making it difficult to meet the requirements of nuclear power plant fire protection design. In recent years, with the development of artificial intelligence technology, intelligent fire prediction models based on neural networks have gradually become a research hotspot. This study aims to combine fire numerical simulation and deep learning neural network technology to research an intelligent fire prediction AI surrogate model suitable for nuclear power plant reactor buildings. The first step involves the creation of precise fire numerical models to simulate the variation of environmental parameters across various fire scenarios. This process generates a wealth of data essential for training the neural network. Then, leveraging the powerful nonlinear fitting capability of deep learning neural networks, an AI surrogate model for fire temperature field prediction is constructed to improve the simulation efficiency and analysis capability of fire protection design.

With the ongoing maturation of artificial intelligence, a proliferation of AI-based techniques has emerged. Consequently, the application of these intelligent methods for predicting diverse temperature fields has become a focus of scholarly research. Chen et al.[3], through simulated evacuation of nuclear power plant technical corridors, combined with fire smoke spread conditions and optimal emergency rescue routes for different personnel injury accident locations, determined the emergency rescue and evacuation plan for fire scenarios within the technical corridors of that nuclear power plant. Guo[2], by studying the ceiling temperature, power changes, and smoke settlement patterns when vertical cables against walls burn in confined spaces similar to those in nuclear power plants, and improving the fire source power prediction model, could well predict the fire source power of vertical cables against walls in confined spaces based on ceiling temperature; The studies by Lin et al. [4]introduced experimentally obtained data into CFD models and FDS, thereby verifying the accuracy of the models in predicting the fire spread process during cable burning[2]. Jin, [5] predicted the temperature field of CFRP-strengthened concrete box girders under solar radiation based on the BP neural network. Yang et al. [6]used computational fluid dynamics software Fluent to simulate the temperature field distribution during the heating stage of large pressure vessel heat treatment, and used the simulation results to train a neural network to predict the temperature at different layers of the vessel. Scholarly work has largely prioritized fire prevention and risk assessment, with a notable absence of intelligent detection and control systems designed specifically for reactor buildings in nuclear power plants post-outbreak.

2. Numerical Simulation of Fires in Nuclear Power Plant Reactor Buildings

2.1 Nuclear Reactor Building FDS Fire Modeling

As a sophisticated tool for fire dynamics simulation, FDS enables researchers to monitor and assess the dynamic behavior of smoke, thermal fields, and hazardous gases in fire scenarios. The data it produces serves as an empirical basis for diverse fire investigation studies [7-8]. FDS utilizes a low Mach number approximation of the Navier-Stokes equations, appropriate for simulating heat-driven, low-velocity flows. By processing the N-S equations using a spatial filtering method, high-frequency, small-amplitude acoustic pressure fluctuations can be removed while preserving changes in physical quantities such as pressure and temperature [8]. The equation calculation uses Large Eddy Simulation (LES) to handle turbulent flow.

2.2 Fire Scenario Setting

The interior of a nuclear power plant building houses numerous critical components, including electrical modules and extensive cable systems. Therefore, the fire is assumed to start from a temporary ignition source inside the building, igniting the cables above and causing a fire. Due to the well-sealed characteristics of the nuclear power plant environment [9-10], the simulation boundary conditions are set with an ambient pressure of 0.1MPa, an initial temperature of 20°C, no wind, and a gas velocity of 0 m/s. According to the recommended value for flame spread rate on horizontal cable trays mentioned in NUREG/CR-6850 (a Nuclear Regulatory Commission technical document) compiled by EPRI and the U.S. Nuclear Regulatory Commission (NRC) Office of Nuclear Regulatory Research (RES), the flame spread speed for XLPE cables is 0.3mm/s. Since the model is large, to analyze the simulation results more clearly, the simulation duration is set to 6000s.

2.3 Meshing

The overall dimensions of the simulated object area are 11m×15m×10m, with a total area of about 1650m2. Referring to the quantitative calculation method of Feng Wei [9] et al., the grid size is taken as 1/4 of the characteristic flame diameter, with the specific formula as follows (1). Considering computational accuracy, computer performance, and simulation time, a uniform grid size of 0.2m × 0.2m × 0.2m is adopted, with a total number of grids being 206250. Based on the Fast Fourier Transform (FFT) formula, a sensitivity analysis of the grid size is conducted and verified.

$$D^{*}=\left[\frac{Q}{\rho_{\infty}C_{P}T_{\infty}\sqrt{g}}\right]^{(2/5)} \tag{4}$$

Where: Q ——Heat release rate of the fire source, unit: kw; ρ_{∞} ——Air density, taken as 1.2 kg/m³; C_P ——Specific heat of air, taken as 1kJ/(kg·K); T_{∞} ——Ambient air temperature, taken as 293K; g ——Gravitational acceleration, taken as 9.8m/s^2.

2.4 Fire Model Establishment

2.4.1 Fire source setting

Referring to the setting of temporary ignition sources in the NUREG2233 manual, a 0.8m cubic fire source, with a power density of 278 kW/m², was configured below the cable tray. It was set to burn steadily, emulating a fire that spreads vertically upward.

2.4.2 Material parameter settings

There are two materials involved in the simulation, concrete and XLPE, and their basic parameter settings are shown in Table 1.

Table 1. Simulated Parameter Settings

Material	Thermal Conductivity W/m·k	Density kg/m^3	Specific Heat Capacity KJ/(kg·K)
Concrete	1.8	2280	1.04
XLPE	0.42	980	1.85

2.4.3 Combustion reaction settings

This paper mainly considers the fire spread law and temperature change law when electrical fires in nuclear power plant buildings ignite a large number of cables. Referring to the relevant fire combustion characteristic parameters of the cable material XLPE (chemical formula $C_3H_{4.5}Cl_{0.5}$) for nuclear power plants mentioned in the NUREG/CR-6850 report by the U.S. Nuclear Regulatory Commission (NRC), as shown in Table 2, and accordingly setting the ignition parameters. Based on research, XLPE is a thermosetting cable, and generally the HRRPUA range for thermosetting cables is 200~300 kW/m². To ensure simulation accuracy, the HRRPUA value in this paper is 250 kW/m², and the cable ignites when the temperature reaches 250°C. For the combustible material $C_3H_{4.5}Cl_{0.5}$ in this paper, its combustion reaction in air is defined as Equation (5) [10].

$$2C_3H_{4.5}Cl_{0.5} + 10Air(0.21O_2 + 0.78N_2) = 0.05CO_2 + 0.1CO + HCl + 4H_2O + 5.85C + 7.89N_2 \quad (5)$$

Table 2. Fire Burning Characteristic Parameters

Parameter	Values	Source
Molecular Formula	C3H4.5Cl0.5	Mixture of C3H5Cl and C2H4
HRR(max)/kw	702	NUREG/CR-6850(EPRI 1011989), App. G
Heat of CombustionkJ/kg	10300	SFPE Manual (EPRI 1011989), App. G
CO2-Yirld/kg/kg	0.63	SFPE Manual, 4th ed., Table 3-4.16
Soot-Yield/kg/kg	0.175	SFPE Manual, 4th ed., Table 3-4.16
CO-Yield/kg/kg	0.085	SFPE Manual, 4th ed., Table 3-4.16
Thermal Radiation Fraction	0.53	SFPE Manual, 4th ed., Table 3-4.16

2.4.4 Combustion reaction settings

As the main combustible material in nuclear power plant fires, cable materials belong to the polymer category, and their combustion process is affected by various internal and external factors, including the structure of the polymer, thermal degradation characteristics, heat release, air diffusion, and ignition sources [10-12]. Additionally, cable fire spread behavior, pyrolysis kinetics, and flame spread characteristics are also key factors [14-15]. As a thermosetting material, the secondary combustion characteristics of cables mainly involve their pyrolysis and combustion behavior under fire conditions, usually involving gas-phase combustion processes, including initial temperature rise, decomposition reactions, and final residue formation. During this process, a large amount of heat is released. The heat generated during combustion not only drives the combustion reaction but also feeds back to the cable surface, further heating the surrounding materials, prompting materials in unburned areas to continue undergoing thermal decomposition and oxidation, leading to more pyrolysis and combustion phenomena. Such a cycle allows the cable combustion to sustain, resulting in fire spread [13]. Cable fire spread behavior is significantly influenced by the pyrolysis kinetics and flame spread characteristics of their materials [14-15].

2.5 Fire Simulation Result Analysis

2.5.1 On the simulation results of heat release rate

The simulation's combustion configuration leads to rapid fire development from the temporary source. Ignition of the cables above is induced at a temperature of 250°C. The cable material contributes to a slow fire propagation rate, and the heat release rate peaks within 3000 seconds. After a sustained fire for 3000 seconds, the heat release rate begins to slowly decrease. The simulation can largely reflect the impact of the heat release rate during combustion on the building and equipment (Figure 1).

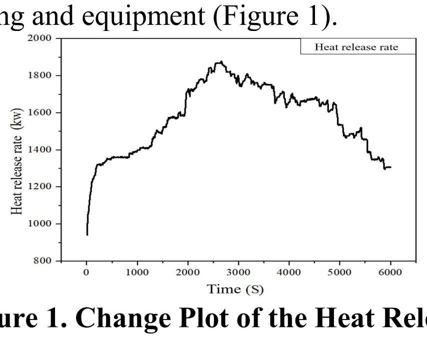


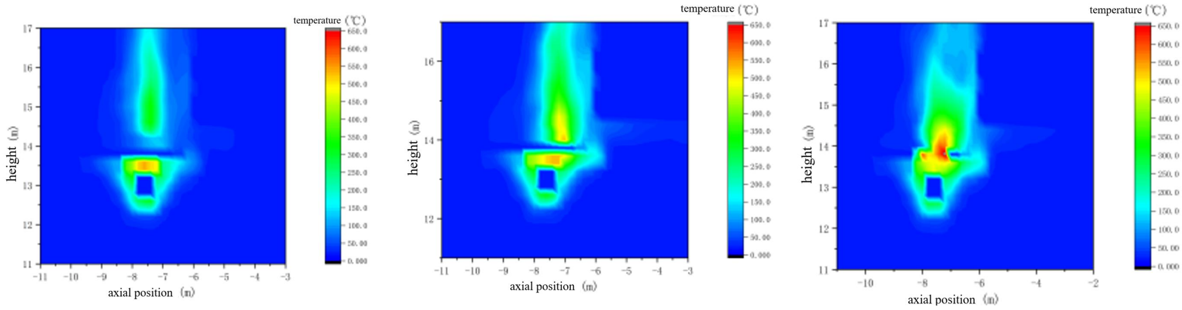
Figure 1. Change Plot of the Heat Release Rate

2.5.2 Fire area temperature simulation result analysis

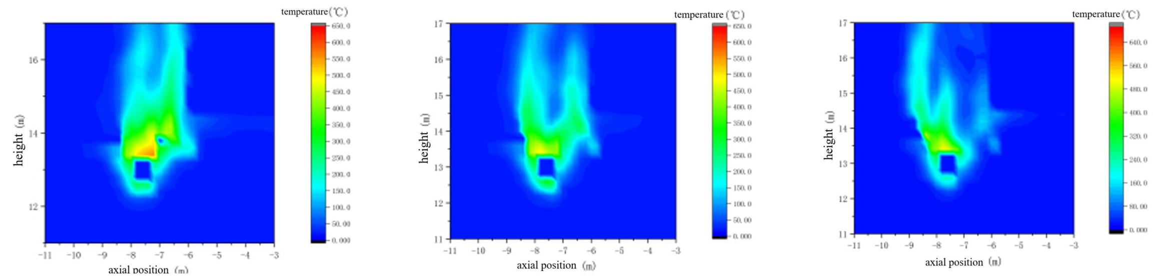
The combustion process of cables mainly goes through four stages: preheating, ignition, spread, and extinction [14], as shown in Figure 2. Before ignition, the overall maximum temperature of the cable appears at the location of the ignition source. Upon reaching the cable's ignition temperature, which is driven by the continuously rising temperature of the fire source, the cables initiate combustion. The subsequent flame propagation culminates in peak thermal output at approximately 1000 seconds. As combustion continues, the flame gradually spreads upward and to the left and right from the center of the fire source, and may eventually extinguish due to insufficient oxygen.

2.5.3 FDS numerical simulation efficiency analysis

As a full-scale high-fidelity model is used for FDS simulation work, this simulation uses the Shanghai Jiao Tong University supercomputing platform "Siyuan No.1" as the hardware facility. This cluster has a total computing power of 6 PFLOPS (petaflops per second), which is a leading supercomputing cluster among domestic universities. The CPU uses dual-socket Intel Xeon ICX Platinum 8358 32-core, with a main frequency of 2.6GHz, totaling 938 compute nodes; the GPU uses NVIDIA HGX A100, with a total of 92 GPU cards. The compute nodes are interconnected using Mellanox 100 Gbps Infiniband HDR high-speed interconnection, and the parallel storage aggregate storage capacity reaches 10 PB. Despite using such high-performance computing resources, the numerical simulation time is still very long, as detailed in the Table 3 below.



(a)Temperature Distribution Contour Map at X=5.6m in 100s (b)Temperature Distribution Contour Map at X=5.6m in 500s (c)Temperature Distribution Contour Map at X=5.6m in 1000s



(d)Temperature Distribution Contour Map at X=5.6m in 2000s (e)100 s Z-plane Temperature Distribution Cloud Map (f)6000 s Z-plane temperature distribution cloud map

Figure 2. Cloud map of CO Concentration Distributio

Table 3. Cable Fire Simulation Duration in Nuclear Power Plant Reactor Building

Serial Number	Simulation Scenario	Simulated Configuration	Simulation Duration	Actual Runtime
1	Nuclear power plant reactor building fire simulation	Jiaotong University Supercomputing Platform	6000s	15 days
2	Nuclear power plant reactor annular fire simulation	Jiaotong University Supercomputing Platform	3600s	30 days
3	Nuclear power plant electrical cabinet fire simulation (single cabinet)	Jiaotong University Supercomputing Platform	3600s	4 days
4	Nuclear power plant electrical cabinet fire simulation (one set of cabinets)	Jiaotong University Supercomputing Platform	800s	8 days

Thus, FDS fire dynamics numerical simulation requires huge computational resources and high time costs, making it often difficult to adopt high-precision simulation in practical engineering. To solve this "bottleneck" problem, this paper explores the use of artificial neural network technology to establish an AI surrogate method for predicting and analyzing the temperature field of cable fires in nuclear power plant reactor buildings, in order to achieve efficient and accurate fire temperature field prediction.

3. Cable Fire Temperature Field Prediction Model Based on CNN-Bi-LSTM Model

With the rapid development of artificial intelligence technology, using AI technologies such as deep learning algorithms to replace numerical simulation has become an important technical development paradigm. Based on the FDS simulation of the nuclear power reactor building in the previous section, which derived the law of temperature field changes inside the building caused by fire, this data is input into the CNN-Bi-LSTM network (i.e., Convolutional Neural Networks + Bidirectional Long Short-Term Memory) to predict the temperature field distribution.

3.1 Bi-LSTM Network Structure

LSTM is an advanced variant of Recurrent Neural Network (RNN), specifically designed to handle long-term dependent sequence information. LSTM, through its unique network structure including feedback loops, can pass information from one time step to the next. This structure enables LSTM to effectively capture long-term dependencies in sequences. The core of LSTM is the memory cell, which is responsible for storing and updating information. Unlike traditional neurons, the LSTM unit contains three gating mechanisms: input gate, forget gate, and output gate. This bidirectional long short-term memory network consists of three LSTMs layered, which not only retains the ability of LSTM to preserve long-term dependencies, which is beneficial for handling events like fires with long time intervals, but also considers the influence of changes in preceding and following data. Bi-LSTM is a further improvement based on LSTM, composed of a forward LSTM network and a reverse LSTM network, introducing context information of the time series, and can train the influence of future information on the current state. Therefore, for time series prediction problems, Bi-LSTM can better reflect the changing trend of fire development.

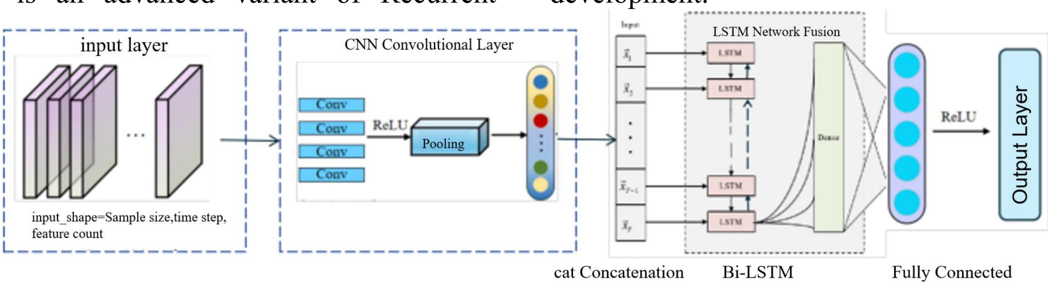


Figure 3. CNN-Bi-LSTM Network Architecture Diagram of Fire Temperature Field

Compared with unidirectional LSTM, BiLSTM can more comprehensively capture information in the sequence, thereby improving the model's understanding and prediction ability for sequence data, making it very suitable for complex pattern recognition problems such as fire prediction. To obtain the three-dimensional spatial temperature distribution features from FDS simulation, this study designs a fire temperature field prediction algorithm based on the CNN-Bi-LSTM deep learning model (specific structure refer to Figure 3). The model first passes through a convolutional layer, whose main function is to extract spatial distribution features from the input temperature field data. This layer is configured with the same number of input and output channels as the feature dimension of the input data, and uses a convolution kernel of size 3 and border padding of size 1 to keep the output sequence length unchanged. Following the convolutional layer is the bidirectional long short-term memory network layer, which is responsible for capturing temporal dependencies in the data. The forward LSTM is responsible for extracting the temporal features of fire temperature development, and the reverse LSTM is responsible for predicting the future spatial temperature field. The model finally outputs through a fully connected layer. This model takes t (fire occurrence time), T (planar grid spatial sampling temperature field), HRR (fire source heat release rate), HC (heat of combustion), and v (cable flame spread speed) as input values, and outputs the spatial coordinates (x, y, z) of 666 sampling points in the fire field and temperature (T) over time t as the output vector. The numerical ranges of these variables differ greatly, which may cause the neural network to converge slowly during training and increase training time. Since the activation function of the neural network is usually designed to handle values in the range of [-1,1], a larger numerical range may have a disproportionate impact on network performance. To reduce the potential adverse effects of these variables on neural network training and to match the input values with the expected input range of the activation function, normalization processing is adopted to map the data to the interval [0,1]. In the network structure, the number of hidden layer neurons is 64, the input feature dimension is 5, and the output dimension is 666. To reduce the risk of overfitting, a Dropout of 0.2 units is introduced after each LSTM layer. The initial learning rate is set to 0.0003, and the training epoch is 200 times. The LSTM network extracts the time series features of the cable fire temperature distribution in the building at each time step and quickly encodes these features into the neural unit parameters of the network one by one to achieve prediction of unknown fire temperature changes. A sliding window is used to generate training samples (window length 120 seconds, predicting the next 60 seconds); an Attention mechanism is introduced to strengthen feature extraction at key time points; the MAE loss function is used with the Adam optimizer to dynamically adjust the learning rate.

3.2 Construction of Training Dataset

This study uses spatiotemporally discrete temperature data generated by numerical simulation to provide basic data support for the training and verification of the neural network model. Among them, 80% of the data is used as training samples for parameter optimization of the neural network model, and 20% of the data is used as a prediction verification set to evaluate the model's generalization ability and prediction accuracy.

Taking the FDS fire field numerical simulation of Scenario 1 in Table 3 as an example, a total of 666 temperature monitoring points were set, generating a total of 166,198 sets of spatiotemporal-temperature data. On this basis, the original data is scientifically screened: 294 representative time nodes are selected from each measuring point, and finally a training sample set containing 82,804 sets of spatiotemporal-temperature data is constructed. This data screening strategy not only ensures the spatial coverage and temporal continuity of the training samples but also significantly improves computational efficiency. It should be noted that given the large scale of the data, Table 4 only shows some typical training samples to illustrate the basic structure and organization of the data.

3.3 AI Prediction Result Analysis

This study conducted a systematic regression performance evaluation of the constructed CNN-Bi-LSTM neural network model, and Figure 4 shows the detailed regression analysis results. In terms of model fitting effect, the training dataset obtained a correlation coefficient (R value) of 0.99637, indicating that the network achieved a very high fitting accuracy for the training samples. The correlation coefficient of the validation set is 0.98133, this excellent performance confirms that the model has good generalization ability and can effectively avoid overfitting. It is worth noting that the prediction accuracy of the test set is also excellent, with a correlation coefficient of 0.98313, indicating that the model has reliable prediction performance for unknown data.

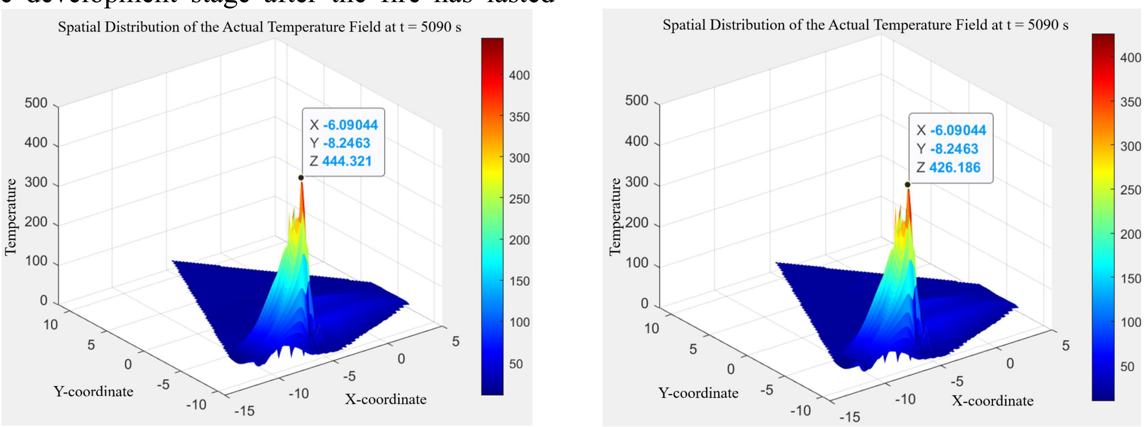
Table 4. Partial Training Data

Serial Number	Coordinate X/m	Coordinate Y/m	Coordinate Z/m	Time t/s	Temperature T/°C
1	-6.06	-7.25	14.38	4160.0	247.0
2	-6.06	-8.25	14.38	1150.00	20.00
3	-5.53	-2.77	14.33	2240.00	20.00
4	-11.5	-9.66	13.00	936.00	29.90
5	-5.45	-9.66	14.50	432.00	57.40
6	-8.96	-0.16	16.13	2720.00	20.00
7	-6.06	-8.25	14.38	1150.00	20.00
8	-5.53	-7.77	14.33	5150.00	341.00
16	-5.53	-2.77	14.33	324.00	20.00
17	-5.53	-8.27	14.33	3830.00	138.00

18	-6.06	-8.25	14.38	1150.00	20.00
19	-5.45	-9.66	14.50	720.00	56.20
20	-6.06	-7.25	14.38	4220.00	322.00
21	-11.58	-6.44	14.38	144.00	20.00
22	-5.53	-8.27	14.33	2060.00	165.00
23	-6.06	-7.25	14.38	5900.00	156.00

Based on the trained neural network model, this study conducted a systematic prediction evaluation of all spatiotemporal-temperature data. The error distribution characteristics of the prediction results are as follows: From the perspective of overall prediction accuracy, the model exhibits excellent performance, with 95.8355% of the predicted data having relative errors controlled within 20%, and even 92.8188% of the data having prediction errors not exceeding 10%. This result indicates that the neural network model has high reliability in predicting the fire temperature field. Further analysis of the error distribution pattern found that samples with relative errors exceeding 20% are mainly concentrated in the initial stage of the fire (the first 100 seconds). This stage has the following characteristics: 1) The fire temperature is generally below 50°C; 2) The heat release rate has not yet reached a stable state; 3) The thermal impact on the building structure is relatively limited. Therefore, the prediction error in this stage has a negligible impact on the overall assessment. It is worth noting that samples with errors between 10% and 20% mainly appear in the development stage after the fire has lasted for 1 hour. The causes of errors in this stage can be attributed to: 1) The fire plume movement exhibits unstable characteristics; 2) Local temperature extremes fluctuate; 3) The overall heat release rate tends to be stable. Although there are certain deviations between the prediction results and the instantaneous measured values, since the system has entered a quasi-steady state, these errors will not have a substantial impact on the overall temperature field assessment.

This paper selects the comparative analysis results of the FDS simulated temperature field and the AI predicted temperature field in the plant space at the time of 5090s, as shown in the Figure 4. From the perspective of spatial distribution characteristics, the two show highly consistent distribution laws: the temperature peaks are concentrated near the projection area of the fire source, while the lowest temperatures are distributed in the peripheral edge areas far from the fire source. The overall temperature field presents a typical "mountain peak" gradient distribution, which is consistent with fire dynamics theory and actual observation results.



(a)Real temperature distribution (b)Predict temperature distribution

Figure 4. Spatial Temperature at 5090s

In terms of quantitative analysis, there is an 8.3% relative error between the predicted temperature peak and the measured value. This error mainly stems from the following factors: 1) the plume movement above the fire source exhibits significant instability; 2) the thermal convection process in the high-temperature region exhibits random pulsating characteristics; and 3) flame oscillations cause continuous fluctuations in local temperature extremes. Despite these influencing factors, the neural network model can still capture the overall distribution characteristics of the temperature field relatively well, and the spatial correlation between the predicted results and the measured data is good. The error range fully meets the accuracy requirements for engineering applications. Particularly noteworthy is the model's accurate prediction of temperature gradient changes, correctly reflecting the temperature decay law during the thermal plume diffusion process. This characteristic is of great significance for assessing the heating status of building components and key equipment, indicating that this neural network model has reliable engineering application value in fire field temperature field reconstruction.

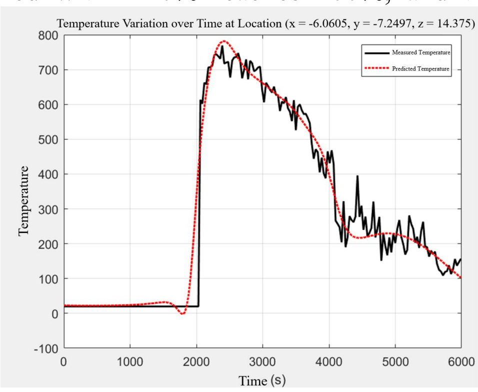
3.4 AI Prediction Temperature Field Time History Analysis

This paper conducted a systematic time history characteristic analysis of the spatiotemporally discrete temperature data predicted by the neural network model. According to the spatial distribution characteristics of the measuring points, they can be divided into two major types: measuring points in the area adjacent to the fire source and measuring points in the area far from the fire source, corresponding to the typical temperature time history curves shown in Figure 5(a) and (b) respectively. To deeply analyze the prediction accuracy, two representative characteristic measuring points were selected for research:

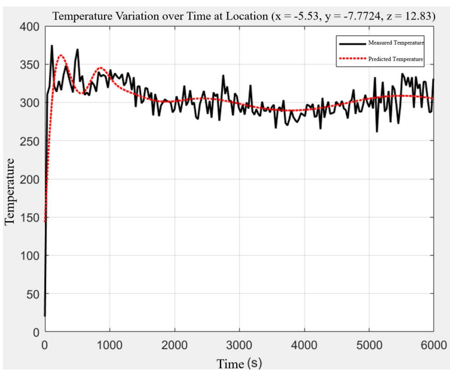
(1) Measuring point on the cable tray directly above the fire source: Among them, the proportion of data with prediction errors controlled within 20% reaches 100%, and the proportion of high-precision prediction data with errors not exceeding 10% is 94.33%. The temperature time history curve accurately reproduces the heating characteristics of the fire source area.

(2) Measuring point on the cable tray far from the fire source: The proportion of predicted data within the 20% error range is 98.15%, and the proportion of high-precision data within the 10% error range is 89.91%, successfully simulating the gradual temperature rise and fluctuation process in the far field area.

The analysis results show that the neural network model can accurately capture the time history temperature change characteristics of measuring points at different spatial locations. Especially in the area adjacent to the fire source, although there is strong thermal disturbance, the model still maintains excellent prediction accuracy (94.33% data error <10%). This performance verifies the applicability of this neural network in complex fire environments. The established neural network model can accurately predict the fire temperature distribution characteristics, and the prediction accuracy fully meets the requirements of engineering applications. Especially in the vigorous development stage of the fire (period of higher temperature), which is crucial for the safety assessment of key equipment and structures in nuclear power plants, the model demonstrates excellent prediction performance, providing a reliable data basis for subsequent thermal-mechanical coupling analysis.



(a)Comparison Chart of Measured and Predicted Temperatures at Monitoring Points near the Fire Source



(b)Comparison Chart of Measured and Predicted Temperatures at Points away from the Fire Source

Figure 5. Comparison between Measured and Predicted Temperature Distributions

4. Conclusion and Outlook

This study establishes an integrated framework that leverages the synergy between numerical simulation and artificial intelligence. High-fidelity fire scenarios within nuclear reactor buildings are constructed using the Fire Dynamics Simulator (FDS), yielding detailed spatiotemporal data on the evolving three-dimensional temperature field. Based on the simulation data, a deep learning network model structure based on CNN-Bi-LSTM is constructed.

This model can accurately predict the fire development process by learning the complex nonlinear relationships in fire scenarios, and on this basis, the applicability and prediction accuracy of the neural network in complex fire environments are systematically studied. The main research conclusions are as follows:

(1) Model Construction and Optimization: The model takes spatial coordinates (X, Y, Z) and fire time (t) as input and temperature (T) as output, and achieves accurate mapping of nonlinear temperature spatial distribution and time history evolution relationships through the LSTM architecture model that can reflect temporal characteristics. The training data uses FDS simulation results. Through spatial uniform sampling and time node screening, the computational efficiency is significantly improved while ensuring data representativeness.

(2)Prediction Performance Verification: In Scenario 1, the proportion of data with prediction error ⩽ 10% is 87.82%, the overall correlation coefficient R=0.99517, and the temperature peak error is 11.3%, successfully reproducing the "mountain peak" distribution characteristics; In Scenario 2, the proportion of data with prediction error ⩽10% is 89.38%, the error in the high-temperature area is only 4.3%, accurately simulating the thermal plume diffusion law in the annular space; In Scenario 3, the error in the high-temperature area (>300° C) is ⩽5%, and 96.12% of the data have errors ⩽ 20%. Moreover, the simulation efficiency is significantly better than the computational efficiency of traditional CFD methods, up to thousands of times higher than that of traditional CFD methods.

(3) Spatiotemporal Characteristic Analysis: The model can accurately capture the gradient changes between the fire source peak area and the far-field low-temperature area. The errors mainly originate from plume instability and local flashover phenomena; The proportion of prediction error ⩽ 10% for measuring points directly above the fire source is 95.48%, and the error in the smoke exhaust area is slightly higher (90.40%), but both meet engineering requirements. The unique "temperature rise-attenuation" curve of the enclosed space is successfully reproduced, reflecting the coupling effect of combustible consumption and passive smoke exhaust.

(4) Engineering Applicability: The prediction accuracy of the model in key high-temperature areas (error generally <10%) fully complies with the requirements of standards such as GB/T 9978.1-2019, providing an efficient and reliable technical means for fire safety assessment of nuclear power facilities. In the future, the prediction accuracy in the far field can be further improved by increasing boundary measuring point data.

In summary, the neural network fire temperature field prediction model established in this chapter combines high accuracy and high efficiency, providing a new solution for fire dynamic deduction and emergency decision-making in complex industrial scenarios.

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