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Research on 3D Neutron Flux Prediction Method for Lead-Cooled Fast Reactors Based on ARGA-3DCNN

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Abstract

Three-dimensional prediction of neutron flux is crucial for reactor core design, optimization, and safety analysis. However, due to the compact space of micro-scale lead-cooled fast reactors and the difficulty of detector placement, existing methods predominantly focus on the two-dimensional level, with limited attention to three-dimensional flux prediction. This paper proposes a Genetic Algorithm-Enhanced 3D CNN with Multi-Head Self-Attention and Residual Connections (ARGA-3D CNN) model that integrates Residual Network (ResNet) and Multi-head Self-Attention mechanism (MSA). This model can effectively capture the spatial distribution characteristics of core neutron flux and address spatial dependency issues. ResNet mitigates gradient vanishing and explosion, enhancing training stability, while MSA strengthens key region identification. Furthermore, a genetic algorithm optimizes hyperparameters to further improve core neutron flux prediction accuracy. Experiments construct a dataset based on calculations from the Monte Carlo particle transport simulation software SuperMC, which is used to train and optimize the ARGA-3D CNN model for prediction. Results demonstrate that, compared with SuperMC calculations, the model achieves Mean Absolute Error (MAE), Mean Squared Error (MSE), and coefficient of determination (R^2) metrics of $3.19\$\times10^{\{-6\},2.14\times10}\{-11\}\$$, and 0.9735, respectively. Computational efficiency is significantly improved, with single predictions requiring only seconds. Compared with traditional network models such as Convolutional Neural Network (CNN), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM), the prediction performance is superior. The ARGA-3D CNN model exhibits high accuracy and computational efficiency in three-dimensional neutron flux prediction, providing a novel method for rapid prediction of nuclear reactor core parameters with practical value and significance.

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Preamble

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Three-Dimensional Neutron Flux Prediction for Lead-Cooled Fast Reactors Based on ARGA-3DCNN

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Abstract

[**Background**] Three-dimensional prediction of neutron flux is crucial for reactor core design, optimization, and safety analysis. However, due to the compact spatial configuration of small lead-cooled fast reactors and the difficulty of detector placement, existing methods primarily focus on two-dimensional analysis, with limited attention to three-dimensional flux prediction. [**Purpose**] This paper proposes a Genetic Algorithm-Enhanced 3D CNN with Multi-Head Self-Attention and Residual Connections (ARGA-3D CNN) model that integrates Residual Networks (ResNet) and Multi-Head Self-Attention (MSA) mechanisms. This model efficiently captures the spatial distribution features of neutron flux in reactor cores and addresses spatial dependency issues. [**Methods**] The ARGA-3D CNN model employs 3D convolutional neural networks to effectively capture the spatial distribution of neutron flux in the reactor core. ResNet alleviates vanishing and exploding gradient problems, enhancing training stability, while MSA strengthens the identification of key regions. Additionally, a Genetic Algorithm (GA) optimizes hyperparameters to further improve prediction accuracy. The model is trained and optimized using a dataset constructed from Monte Carlo particle transport simulation results obtained with SuperMC software. [**Results**] The results demonstrate that compared to SuperMC calculations, the ARGA-3D CNN model achieves Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 values of 3.19$\times10^{-6}$, 2.14×10^{-11}, and 0.9735, respectively. Computational efficiency is significantly improved, with each prediction requiring only seconds. Compared to traditional models such as Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, and Transformer, the prediction performance is superior. **Conclusions** The ARGA-3D CNN model provides a high-precision and computationally efficient method for predicting three-dimensional neutron flux

in reactor cores. It offers a new approach for rapid prediction of nuclear reactor core parameters, which holds significant practical value and implications for reactor design, operation, and safety analysis.

Keywords: Lead-cooled fast reactor, Neutron flux, 3D convolutional neural network, Multi-Head Self-Attention, Residual network, Genetic algorithm

Introduction

In the development of nuclear energy technology, lead-cooled fast reactors have attracted widespread attention in recent years as an advanced reactor type with unique advantages. Lead-cooled fast reactors demonstrate broad application prospects in the nuclear energy field due to their excellent neutron physics characteristics, high fuel utilization efficiency, and favorable safety performance. However, in core design, operational optimization, and safety analysis, the precise prediction of core neutron flux distribution is particularly critical as it serves as an important parameter for evaluating core performance. As the primary energy carrier in nuclear reactions, neutron flux distribution directly affects reactor power output and fuel burnup, and is also related to key factors such as reactivity control, thermal-hydraulic characteristics, and irradiation behavior. Traditional neutron flux prediction methods, such as numerical calculations based on deterministic transport theory and empirical models, can provide effective results to a certain extent, but often suffer from high computational costs, slow calculation speeds, and insufficient adaptability to complex operating conditions when facing complex core structures and multi-physics coupling problems.

In recent years, artificial intelligence technology, particularly deep learning algorithms, has been widely applied to the prediction of nuclear reactor physical parameters due to its advantages in processing large-scale data and efficient computation. For instance, Wang et al. proposed a core parameter prediction method based on Backpropagation Neural Network (BPNN) that effectively improved prediction accuracy and reduced computational resource consumption. Palmi et al. developed a method based on Artificial Neural Network (ANN) for predicting core loading scheme reactivity and fuel cycle length, accurately forecasting reactivity changes and fuel cycle duration under different core loading configurations. Additionally, Bei et al. developed a three-dimensional surrogate model based on BPNN, significantly improving computational efficiency and demonstrating particular advantages in neutron flux prediction for molten salt reactors. Chen et al. further enhanced the prediction accuracy of neutron flux and keff by optimizing the Extreme Learning Machine (ELM) model combined with whale optimization algorithm, achieving remarkable results in improving training efficiency. Although these studies have made significant progress in predicting reactor neutron flux and key parameters, existing methods often face challenges in balancing computational accuracy and efficiency when dealing with spatially compact and structurally complex cores, particularly in handling three-dimensional neutron flux distribution.

To improve the prediction accuracy of three-dimensional neutron flux distribution in reactor cores and address the limitations of existing methods in handling complex spatial structures and nonlinear relationships, this paper proposes a three-dimensional convolutional neural network model that combines residual networks and self-attention mechanisms (Genetic Algorithm-Enhanced 3D CNN with Multi-Head Self-Attention and Residual Connections, ARGA-3D CNN). This model effectively avoids gradient vanishing problems through the introduction of residual structures, while utilizing self-attention mechanisms to automatically identify and focus on key features in the input data, thereby improving prediction accuracy for three-dimensional neutron flux distribution in reactor cores. Genetic algorithm optimization of network hyperparameters significantly enhances model performance. Experimental results demonstrate that the ARGA-3D CNN model can efficiently process three-dimensional complex data, showing remarkable advantages particularly in three-dimensional neutron flux prediction.

1.1 Three-Dimensional Convolution Module

Three-Dimensional Convolutional Neural Network (3D CNN) represents an extension of Convolutional Neural Network (CNN) for three-dimensional data processing. By introducing three-dimensional convolution kernels, it can simultaneously extract spatial and temporal features, overcoming the limitation of two-dimensional convolutional neural networks (2D CNN) that can only capture two-dimensional spatial features. In Figure 1: see original paper, when 2D CNN is applied to a single image, it slides only in spatial dimensions, producing a two-dimensional output, whereas in Figure 1: see original paper, 3D CNN slides in both spatial and temporal dimensions, preserving temporal information in a three-dimensional volume output. This 3D convolution operation is particularly suitable for tasks such as video analysis, action recognition, and medical image processing, demonstrating significant advantages over 2D convolution.

In three-dimensional convolution, the depth of the convolution kernel is typically smaller than the depth of the input data (i.e., the kernel size is smaller than the number of channels), as shown in [Figure 2: see original paper], allowing the filter to slide in three directions: height, width, and channels. Each time the convolution kernel moves to a new position, element-wise multiplication and addition operations are performed to produce an output value. Since the filter slides throughout the three-dimensional space, the output data is also arranged in a three-dimensional structure. The three-dimensional convolution formula is as follows:

$$Y(t,i,j) = \sum_{d}\sum_{m}\sum_{n} X(t+d, i+m, j+n) \cdot W(d,m,n) + b$$

where $Y(t,i,j)$ represents the value of the output feature map at time step t and position (i,j), $X(t+d, i+m, j+n)$ represents the input data at time step $t+d$

and position $(i+m, j+n)$, $W(d, m, n)$ represents the weight of the convolution kernel at depth d, height m, and width n, and b represents the bias term. The convolution kernel size is $D \times k \times k$ (temporal depth $\times$ height $\times$ width).

In this paper, the three dimensions of the three-dimensional convolution operation correspond to the spatial coordinate axes of the reactor core. The convolution kernel performs multi-dimensional sliding operations on the input data, equivalent to extracting local spatial features of neutron flux distribution at different core locations. Each convolution output can be regarded as the neutron flux feature response within a specific spatial neighborhood, thereby helping the network capture the spatial distribution patterns of three-dimensional flux within the core structure.

1.2 Multi-Head Self-Attention Module

Multi-Head Self-Attention (MSA) enhances the model' s ability to process different information through parallel computation of multiple attention heads. Each attention head calculates its own attention scores by performing linear transformations on input queries (Q), keys (K), and values (V), and then performs weighted summation on the results to capture different subspace features of the input. Multiple attention heads working in parallel enable the model to simultaneously focus on information in different subspaces, thereby improving the model' s expressive capability and ability to capture long-range dependencies. [Figure 3: see original paper] illustrates the implementation process of the multi-head attention mechanism: each head extracts features from input Q, K, and V through linear transformations, then concatenates (Concat) the output of each head, and finally obtains the final output through a linear transformation.

The specific calculation process is as follows: For each attention head, attention scores are first calculated:

$$\text{Attention}(Q, K, V) = \text{Softmax}(\text{score}(Q, K)) \cdot V$$

where $\text{score}(Q, K)$ is typically calculated through dot product. Then, the outputs of multiple heads are combined through concatenation (Concat), and the final result is obtained through linear transformation:

$$\text{MultiHeadSelfAttention}(Q, K, V) = \text{Concat}(\text{head}_1, \text{head}_2, \ldots, \text{head}_h) \cdot W^O$$

where W^O is the final weight matrix. This mechanism enables the model to simultaneously capture multi-level feature information in different subspaces, thereby enhancing overall representation capability and generalization ability.

This paper employs multi-head self-attention mechanism, whose basic principle is that through parallel computation of multiple attention heads, the model

can automatically identify key regions in the core neutron flux distribution and perform weighted adjustments to the overall core flux based on neutron flux in these regions. This enables more accurate capture of global spatial features and enhances modeling capability for complex spatial structures.

1.3 Residual Connection Module

Residual connections represent an effective technique for addressing gradient vanishing problems in deep network training. By directly passing input data to deeper layers of the network, they avoid gradient attenuation during back-propagation, thereby accelerating gradient propagation. The core of the ResNet (Residual Network) structure proposed by He et al. in 2015 is the introduction of residual connections. [Figure 4: see original paper] describes two module structures in neural networks: a normal block is the basic building unit in neural networks, typically consisting of weight layers and activation functions, where input x undergoes linear transformation and nonlinear activation to output $f(x)$. The residual connection block is a key component in ResNet, which addresses degradation problems in deep networks through residual learning. The residual connection block includes weight layers, activation functions, and residual connections. Input x first undergoes linear transformation through weight layers, then passes through activation functions to obtain $f(x)$. Subsequently, $f(x)$ is added to the original input x to obtain the final output. This structure can be expressed as:

$$y = f(x) + x$$

where y is the output, $f(x)$ is the result processed by weight layers and activation functions, and x is the input.

The physical significance of employing residual connections in this paper lies in preserving original input information, avoiding gradient vanishing problems in deep neural network training, and thereby helping the network better transmit spatial distribution features of core neutron flux. Particularly when dealing with nonlinear and complex flux distributions in the core, residual connections ensure that the model can more accurately express dependencies between regions, thereby improving the model' s learning capability for neutron flux distribution.

1.4 AR-3D CNN Model

The innovation of the AR-3D CNN model lies in its combination of residual networks, multi-head self-attention mechanisms, and three-dimensional convolutional neural network structures. This integration addresses the complex requirements of core neutron flux distribution prediction tasks, improving model prediction accuracy, computational efficiency, and robustness while enhancing the capability to process three-dimensional spatial data. The overall workflow is shown in [Figure 5: see original paper]. The model includes the following main

steps: (1) In processing input layer data, 3D CNN extracts three-dimensional spatial features of core neutron flux data, combined with Batch Normalization (BatchNorm) and ReLU activation functions to enhance nonlinear expressive capability; (2) Multiple residual 3D convolution blocks (Residual 3DConvBlock) extract deep features, avoiding gradient problems and learning complex spatial dependencies; (3) The multi-head attention layer (Multi-Head Attention Layer) dynamically focuses on key regions, enhancing feature learning and noise robustness; (4) The fully connected layer (Fully Connected Layer) further integrates features to complete nonlinear mapping and final prediction; (5) The average pooling layer (Average Pooling Layer) aggregates feature maps to optimize output results.

1.5 ARGA-3D CNN Model

This paper combines deep learning with genetic algorithm optimization methods, employing a hyperparameter optimization strategy based on validation set loss minimization. In this approach, the deep learning model first performs feature extraction and multi-task prediction modeling on input data. The network structure includes 3D convolutional layers, residual connection layers, and multi-head attention mechanism modules, aiming to capture spatiotemporal features and global dependency relationships of input features. Subsequently, the genetic algorithm defines the negative value of the loss function (Huber loss) on the validation set as the fitness function:

$$\text{Fitness} = -\text{Huber}(Y_{\text{true}}, Y_{\text{pred}})$$

where N represents the number of validation set samples, $Y_{\text{true}}^{(i)}$ represents the true value of the i-th sample, and $Y_{\text{pred}}^{(i)}$ represents the predicted value of the i-th sample. The Huber loss function combines the advantages of Mean Squared Error (MSE) and Mean Absolute Error (MAE), improving robustness to outliers while ensuring smoothness, thereby optimizing model stability and convergence.

The ARGA-3D CNN model extracts three-dimensional features through 3D CNN and utilizes genetic algorithms to optimize model parameters, improving prediction accuracy and generalization capability. The overall workflow is shown in [Figure 6: see original paper], comprising two main parts: the prediction process and the genetic algorithm optimization process. First, input data undergoes preprocessing, followed by initialization and optimization of the 3D CNN model to extract spatial features of core neutron flux. Then, the optimal model is constructed and trained to output prediction results. Subsequently, the genetic algorithm optimizes hyperparameters through selection, crossover, and mutation operations to iteratively search for the optimal hyperparameter combination, further improving model prediction accuracy and generalization capability. Finally, the optimal hyperparameters are output to ensure the model achieves optimal performance in complex three-dimensional data scenarios.

2.1 Core Model

This experiment uses the Monte Carlo particle transport simulation software SuperMC to construct a lead-cooled fast reactor model. The number and materials of core components are summarized in . As shown in [Figure 7: see original paper], the core components adopt the hexagonal prism shape commonly used in fast reactors, with the core divided into three regions from inside to outside: the active zone, reflector zone, and shielding zone. The active zone consists of 101 assemblies, including 92 fuel assemblies (primarily composed of 19.75% enriched UO_2) and 9 control rod assemblies. The reflector zone comprises 98 assemblies using lead-bismuth eutectic material. The shielding zone contains 54 assemblies made of boron carbide. Additionally, there are 4 safety rods, 3 control rods, and 2 compensation rods, with materials being 90%^{10}B boron carbide, boron carbide, and 90%^{10}B boron carbide, respectively.

SuperMC is a large-scale nuclear neutronics design and radiation safety evaluation software system independently developed by the Institute of Nuclear Energy Safety Technology (INEST), Hefei Institutes of Physical Science, Chinese Academy of Sciences. Based on the Monte Carlo method, this software can perform accurate neutron transport calculations for complex nuclear systems and is widely applied in various aspects of nuclear reactor design, radiation safety analysis, and nuclear engineering. SuperMC can handle reactor models with complex geometries and effectively simulate multi-material interfaces, providing high-precision neutron flux calculations. Its main functions cover various important analyses in nuclear energy systems, including radiation transport, fuel depletion, radiation activation, dose assessment, and other comprehensive neutron safety analyses. [Figure 8: see original paper] shows the overall structure of the lead-cooled fast reactor core constructed using SuperMC.

2.2 Experimental Dataset and Evaluation Metrics

The dataset was obtained through core simulation programs calculating core neutron flux density under steady-state conditions. Input data includes positions of three control rods, positions of two compensation rods, and 30,000 spatial coordinate information entries, which together describe the physical state of the core and its influence on neutron flux distribution. Output data consists of 30,000 neutron flux values corresponding to the spatial coordinates, reflecting neutron flux intensity at various core positions under different operating conditions, as shown in . To ensure model training stability and efficiency, all input and output data were normalized. Through this dataset, the model learns the complex nonlinear relationship between input parameters and neutron flux distribution, thereby achieving accurate prediction of core neutron flux.

This experiment employs four widely used metrics—MAE, MSE, Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2)—to measure model accuracy and evaluate prediction performance, reflecting the model' s fitting effect. The formulas are as follows:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\%$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

where y_i is the true value, $\hat{y}_i$ is the predicted value, n is the sample size, and $\bar{y}$ is the mean of true values. The R^2 value ranges from [0,1], with values closer to 1 indicating better model fitting.

This experiment employs a genetic algorithm to adjust neural network hyperparameters to optimize model performance. Genetic algorithms can perform global optimization in high-dimensional search spaces, gradually finding optimal hyperparameter combinations. Specific parameter settings are as follows: population size of 50, generations of 100, crossover probability of 0.8, mutation probability of 0.1, and roulette wheel selection method for individual selection. This parameter configuration achieves a good balance between computational efficiency and search precision, effectively avoiding local optima and ensuring global optimization effectiveness.

Due to the relatively complex structure and large volume of the dataset, this experiment adopts a hybrid strategy for hyperparameter optimization. The learning rate is treated as a continuous hyperparameter and searched on a logarithmic scale, while other hyperparameters (such as batch size, number of attention heads, and number of fully connected layer nodes) employ discrete selection strategies. This hybrid strategy balances computational efficiency and search precision, allowing the optimization process to both finely adjust the learning rate and find optimal values within the limited set of discrete hyperparameters.

After multiple iterations and optimization by the genetic algorithm, a final hyperparameter configuration was determined, as shown in . The specific hyperparameters are: learning rate 1.17$×10^{-4}$, batch size 16, number of attention heads 4, and number of fully connected layer nodes 1024, representing the optimal solution for model performance within the current search space. During training, both training loss and validation loss decreased significantly, as shown in [Figure 9: see original paper], indicating that the model gradually converged and achieved good performance during the learning process. The loss curves show that loss values stabilized as training progressed, validating the effectiveness of the optimization process.

2.4 Comparative Experiments

To comprehensively evaluate the effectiveness of the proposed ARGA-3D CNN model, we conducted comparative experiments with various advanced deep learning prediction models. The comparison models include traditional CNN, ANN, Long Short-Term Memory (LSTM) networks, and Transformer, all of which are widely used in prediction tasks. All models were trained and tested on the lead-cooled fast reactor core three-dimensional neutron flux dataset.

The comparative experimental results are shown in . In terms of MAE and MSE, ARGA-3D CNN achieves errors of only 3.19$×10^{-6}$ and 2.14$×10^{-11}$, respectively, which is more than double the improvement compared to CNN, ANN, LSTM, and Transformer. This indicates that the method possesses extremely high precision in predicting neutron flux values and can effectively avoid common prediction bias issues in traditional methods. Due to the complex spatial distribution characteristics of three-dimensional neutron flux, traditional CNN and ANN suffer from limited local receptive fields, making it difficult to effectively model global spatial relationships and resulting in larger prediction errors. ARGA-3D CNN combines residual networks, multi-head self-attention mechanisms, and three-dimensional convolutional neural networks, enabling better learning of global spatial features. Although Transformer also possesses strong global modeling capabilities, its computational complexity is higher when processing three-dimensional spatial data, and its ability to capture local features is relatively weaker, resulting in inferior performance compared to ARGA-3D CNN in this experiment.

In terms of MAPE, ARGA-3D CNN achieves a relative error of only 2.13%, representing a reduction of over 60% compared to CNN, ANN, LSTM, and Transformer. For R^2, ARGA-3D CNN achieves the best fit of 0.9735, significantly higher than CNN' s 0.9118, ANN' s 0.9134, LSTM' s 0.9212, and Transformer' s 0.9516. This demonstrates that ARGA-3D CNN' s advantage in three-dimensional spatial feature extraction enables it to effectively learn the nonlinear characteristics of neutron flux and construct a prediction model that better conforms to physical laws. To further visually demonstrate the performance of different models, this paper provides visualization of experimental results.

The neutron flux distribution predicted by the ARGA-3D CNN model was compared with the distribution calculated by the Monte Carlo program on the test dataset. Considering that there are certain relative errors between predicted and calculated values, one instance was randomly selected from the test dataset to evaluate the surrogate model' s performance. [Figure 10: see original paper] shows a two-dimensional comparison of predicted versus actual neutron flux distribution, while [Figure 11: see original paper] provides a three-dimensional comparison. Overall, the predicted neutron flux distribution matches well with the actual distribution, with the highest neutron flux observed in the reactor core, which is completely consistent with the expected behavior of neutron flux

in reactor cores.

In summary, ARGA-3D CNN significantly outperforms other models in neutron flux prediction tasks through deep three-dimensional convolutional feature extraction, improved training stability from residual networks, and global information modeling from self-attention mechanisms. Compared to CNN, ANN, LSTM, and Transformer, ARGA-3D CNN exhibits lower errors, more accurate predictions, and greater stability, while maintaining good robustness in complex data environments. This provides a new, efficient, and accurate prediction method for nuclear reactor design and safety assessment, with certain application prospects.

2.5 Ablation Experiments

To deeply analyze the contribution of each module of ARGA-3D CNN to overall model performance, we conducted ablation experiments by separately removing the genetic algorithm (AR-3D CNN), residual network (A-3D CNN), multi-head self-attention mechanism (R-3D CNN), and global average pooling layer (AR-3D CNN(NAP)), and comparing the performance changes of each version to verify the impact of different modules on final prediction results. The experimental results are shown in .

As shown in , each module in the proposed ARGA-3D CNN network effectively enhances performance on three-dimensional neutron flux prediction tasks. The introduction of Genetic Algorithm (GA) for hyperparameter optimization significantly enhances the network' s global search capability, reduces the risk of local optima from manual tuning, and further improves model accuracy and stability. The ResNet module alleviates gradient vanishing and explosion problems through skip connections in deep structures while enhancing feature transmission efficiency, making a particularly prominent contribution to network performance. MSA can accurately capture global dependency relationships of input data in three-dimensional space, helping the model focus on key regions and suppress interference, making predictions more accurate. The Global Average Pooling (GAP) layer compresses channel dimensions and reduces redundant parameters while maintaining the integrity of main features, thereby improving network generalization capability. When GAP is removed, the network' s utilization of detailed features decreases, resulting in slightly degraded reconstruction performance. Overall, the synergistic effect of these modules enables ARGA-3D CNN to have stronger adaptability and higher prediction accuracy for complex three-dimensional neutron flux data, laying a solid foundation for subsequent prediction and analysis of key parameters in nuclear reactor cores.

2.6 Timing Experiments

This experiment aims to evaluate the timeliness advantages of the proposed ARGA-3D CNN model, particularly in comparison with the nuclear energy simulation software SuperMC. All timing experiments were conducted under the

same hardware environment to ensure comparability. The experimental computer configuration is: AMD Ryzen 7 5800 CPU, 32GB memory, and NVIDIA GeForce RTX 3060 GPU. Timeliness was evaluated by comparing the time required for both methods to predict three-dimensional neutron flux. When using SuperMC with 12-core parallel computing, the time required to complete one full prediction is on the order of minutes. In contrast, when using the ARGA-3D CNN model for the same prediction, the computation time is only 0.4011 seconds. This demonstrates that the model has significant advantages in computational timeliness, particularly when handling complex prediction tasks, as it can complete calculations in extremely short time, substantially improving processing efficiency.

Conclusions

This paper proposes a three-dimensional neutron flux prediction model based on ARGA-3D CNN, aiming to address the complex spatial feature extraction challenges in lead-cooled fast reactor core neutron flux distribution prediction while significantly improving prediction accuracy and computational efficiency. The main conclusions are as follows:

1) By introducing ResNet and MSA, the model effectively alleviates gradient vanishing problems and enhances global information modeling capability, thereby improving prediction accuracy in neutron flux prediction tasks and reducing prediction errors compared to traditional methods. Compared to CNN, ANN, LSTM, and Transformer, the ARGA-3D CNN model demonstrates superiority across evaluation metrics including MAE, MSE, MAPE, and R^2, and requires only 0.4011 seconds to predict 30,000 data points, representing a substantial improvement in computational efficiency compared to traditional calculation software.

2) Combining genetic algorithm optimization of hyperparameters further improves model robustness and accuracy. The optimized hyperparameter configuration enables the model to perform more efficiently in large-scale core data prediction tasks while possessing stronger generalization capability.

In summary, the model proposed in this paper provides a new approach for efficient prediction of three-dimensional neutron flux, particularly holding certain application prospects in nuclear reactor design and safety assessment. In future work, more diverse datasets covering different operating conditions and scenarios will be introduced to further enhance the model' s adaptability and robustness in practical applications.

Author Contributions

MO Ziwen is responsible for overall paper design, neural network programming, and drafting; YANG Zihui is responsible for critical review of the article and

research funding support; LI Zhongyang and SUN Guomin are responsible for technical support and guidance; LI Zhaodong is responsible for acquiring valid core data and data analysis.

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Note: Figure translations are in progress. See original paper for figures.

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