

Hybrid Deep Learning-Metaheuristic Integration for Contaminated Area Prediction and Source Term Inversion of Nuclear Energy Safety

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Abstract

Nuclear energy safety is indispensable to balancing the dual goals of harnessing nuclear energy and mitigating the risks of radioactive leakage, which is critical to global energy transition and environmental protection efforts. A Hybrid deep learning approach combined with metaheuristic algorithms for predicting contaminated areas and inverting source term parameters in nuclear explosion models was designed, and a metaheuristic algorithm was used to invert the source term parameters of nuclear explosion. The physical processes of particle distribution, deposition mechanisms, radioactive activity, and biological dose resulting from nuclear explosion radioactive clouds were simulated. The relationship between explosion parameters and contaminated areas is systematically analyzed. Subsequently, radiation safety standards are employed to quantitatively evaluate contamination levels. A hybrid deep learning methodology is then developed to construct a rapid prediction model for contaminated areas. Finally, metaheuristic algorithms are utilized to invert explosion source term parameters, with comparative analysis of different algorithms' stability and accuracy. Results demonstrate that the integration of Bayesian optimization (BO) and attention mechanisms significantly enhances model prediction accuracy. Metaheuristic algorithms exhibit fast convergence speeds and excellent search capabilities in inverting nuclear explosion source parameters. This research contributes to enhancing the effectiveness of nuclear emergency response actions, provides a scientific basis for disaster assessment and rescue operations in nuclear environments, and offers a robust technical toolkit for safeguarding nuclear energy safety in extreme accidental or intentional nuclear event scenarios.

Full Text

Preamble

Nuclear energy safety is indispensable for balancing the dual objectives of harnessing nuclear power while mitigating the risks of radioactive leakage, which is critical to global energy transition and environmental protection efforts. This study develops a hybrid deep learning approach combined with metaheuristic algorithms for predicting contaminated areas and inverting source term parameters in nuclear explosion models. The physical processes of particle distribution, deposition mechanisms, radioactive activity, and biological dose resulting from nuclear explosion radioactive clouds were simulated, and the relationship between explosion parameters and contaminated areas was systematically analyzed. Radiation safety standards were then employed to quantitatively evaluate contamination levels. A hybrid deep learning methodology was subsequently developed to construct a rapid prediction model for contaminated areas. Finally, metaheuristic algorithms were utilized to invert explosion source term parameters, with comparative analysis of the stability and accuracy of different algorithms. Results demonstrate that the integration of Bayesian optimization (BO) and attention mechanisms significantly enhances model prediction accuracy. Metaheuristic algorithms exhibit fast convergence speeds and excellent search capabilities in inverting nuclear explosion source parameters. This research contributes to enhancing the effectiveness of nuclear emergency response actions, provides a scientific basis for disaster assessment and rescue operations in nuclear environments, and offers a robust technical toolkit for safeguarding nuclear energy safety in extreme accidental or intentional nuclear event scenarios.

Keywords: Radioactive deposition, Hybrid deep learning, Metaheuristic algorithm, Parameter inversion

Introduction

Nuclear energy safety is the foundational prerequisite for the sustainable development and widespread application of nuclear power, as it directly safeguards human life, property, and ecological environments from the hazards of radioactive contamination and nuclear accidents [1-3]. Various destructive effects—including instantaneous radiation ionization [4-6], photothermal radiation [7], and radioactive contamination [8]—are generated and can propagate to areas far from the explosion site. The radioactive smoke cloud produced by the explosion, while potentially not causing immediate mass casualties, can result in large-scale radioactive contamination extending over tens, hundreds, or even thousands of kilometers, leading to significant casualties and extensive environmental pollution over considerable periods. Therefore, investigating the dispersion patterns of nuclear explosion smoke clouds, the radioactive deposition areas following explosions, and nuclear explosion source information is critically important [9].

Numerous systems for predicting nuclear particle diffusion and deposition have been developed, including the Defense Land Fallout Interpretive Code (DELFI) [10, 11], the Weapons Systems Evaluation Group (WSEG) series [12], and the Lagrangian Gaussian Puff Model (LGPM) [13, 14]. Zheng D Q et al. [15] developed and validated a key technique for nuclear accident emergency response that utilizes real-time observational data to dynamically correct predictions from atmospheric dispersion models. The core of this approach involves integrating short-term model forecasts with real-time observational data to generate an optimized “analysis field” that more accurately reflects the current state and approximates reality. Cao, B. et al. [16] developed a radioactive nuclide atmospheric dispersion calculation code (RADC) based on the Gaussian plume model, employing a Bayesian MCMC method for uncertainty analysis of model parameters. Bouville A et al. [17] proposed a methodology for assessing external exposure doses from radioactive fallout following nuclear explosions. Its core lies in using the arrival time of fallout and the exposure rate at 12 hours post-detonation as key input data to estimate doses received by different age groups and human organ tissues. Dahia et al. [18] evaluated the atmospheric dispersion of continuously released radioactive pollutants following nuclear power plant accidents using the Gaussian plume approach.

While these studies have primarily established radioactive diffusion models and analyzed pollution evolution processes, playing crucial roles in nuclear explosion consequence assessment, nuclear accident emergency response, and radioactive waste management, the computational time required by these models limits their ability to rapidly provide relationships between nuclear explosion parameters and radiation deposition contamination areas.

The combination of nuclear safety with artificial intelligence has shown broad application prospects [19]. Currently, neural networks (NN) have been widely applied in key fields such as nuclear explosion pattern recognition [20], radiation field prediction [21], and nuclear power plant control [22]. Trained NN offer rapid computation speeds and enhanced prediction efficiency. Marija Boznar et al. [23] employed NN to predict environmental SO₂ concentrations in highly polluted industrial areas with complex terrain. Wang et al. [24] utilized NN to bypass physical model calculations, achieving prediction of gas release concentrations at specific off-site locations based on input parameters. Ma et al. [25] constructed a series of novel machine learning (ML) models to predict pollutant gas concentrations, identify emission source parameters, and compared the performance of various ML models. Qiu et al. [26] proposed a method for predicting harmful gas atmospheric diffusion and estimating pollution sources based on artificial neural networks (ANN), particle swarm optimization (PSO), and expectation maximization (EM). Zheng et al. [27] introduced a method for identifying nuclear explosion source parameters by combining genetic algorithm (GA) with PSO algorithm. These studies demonstrate that NN and optimization algorithms can serve as powerful tools for pollution prediction, source parameter assessment, and risk analysis. However, improving prediction accuracy and selecting optimal solutions for source parameter evaluation remain

pressing challenges that require resolution. We introduce a hybrid deep learning approach combined with the Python Metaheuristic Evolutionary Algorithm Library (MEALPY) to address these challenges [28, 29].

This research investigates pollution area prediction in extreme nuclear energy safety emergencies and source parameter inversion based on hybrid deep learning and metaheuristic algorithms. The effects of different nuclear explosion yield (Q), wind speed (v), wind shear (u), and fission fraction (f_f) on the on-site radiation dose distribution one hour after nuclear explosion were analyzed. Then, a dataset of nuclear explosion parameters and corresponding pollution areas in different radiation zones was established based on radiation source safety standards. Hybrid deep learning was employed to establish the implicit functional relationship between nuclear explosion parameters and pollution areas, and the impact of different network architectures on prediction accuracy was analyzed through error evaluation indicators and error graphs. MEALPY was utilized to perform parameter inversion, with eight optimization algorithms including AO, BBO, and EFO. Through box plot and adaptive curve analysis, the performance of different optimization algorithms in terms of robustness and accuracy was evaluated. This research provides a scientific basis for decision-making in nuclear emergency management and holds significant practical importance and value.

II. Theoretical and Simulation Models

To further explore the evolution mechanism of radioactive deposition in nuclear safety emergencies, reveal the intrinsic correlations between parameters and radiation contamination areas, and achieve parameter inversion, this study adopts a framework combining hybrid deep learning and metaheuristic algorithms for prediction and inversion under the WSEG-10 model. The overall architecture is illustrated in Fig. 1 [Figure 1: see original paper]. Fig. 1 depicts three main steps: simulating and analyzing the formation, growth, and transport processes of nuclear explosion smoke through theoretical programs, as well as key physical processes including sedimentation mechanisms, radioactive activity, and biological dose calculations in Fig. 1(a). Fig. 1(b) shows the combination of various hybrid deep learning methods such as Bayesian optimization (BO), convolutional neural networks (CNN), long short-term memory networks (LSTM), and attention mechanisms based on radiation source safety standards to achieve more accurate prediction. Fig. 1(c) shows the inversion of nuclear explosion source parameters by metaheuristic algorithms.

A. WSEG-10 Model

In nuclear safety emergencies, the temperature in the nuclear reaction zone rises to tens of thousands of degrees Celsius, while the pressure increases to tens of billions of atmospheres. Under such extreme high-temperature and high-pressure conditions, the nuclear device instantaneously vaporizes into plasma, heating and pressurizing the surrounding cold air. The rapidly expanding gas

forms a short-lived giant fireball. This fireball rapidly rises and expands, forming a mushroom-shaped smoke cloud. The smoke cloud generates strong vortex motion internally, and powerful suction and entrainment effects trap ground dust and other substances within the smoke cloud. When the cloud reaches its maximum height, the temperature and pressure inside the cloud become similar to the surrounding atmosphere, the vortex motion dissipates, upward cloud movement ceases, and the system enters the turbulent separation stage.

To study the phenomenon of smoke cloud diffusion, the WSEG-10 model from the weapons systems evaluation group series was introduced. WSEG-10 is an empirical local subsidence prediction model based on early nuclear test data that assumes 80% of radioactive material settles locally. The WSEG-10 simulation of radioactive smoke diffusion is primarily divided into four processes: initial smoke state setting, dynamic smoke diffusion process, settling mechanism, and biological dose calculation.

In the initial state setting of the smoke cloud, based on nuclear explosion empirical data, the center height of the stable radioactive smoke cloud geometric structure can be obtained as [8, 30]:

$$Hc = 44 + 6.1 \ln(Q) - 0.205 |\ln(Q) + 2.42| (\ln(Q) + 2.42)$$

where Q is the nuclear explosion yield measured in megatons (Mt), and Hc is the center height of the stable radioactive cloud geometry measured in kilometers (km). Assuming radioactivity in a stable radioactive cloud follows a normal distribution in both vertical and horizontal directions, the radioactive density function $\rho(x, y, h)$ is expressed as:

$$\rho(x, y, h) = \frac{1}{(2\pi)^{3/2} \sigma_o^2 \sigma_h} \exp \left(-\frac{x^2 + y^2}{2\sigma_o^2} - \frac{(h - Hc)^2}{2\sigma_h^2} \right)$$

where x and y are the distances in the downwind and crosswind directions respectively, h is the height above the ground, σ_o is the horizontal diffusion parameter, and σ_h is the vertical diffusion parameter. The horizontal diffusion parameter σ_o is expressed as:

$$\sigma_o = \exp \left(0.7 + \frac{\ln(Q)}{4.0 + (\ln(Q) + 5.4)^2} \right)$$

The vertical diffusion parameter σ_h is expressed as:

$$\sigma_h = 0.18Hc$$

During the dynamic diffusion process of smoke clouds, over time, the range of stable radioactive smoke clouds expands and their position shifts horizontally,

causing sediment to fall to the ground. This horizontal movement is primarily influenced by three effects. The first effect is the circulation effect, which causes early settling particles to be swept toward the center of the cloud, resulting in a settling pattern that is compressed near the ground explosion origin. The second effect is the wind effect, where the vertical range of the smoke cloud is influenced by an effective wind vector that transfers the radioactive dust cloud in the downwind direction. The third effect is the wind shear effect, which contributes to smoke cloud expansion and diffusive settling. The combined effects of circulation, wind, and wind shear are reflected in the downwind diffusion parameters (σ_x) and crosswind diffusion parameters (σ_y).

The formula for the downwind diffusion parameter σ_x is:

$$\sigma_x = \sigma_o^2 + 8\sigma_o^2 + 2\sigma_o^2$$

The downwind settlement activity distribution f_x is given by:

$$f_x = \frac{Q \cdot SNC \cdot \phi \cdot g(x) \cdot f_f}{\sqrt{2\pi}\sigma_x}$$

where f_f is the fission fraction ($0 < f_f \leq 1.0$), and SNC is the source normalization constant with $SNC = 2 \times 10^6$. ϕ is the empirical function for wind direction correction.

The formula for the crosswind diffusion parameter σ_y is:

$$\sigma_y = \sigma_o^2 (8|x + 2\sigma_x| \sigma_o^2 L^2 (\sigma_x T_c \sigma_h S_c)^2 L^4 ((x + 2\sigma_x) L_o T_c \sigma_h S_c)^2)^{1/2}$$

where L_o is the wind field action scale, and $L_o = v \cdot T_c$, v is the wind speed. T_c is the time constant, which is related to the smoke cloud height H_c . The specific empirical formula is:

$$T_c = 1.057 \exp\left(\frac{12}{H_c} - 2.5\right)^2 \left(1 - 0.5e^{-(H_c/25)^2}\right)$$

where S_c is the crosswind shear strength, L is the total scale that primarily coordinates the coupling effect between the wind field action scale L_o and downwind diffusion σ_x , with $L^2 = L_o^2 + \sigma_x^2$.

In the analysis of the settlement process, the settlement rate function $g(t)$ and the cumulative settlement function $G(t)$ are introduced to describe the proportion of radioactive activity reaching the ground per unit time and the cumulative settlement amount, where $G(t) = \int_0^t g(t') dt'$.

The function $g(t)$ can be expressed as:

$$g(t) = \frac{t^n}{T_c^{n+1}\Gamma(1 + 1/n)} \exp\left(-\frac{t}{T_c}\right)^n$$

where n is the dynamic index given by:

$$n = \frac{n_0 L^2}{\sigma_o^2 + 0.5\sigma_h^2}$$

And n_0 is the vertical distribution shape parameter, expressed as:

$$n_0 = 1.5 - 0.25 \left(\frac{Hc}{60}\right)^2$$

Γ is the gamma function.

In practical nuclear emergency response, the key requirement is to determine the distribution of radioactive material deposition at different ground locations rather than just temporal changes. Due to observational limitations, ground monitoring radiation doses are typically spatially distributed. The relationship between time and space is given by $g(t)dt = g(x)dx$ and $x = v \cdot t$, where radioactive particles are uniformly blown in the downwind direction by wind speed v , and x is the distance in the downwind direction. Consequently, the spatial settlement distribution $g(x)$ can be expressed as:

$$g(x) = \frac{|x|^n}{L^{n+1}\Gamma(1 + 1/n)} \exp\left(-\frac{|x|}{L}\right)^n$$

The crosswind settling activity distribution f_y can be expressed as:

$$f_y = \frac{1}{\sqrt{2\pi}\sigma_y} \exp\left(-0.5\frac{y^2}{\sigma_y^2}\right)$$

where α_2 is the adjustment factor, given by $\alpha_2 = (1 + 0.001 \cdot Hc \cdot v)(1 - \phi(2x/L_o))$.

The biological dose can be expressed as:

$$D_o = D_{H+1} \cdot B_o$$

where D_{H+1} is the unit time reference dose rate (R/hr) for 1 hour after detonation, calculated as:

$$D_{H+1} = f_x \cdot f_y$$

Biological dose conversion (Bio function) converts physical dose rates into effective human damage, considering permanent accumulation of 10% dose for irreparable damage and repair of 90% dose for repairable damage with a half-life of 30 days.

The second-order approximate formula for calculating biological dose Bo is [31]:

$$Bo = e^{-(0.287+52\ln(t_a/31.6)+0.04475\ln(t_a/31.6)^2)} \left(0.25 + \frac{L^2(L^2 + \sigma_o^2(x + 2\sigma_x)T_c^2)}{\sigma_o^2 + 0.5\sigma_h^2} \right)$$

where t_a is the average expected time for sediment to arrive. Based on the WSEG-10 model described above, radioactive deposition simulation has been achieved, and physical processes including initialization, particle distribution, deposition mechanisms, radioactive activity, and biological dose calculations of stable radioactive smoke clouds have been simulated and analyzed.

B. Pollution Area Prediction Based on Hybrid Deep Learning Model

Due to the serious environmental pollution caused by radioactive deposition, the calculation of radiation pollution area under different parameters has attracted much attention. To increase the accuracy of the pollution area prediction model, we have constructed a hybrid deep learning model that integrates BO, CNN, Long Short-Term Memory Network (LSTM), Gated Recurrent Unit (GRU), Bidirectional Long Short-Term Memory Network (BiLSTM), and Attention mechanism to achieve high-precision prediction. Firstly, the WSEG-10 model is used to calculate the radiation pollution area corresponding to different parameters, and then a dataset of parameters and pollution area is constructed. Then, the hybrid deep learning model with multiple components was built, trained, and tested [32-35].

The proposed hybrid deep learning model includes four parts: CNN, time series algorithms (LSTM, GRU, BiLSTM), attention mechanism, and BO. Among them, CNN, as a deep neural network with convolutional architecture, can efficiently extract feature information while reducing model complexity and modeling parameters due to its shared weights and local connections. The use of time series analysis represents an improved approach based on Recurrent Neural Networks (RNNs), designed to address the gradient vanishing and exploding problems encountered by RNNs when processing long sequence data. The Attention mechanism dynamically adjusts the weight allocation of input features, enabling the model to adaptively focus on the most critical input components for the task. Finally, BO is employed to efficiently search the hyperparameter space, which can identify near-optimal hyperparameter combinations in fewer iterations and significantly enhance model performance. By progressively incorporating these modules, the accuracy of nuclear explosion contamination area prediction is continuously improved.

C. Source Term Parameter Inversion Based on MEALPY

To accurately analyze the diffusion of radioactive materials in nuclear explosions, predictive models must rely on precise nuclear explosion parameters, including meteorological parameters, explosion center coordinates, and Q . Therefore, the accuracy of nuclear explosion source parameters significantly affects the effective implementation of subsequent nuclear emergency response measures. However, in practical situations, obtaining accurate values of nuclear explosion source terms is extremely challenging. Here, metaheuristic algorithms were employed to invert the parameters (i.e., explosion center position, Q , v , u). Metaheuristic algorithms represent a general term for iterative optimization algorithms inspired by nature, which are classified into Swarm Intelligence (SI) algorithms, Evolutionary Algorithms (EA), Physics-based Algorithms (PhA), and Human-like Algorithms (HLA). Optimization algorithms are mainly categorized into four types:

Swarm Intelligence (SI), inspired by natural group behaviors (e.g., Ant Colony Optimization (ACO) by ant foraging [36], Artificial Bee Colony (ABC) by collective bee behavior [37]); Evolutionary Algorithms (EA), based on biological evolution (e.g., Genetic Algorithm (GA) by Darwin's evolution theory [38], Differential Evolution (DE) that iteratively preserves adaptive individuals from a random initial population to simulate evolution [39]); Physical Algorithms (PhA), relying on physical laws (e.g., Electromagnetic Field Optimization (EFO) by physics' electromagnetic field theory [40], Multi-Verse Optimizer (MVO) by physics' multiverse theory [41]); and Human-Inspired Algorithms (HLA), simulating human thinking/behavior (e.g., Human Cognitive Optimization (HCO) by human memory, learning and reasoning, Battle Royale Optimization (BRO) by group brainstorming via random generation and optimal solution selection). Using these eight algorithms (ACO, ABC, GA, DE, EFO, MVO, HCO, BRO), a nuclear explosion pollution source parameter inversion model was built, providing strong technical support for post-nuclear explosion environmental monitoring and emergency response.

III. Results and Discussion

Based on the principles of cloud transport, settling mechanism, radioactive activity, and biological dose calculation in WSEG-10, numerical simulation was conducted to obtain the radiation dose distribution within one hour after a nuclear explosion. To investigate the relationship between parameters and dose distribution, controlled variable studies were performed for four key parameters: nuclear explosion yield (Q), wind speed (v), wind shear (u), and fission fraction (f_f). Since f_f is directly proportional to radiation deposition and changes in f_f will cause corresponding changes in the deposition dose, and changes in f_f affect the deposition dose magnitude but not the deposition area shape, f_f was set to 0.67 for this analysis. The relationship between Q , v , u , and the radiation deposition dose is shown in Figure 2 [Figure 2: see original paper]. The contour lines of on-site radiation doses exhibit elliptical patterns, with their major axis

orientation aligned with the wind direction v .

Firstly, with v and u set to 6 km/h and 2.91 h^{-1} , respectively, Q was varied sequentially as 0.04, 0.4, and 4 Mt. The on-site dose distribution 1 hour after nuclear explosion are shown in Fig. 2(a), 2(b), and 2(c). As Q increases, the radiation deposition dose gradually increases, and the contaminated area expands. Then, with Q and u set to 0.04 Mt and 2.91 h^{-1} , respectively, v was varied as 6, 10, and $26 \text{ km} \cdot \text{h}^{-1}$. The corresponding dose distributions are shown in Fig. 2(d), 2(e), and 2(f). As v increases, the radiation deposition dose gradually decreases, and the ellipse representing the contaminated area becomes narrower in the minor axis direction while elongating in the major axis direction. Finally, with Q and v set to 0.04 Mt and 9.7 km/h, respectively, u was varied as 0.76, 4.36 and 7.95 h^{-1} . The corresponding dose distributions are shown in Fig. 2(g), 2(h) and 2(i). It can be concluded that as u increases, the radiation deposition dose gradually decreases while the contaminated area expands. From Fig. 2, the major axis length of the ellipse corresponding to the contaminated area primarily depends on Q and v , while the minor axis length primarily depends on u .

To comprehensively evaluate the radiation conditions in a nuclear explosion environment, pollution areas were calculated based on basic standards for ionizing radiation protection and radiation source safety. The relationship between radiation deposition dose and human injury is presented in Table 1. According to the varying degrees of damage caused by radiation deposition dose to the human body, radiation areas are classified into six levels: negligible dose, sub-clinical dose, mild radiation sickness dose, moderate radiation sickness dose, severe radiation sickness dose, and lethal dose. The negligible dose range (0-50 R) has minimal impact on the human body. To calculate pollution areas, a filtering approach was implemented to automatically determine the number of different regions in the computational grid and multiply this number by the corresponding area of each grid to obtain the pollution area. Additionally, to avoid inaccurate pollution area calculations due to range limitations, a larger computational range of $100 \times 100 \text{ km}^2$ grid was selected.

Fig. 3 shows the relationship curve between different nuclear explosion parameters and corresponding contaminated areas. Fig. 3(a) demonstrates that as Q increases, the area of each radiation zone also increases. Fig. 3(b) illustrates the effect of v on the area of each radiation region. As v increases, the area of the 50-1000 R region increases, while the area of the region exceeding 1000 R decreases. This occurs because v promotes radiation diffusion and reduces radiation concentration in the original heavily polluted area. Fig. 3(c) shows the relationship between f_f and contaminated area. When f_f is low, the contaminated area is zero. As f_f increases, the contaminated area also increases. Fig. 3(d) demonstrates the effect of u on the area of each radiation region. As u increases, the area of the 50-500 R region increases, while the area of the region exceeding 500 R decreases.

A total of 1200 datasets were generated within parameter variation ranges of Q

(0.01-1 Mt), v (0.5-9 km/h), u (0.252-1.152 h^{-1}) and f_f (0.2-1). These data were divided into training and testing sets in a 7:3 ratio. The input features consist of nuclear explosion parameters (Q , v , u , f_f), while the outputs correspond to pollution areas for each radiation zone. To accurately predict the mapping relationship between radiation contamination areas and nuclear explosion parameters, a hybrid deep learning methodology was employed to construct a prediction model.

Fig. 4 presents a performance comparison of different deep learning models for predicting contaminated areas at subclinical dose levels. Fig. 4(a)-Fig. 4(i) respectively show CNN, GRU, LSTM, CNN-LSTM, CNN-GRU, CNN-LSTM-Attention, CNN-BiLSTM-Attention and BO-CNN-BiGRU-Attention models. Based on the R^2 indicators of each model, CNN, LSTM, CNN-LSTM, CNN-LSTM-Attention, and BO-CNN-LSTM-Attention achieved scores of 0.8555, 0.9778, 0.9727, 0.989, and 0.998 respectively, demonstrating that continuous optimization of the model structure significantly improves prediction accuracy. Specifically, the CNN-LSTM-Attention model outperforms CNN-LSTM and CNN-GRU, as the attention mechanism can adaptively focus on key information within the input sequence, thereby improving model prediction accuracy. The BO-CNN-LSTM-Attention model demonstrates superior performance compared to the CNN-LSTM-Attention model, as BO can automatically search for the optimal hyperparameter combination, further enhancing prediction accuracy. Therefore, hybrid deep learning methods can significantly improve model predictive capabilities.

To evaluate the performance of various hybrid deep learning models, loss curves, multi-evaluation index radar charts, prediction error curves, and box plots were introduced for in-depth analysis of each model. Fig. 5 presents the comparative performance of various models and evaluates the advantages of hybrid deep learning methods from multiple perspectives, which can help optimize prediction model design. Fig. 5(a) shows the loss curves of each model. Fig. 5(b) displays the radar chart of multiple evaluation metrics for each model, indicating that the BO-CNN-LSTM-Attention model achieves the best overall metrics. Fig. 5(c) shows the error curves of each model, which plots the error distribution between predicted and true values. Analyzing the shape and distribution of the error curves helps identify systematic bias in models and evaluates their predictive capabilities across different data intervals. Fig. 5(d) shows the RMSE boxplots corresponding to different prediction models, indicating that hybrid deep learning models perform relatively stable under different random seeds, verifying the reliability of the BO-CNN-LSTM-Attention approach. The introduction of BO for automatic optimal hyperparameter combination search, combined with the dynamic attention mechanism, significantly reduces the minimum loss function value and improves model predictive performance.

To better reflect the feasibility of hybrid deep learning methods, a comparative analysis was conducted on the prediction of mild radiation sickness dose, moderate radiation sickness dose, severe radiation sickness dose, and lethal dose. The

MAE and R^2 indicators of the test set were quantitatively characterized. The performance evaluation indicators of the pollution area prediction model are shown in Table 2. The indicators are the results obtained for different methods under the condition of setting the random seed to 8. To ensure the consistency of the algorithm, the CNN architecture employed here features two convolutional layers: the first convolutional layer uses convolution kernels of size [1,1] with 16 output channels, while the second convolutional layer utilizes kernels of size [3,1] with 64 output channels. In addition to the BO algorithm, LSTM or GRU layers in all other models incorporate 6 hidden units and attention mechanisms to enhance model prediction performance.

BO optimization was performed for the number of hidden layer nodes, initial learning rate, and regularization coefficients. The search range for the number of nodes was set to integers between 10 and 100. The initial learning rate was set between 10^{-3} and 1, with logarithmic transformation applied to accommodate different orders of magnitude. The search range for regularization coefficients was set between 10^{-10} and 10^{-2} , also employing logarithmic transformation. The maximum number of iterations was set to 5 to ensure robust convergence. As shown in Table 2, with continuous algorithm improvement and optimization, predictive capability gradually increases. Furthermore, when BO was introduced, R^2 values increased from 0.81 to 0.99, significantly enhancing the algorithm's predictive ability and verifying BO's effectiveness as an efficient parameter optimization method.

To achieve more accurate inversion of explosion source term, the MEALPY library was introduced to implement multiple metaheuristic algorithms for source term inversion [23, 27]. The specific implementation approach involves setting a parameter set for simulation, randomly extracting radiation settling doses corresponding to monitoring points, and using these as the real radiation field environment. Each random value serves as initial nuclear explosion source parameters input into the WSEG-10 model, obtaining radiation settling doses corresponding to monitoring points. Subsequently, a loss function is constructed using the known actual radiation settling doses of monitoring points. The ACO, ABC, GA, DE, EFO, MVO, HCO, and BRO optimization algorithms are employed for parameter inversion. Differences between source term parameters output by various optimization algorithms and preset true values are compared to evaluate algorithm performance in source term inversion.

The nuclear explosion location was set to coordinates (3 km, 3 km), with Q , f_f , v , u values of 0.1 Mt, 0.67, $10 \text{ km} \cdot \text{h}^{-1}$, and 0.828 h^{-1} , respectively. 500 data points were randomly selected from the simulated radiation deposition dose data. A loss function was constructed using the mean square error (MSE) between true values and predicted values. Different metaheuristic algorithms were then employed to optimize nuclear explosion parameters, with a maximum iteration count of 50 and population size of 10. The minimum value of the custom loss function was identified, and population information for each generation was saved. Finally, fitness curves for selected optimal algorithms were

plotted, with specific inversion results shown in Fig. 6. Fig. 6(a) shows the spatial distribution of random data sampling points, which randomly cover the established parameter space to ensure data representativeness. Fig. 6(b) shows the fitness curves corresponding to metaheuristic algorithms, reflecting their convergence characteristics during the optimization process. The curves exhibit typical exponential decay features, with ABC and ACO algorithms demonstrating faster convergence speeds. The inversion results of the explosion source term parameters of the metaheuristic algorithm are presented in Table 3. The inverted parameters show high consistency with preset true values, indicating that this method demonstrates good applicability and reliability in source term inversion tasks. The proposed method provides new technological paradigms and methodological support for constructing next-generation intelligent nuclear pollution platforms.

IV. Summary

In this study, a fast prediction model was designed using a hybrid deep learning approach to predict radioactive pollution diffusion areas under extreme nuclear energy safety emergencies. Metaheuristic algorithms were employed to invert nuclear explosion source terms. By analyzing the complex relationships between key nuclear explosion parameters (Q , v , u , f_f) and radiation deposition doses and contamination areas, a dataset of nuclear explosion parameters and corresponding contamination areas was constructed. A high-precision BO-CNN-LSTM-Attention prediction model was developed by integrating BO and attention mechanism. The performance of different algorithms for parameter inversion was comparatively analyzed, revealing that ABC and ACO algorithms demonstrate faster convergence speeds. The BO-CNN-LSTM-Attention prediction model developed in this study can provide rapid response capabilities for predicting diffusion areas, helping to more accurately understand the scope and extent of nuclear explosion impacts. This research provides a scientific basis for nuclear energy safety, environmental protection, and public health, and is crucial for decision support and emergency management in crisis situations.

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