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A Genetic-Algorithm-based Neural Network Approach for Radioactive Activity Prediction Postprint

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Abstract

This paper proposes a genetic-algorithm-based artificial neural network (GAANN) model for radioactivity prediction, which is validated using measurement results from a Long Range Alpha Detector (LRAD). The GAANN model integrates the approximation capabilities of Artificial Neural Networks (ANN) with the global optimization capabilities of Genetic Algorithms (GA), thereby theoretically enhancing generalization capability and prediction accuracy. In this model, both the number of hidden nodes and the connection weight matrix of the ANN are optimized through genetic operations. Real-world datasets are applied to the proposed method, and the results are discussed and compared with those of traditional Back Propagation (BP) neural networks, demonstrating the feasibility and validity of the proposed approach.

Full Text

Preamble

A Genetic-Algorithm-Based Neural Network Approach for Radioactive Activity Prediction

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Abstract
This paper proposes a genetic-algorithm-based artificial neural network (GAANN) model for radioactivity prediction, verified using measurement

results from a Long Range Alpha Detector (LRAD). Theoretically, GAANN integrates the approximation capabilities of Artificial Neural Networks (ANN) with the global optimization of Genetic Algorithms (GA), thereby enhancing generalization capability and prediction accuracy. In this hybrid model, both the number of hidden nodes and the connection weights matrix in the ANN are optimized through genetic operations. Real datasets are applied to validate the proposed method, and the results are discussed and compared with those from traditional Back Propagation (BP) neural networks, demonstrating the feasibility and validity of the approach.

Key words
Long range alpha detector, Genetic algorithms, Radioactivity, Prediction

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Introduction

The LRAD detection system typically consists of five units: sample detection (ion chamber and measurement chamber), air-driven component, power supply, signal acquisition unit, and signal processing unit. This technique indirectly detects alpha radioactivity by collecting ions produced by alpha particles inside pipelines, overcoming limitations of direct alpha detection such as short range and inability to penetrate facility walls. Many scholars have conducted preliminary studies confirming that distance, length, diameter, radioactivity, wind speed, and air flux all influence final measurement results [1 5]. Our statistical analysis of LRAD experimental results has demonstrated a nonlinear relationship between testing parameters and measurement outcomes.

In recent years, with the decommissioning of numerous nuclear facilities and increasing demand for waste treatment, existing radioactive pipes require proper handling. To sort and treat alpha radioactive pipes before disposal, radioactivity surveys must be conducted to assess whether pipes meet limit requirements. Alpha particles released by nuclides in pipelines are partially absorbed by pipe walls, making it difficult to detect alpha contamination using external direct testing methods. LRAD technology provides an effective approach to obtain alpha pollution information from inside pipelines.

Methodology

The GAANN model employs a three-layer architecture with m nodes in the input layer, h nodes in the hidden layer, and n nodes in the output layer. The implementation involves two main phases: first determining a basic state space for the connection weights matrix, then encoding both the number of hidden nodes and connection weights into a mixed string comprising integer and real values [7,8]. The experimental data is divided into three parts: training sample ϕ_{11}, ϕ_{12}, cross-validation sample ϕ_{21}, ϕ_{22}, and testing sample ϕ_{31}, ϕ_{32}.

Step 1: Initialize connection weights within [1,1] for training samples ϕ_{11}, ϕ_{12}. Adjust the weights until the desired error tolerance $_{11}$, $_{12}$ is achieved. The maximum and minimum weight values are denoted as u and u , respectively.

Step 2: Encode connection weights and number of hidden nodes. Hidden nodes are encoded as a binary code string, where 1 indicates connection to input and output nodes and 0 indicates no connection. Weights are encoded as a float string with length $H = m \times h + h + h \times n + n$ (where m is the number of input nodes, n is the number of output nodes, and h is the number of hidden nodes). Each string corresponds to a chromosome consisting of multiple gene sections, as illustrated in Table 1.

Step 3: Initialize a population of chromosomes. The length L of each chromosome equals $G + H$, where G is the length of binary code for the number of hidden nodes and H is the length of real-valued code for connection weights.

Step 4: Calculate individual fitness according to Equation 2.

Step 5: Copy the highest-fitness individual directly to a new offspring and select other individuals using the roulette wheel method [9].

Step 6: Apply basic crossover and mutation operations to the control code. If a hidden node is deleted (or added) according to mutation operation, the corresponding control code is encoded as 0. The crossover and mutation operators for weights are implemented as follows:

Crossover operation with probability p : X and X_{1} are a pair of individuals before crossover, while X^{+1} and X_{1}^{+1} are the pair after crossover, where c is a random value within [0,1].

Mutation operation with probability p : X is an individual before mutation, X^{+1} is the individual after mutation, and c is a random value within ($u \quad \delta_1 X$, $u \quad + \delta_2 + X$).

Step 7: Generate the new population and replace the current population. Repeat procedures (Step 4 7) until convergence conditions (min $E_2 <$ $_2$ and min $E_3 <$ $_3$) are satisfied, where $k = 1, 2, 3$ corresponds to the three datasets.

Step 8: Decode the highest-fitness individual to obtain the corresponding number of hidden nodes and connection weights, then output the prediction results.

Model Implementation and Results

To evaluate model performance, representative ^{239}Pu sources were selected: a strong source (3200.00 Bq) and a weak source (24.05 Bq). A prediction model was established where measured distance, tube length, diameter, wind speed, and air flow constitute the input layer, and ionization voltage serves as the output layer. In this configuration, the ionization voltage value represents radioactivity intensity as a linear prediction output. The relationship between radioactivity and ionization voltage was established experimentally. After measuring the ionization voltage value, it is compared with the standard source to calculate radioactive intensity.

Model parameters are listed in Table 2. In simulations, a three-layered BP neural network first estimates the basic state space of connection weights, yielding minimum and maximum values of –1.21 and 0.96, respectively. With $\delta_1 = -0.09$ and $\delta_2 = 0.04$, the weight range is set to [–1.3, 1.0]. The number of input neurons is 5 and hidden nodes is 6. The activation function from input to hidden layer is Sigmoid, while from hidden to output layer is Purelin. For the proposed hybrid neural network, the system parameters in Table 2 are applied to training samples and prediction.

To test model performance under the 3200.00 Bq alpha source, training error $_{11} = 0.05$, validation error $_{12} = 0.10$, and testing error $_{13} = 0.10$ were set. The training results are shown in Fig. 1. Under the weak source environment, measurement error is larger, so training error $_{21} = 0.15$, validation error $_{22} = 0.30$, and testing error $_{23} = 0.30$ were set for the 24.05 Bq case, as shown in Fig. 2.

For comparison with other neural network models such as the basic BP neural network, three error metrics commonly used in the literature were employed: mean absolute percentage error (MAPE), maximum absolute percentage error (MAXAPE), and minimum absolute percentage error (MINAPE). Due to the randomness of initial connection weights and thresholds, 50 prediction models were generated.

Error comparisons are presented in Tables 3 and 4. The 95% confidence interval was used for neural network ensemble with parameters from Table 2. The results demonstrate that the approximation capability of this model is superior to the traditional approach for both weak and strong radioactive sources, though error precision remains relatively large for weak sources. This limitation motivates further model improvements to be reported in future publications.

Conclusion

This paper proposes a GA-based neural network approach for LRAD radioactivity survey research. Network structure is optimized and connection weights are adjusted through genetic operators. Experiments with LRAD data demonstrate that the predictive performance of the proposed model exceeds that of tradi-

tional BP neural networks. However, weak radioactive sources exhibit poorer prediction accuracy. Future work should consider improvements including different time windows, prediction horizons, crossover and mutation operators, and dataset classification. This research is currently in progress.

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