Radiation threat assessment based on MEA-BP neural network

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Abstract. In order to promote the effectiveness of radiation threat assessment, this article builds the mind evolutionary algorithm (MEA) to optimize the BP neural network model of radiation threat assessment. The mind evolutionary algorithm was used to optimize the BP neural network model, through global population convergence and local populations of alienation, the network's initial weights and threshold and then training the BP neural network, overcoming the random initial value when the disadvantages of neural network fall into the local optimum. The experimental results show that the evaluation results of the BP neural network optimized by the thinking evolution algorithm are significantly smaller than the mean square error of the BP neural network, this algorithm can quickly and effectively implement radiation threat assessment.

1. Introduction

With the application of high and new technology, electronic warfare is gradually moving towards intelligent, informatization. It becomes more difficult to implement accurate effective reconnaissance warning for enemy radar emitter, we face the threat of surge. Radar emitter threat assessment is indispensable part of radar emitter reconnaissance warning.

For radiator threat assessment, the literature [1] constructs the performance optimization of generalized intuitionistic fuzzy soft set. Literature [2] solves the problem of static threat assessment by combining the theory of intuitionistic fuzzy entropy and VIKOR method. Literature [3-4] respectively introduces intuitionistic fuzzy approximate confidence measures and new concepts such as interval intuitionistic fuzzy sets, to improve the accuracy of threat assessment. Literature [5] considers cloud model to deal with the advantage of fuzzy data, applied to the degree of threat assessment. Literature [6] effectively solves the problem of insufficient input data volume in by constructing the bayesian networks of probabilistic inference ability. Literature [7] introduces threat level sort sorting model and the optimization model in determining weight method to achieve a more accurate estimate. Literature [8] solves the problem of incomplete of radiation source attributes and uncertainty by combining rough set and information entropy for evaluation.

Although above literatures solve the problem of radiator threat assessment in a certain extent, they depend on expert system and a priori knowledge. Models rely on manual calculation and are low degree of automation. Insufficient to make up for the above, literature [9-10] introduces BP neural network, and updates the weight values to get the optimal weights of radiator threat assessment through the training data for supervised learning. The simulation results prove the validity of the model. BP (Back Propagation) neural network is a feedforward neural network with error backward Propagation functions, widely used in various fields of social life[11-13]. But the BP neural network parameters of the initial random, easily trapped in local optimal solution, and the convergence speed is
slow. Mind Evolutionary Algorithm (MEA) is a new type of intelligent Algorithm, and has a good optimization features\cite{14-15}. Aiming at the defects of BP neural network, this article uses MEA for optimization of initial parameters (weights), and builds a radiator threat assessment based on MEA - BP neural network model.

2. Mind Evolutionary Algorithm
Mind evolutionary algorithm is a branch of evolutionary algorithm, by simulating the human mind evolutionary process of optimization. Compared with the traditional evolutionary algorithm, the mind evolutionary algorithm can search more efficient and obtain the global optimal solution at a faster pace. Mind evolutionary algorithm system structure diagram is as follows:

![Mind Evolutionary Algorithm System Structure Diagram](image)

**Figure 1. Mind evolutionary algorithm system structure diagram**

MEA working process is as follows:

Step 1 Generate the initial individual. The objective function scores randomly generated individuals, and produces superior individual and temporary individual according to the individual results.

Step 2 Generate superior subgroups and temporary subgroups. Respectively around the superior individual and temporary individual randomly generating new individuals, and aggregated into superior subgroups and temporary subgroups.

Step 3 Individual convergence. For Step 2 which all individuals are calculated separately, the scores will collect information on the local bulletin boards. After the convergence process again and subgroups mature, scoring the highest individual scores as their child group score.

Step 4 Subgroups alienation. Global information bulletin board record all child groups, and then alienation.

Step 5 Produce the optimal solution. After subgroups alienation being stable, removing scored highest winning subgroups of individuals as the global optimal solution algorithm.

3. BP neural network
BP neural network is a kind of multilayer feedforward neural network, updating weights and threshold through a reverse transmission error. And finally get the optimal solution by the continuous training.
BP neural network is composed of input layer, hidden layer and output layer, and nodes are connected by a certain weight.

The structure of BP neural network is as follows:

The input layer
\[ x_i \]

Hidden layer
\[ \sum_{j=1}^{n} \omega_{ij} x_j - e_i \]

Output layer
\[ y_k = y_k - u_k \]

Among them, \( x_i (i=1,2,\cdots,m) \) is input of neural network. \( y_k (k=1,2,\cdots,n) \) is output of neural network. \( x'_j (j=1,2,\cdots,l) \) is hidden layer nodes of neural network. \( \omega_{ij} \) is the weight of connecting the input layer nodes and hidden layer nodes. \( \omega_{jk} \) is the weight of connecting the output layer nodes and hidden layer nodes. \( e \) and \( f \) are the threshold value of hidden layer and output layer. Assume that the input layer for excitation function \( p(x) \), the hidden layer for excitation function \( g(x) \).

BP neural network learning steps as below:

Step 1 Initialize network structure. Input layer node number is determined by the input data. Output layer node number is determined by the output data, and the number of hidden layer nodes is determined by the prior knowledge or training. Weights and threshold are determined randomly.

Step 2 Hidden layer outputs. Based on the input \( x_i (i=1,2,\cdots,m) \) and the hidden layer excitation function, \( x'_j \) is as follows:

\[
x'_j = p \left( \sum_{i=1}^{m} \omega_{ij} x_j - e_j \right) (1)
\]

Step 3 Output layer output. According to the excitation function and the output layer, \( g(x) \) is as follows:

\[
u_k = g \left( \sum_{j=1}^{n} \omega_{jk} x'_j - f_k \right) (2)\]

Step 4 Calculate error and update the structure coefficient of reverse. Calculating error \( v_k \) firstly. Then update formula is optimized according to the weight and threshold. The learning rate is \( \eta \).

\[
v_k = y_k - u_k \quad (3)
\]

\[
\omega_{ij} = \omega_{ij} + \eta x'_j \left(1-x'_j\right) \sum_{i=1}^{m} \omega_{ij} v_i \quad (4)
\]

\[
\omega_{jk} = \omega_{jk} + \eta x'_j v_k \quad (5)
\]

\[
e_j = e_j + \eta x'_j \left(1-x'_j\right) \sum_{i=1}^{n} \omega_{jk} v_k \quad (6)
\]

\[
e_k = e_k + v_k \quad (7)
\]
4. Radiator threat assessment based on MEA-BP neural network

4.1. The indicator system of radiator threat assessment
Radiator threat assessment is always based on the investigation of radiator parameter information received. PDW (pulse description words) parameters are the most widely used. Traditional PDW parameters of PRI, PA, PW, DOA, RF. Among them, PA refers to the radiator signal transmitter detection budgeting received the amplitude of the pulse. The indicator is susceptible to the influence of many uncertain factors such as atmospheric attenuation, and is not as a general evaluation index. This article selects four indicators used in the literature [10] (PRI, PW, $\Delta DOA$, RF) to construct the index system of radiator threat assessment.

4.2. The model of radiator threat assessment
Based on mind evolutionary algorithm to get the initial threshold and right values in 4.1, and then instead of randomly selected. In this paper.
Concrete implementation steps are as follows:
Step1 Initialize the training set and testing set. The radiator information are received according to the investigation, then to determine the training set and test set.
Step2 Initialize BP neural network structure. According to the input and output of test set, to determine the input nodes and output nodes of BP neural network. Implicit layers are generally determined according to experience. According to the input layer, hidden layer and output layer, the weights and threshold vector are determined.
Step3 Local each population convergence. Randomly generated a number of individuals (on behalf of model weights and threshold), using the normalized after training. The difference of desired output and the actual output as the fitness of MEA algorithm (corresponding to the individual scores). All individuals’ operations according to local convergence bulletin board information.
Step4 Global population alienation. After waiting for each population to mature, according to the global child population of alienation bulletin board information for operation. Constantly updated optimization sub populations until reach the stop condition.
Step5 Based on optimal weight and threshold value, to construct the BP neural network assessment model. The best individuals as the initial weights and threshold of BP neural network.
Step6 Train network and test data. Using training set to train the BP neural network. And BP neural network is constantly updated until it satisfies the requirement of end stop. Inputing test set, and test set outputing of prediction model is the threat level of emitter test set.

5. Radiator threat assessment based on MEA-BP neural network

5.1. The simulation verification
To verify the validity of the proposed algorithm in this paper, radiator threat assessment index system is constructed based on the literature [10]. Using emitter PRF, $\Delta \theta$, PW and RF as the basis of radiator threat degree judgement. Normalized after radiator data such as table 1[10]. BP neural network input node number is 4, corresponding source attribute. The output node number of dimension is 1, corresponding source threat degree. The number of hidden layer nodes is 6. Network parameters Settings: MEA optimization algorithm the population is 200, and winning population is 5. Temporary population is 5, and the number of iterations is 10. BP neural network is 220 iteration, and iterative display interval of 10. The minimum error is 0.0001, and the learning rate is 0.1.
Table 1. Radiator data after normalization

| Radiator | PRF  | Δθ   | PW  | RF   | Threat degree |
|----------|------|------|-----|------|---------------|
| 1        | 0.4473 | 0.0550 | 0.3777 | 0.0540 | 0.3003        |
| 2        | 0.5900 | 0.1920 | 0.4292 | 0.3679 | 0.4386        |
| 3        | 0.4737 | 0.0550 | 0.3237 | 0.0540 | 0.3003        |
| 4        | 0.2493 | 0.1920 | 0.4292 | 0.3679 | 0.3305        |
| 5        | 0.4307 | 0.1516 | 0.3914 | 0.0540 | 0.4257        |
| 6        | 0.3555 | 0.0550 | 0.3237 | 0.0540 | 0.3305        |
| 7        | -0.3301 | -0.1516 | 0.0891 | 0.1662 | -0.2060       |
| 8        | -0.3207 | 0.1920 | 0.3777 | -0.0293 | 0.0076       |
| 9        | -0.3301 | -0.1516 | 0.2864 | -0.0570 | -0.1695       |
| 10       | -0.2493 | 0.1920 | 0.4123 | 0.3190 | 0.4898        |
| 11       | 0.7033 | 0.1920 | 0.3951 | 0.0017 | -0.1090       |
| 12       | 0.4737 | 0.1516 | 0.3237 | -0.0293 | -0.1090       |
| 13       | 0.2776 | 0.0550 | 0.3237 | 0.1087 | 0.2105        |
| 14       | 0.2776 | 0.1920 | 0.2864 | -0.1662 | -0.0611       |
| 15       | 0.0890 | -0.1516 | 0.3419 | 0.0260 | 0.0546        |
| 16       | 0.3389 | -0.1516 | 0.3419 | -0.017 | -0.1620       |
| 17       | 0.5223 | 0.1920 | 0.4292 | 0.4147 | 0.4076        |

5.2. The experimental results

Randomly selecting radiators from the 15 sets in table 1 as training set, and the remaining 5 groups as test set. First of all, using the neural network training set to train network. The four attributes of radiator as input, and threat degree as output. Then, completed test set source attributes as input of the neural network, and the network output is the actual value. Finally, the actual threat degree value and ideal threat degree are compared. To verify the effectiveness and superiority of the proposed algorithm, BP neural network not optimized as a comparison. In all five experiments, the experimental results are as follows:

(1) The simulation for the first time
The emitter threat degree obtained by the proposed algorithm and BP neural network are shown in table 2.

Table 2. Radiator threat degree value firstly

| Threat degree | Radiator x₁ | Radiator x₂ | Radiator x₃ | Radiator x₄ |
|---------------|-------------|-------------|-------------|-------------|
| Ideal value   | 0.3024      | -0.0483     | 0.3003      | 0.4386      |
| MEA-BP        | 0.3207      | -0.0551     | 0.3316      | 0.4352      |
| BP            | 0.3442      | -0.0610     | 0.3681      | 0.4470      |
| -0.3941       | 0.3204      | 0.2105      | -0.1090     | 0.3305      |
| -0.3816       | 0.2829      | 0.2088      | -0.1058     | 0.3914      |
| -0.3531       | 0.2253      | 0.2112      | -0.1408     | 0.4853      |

(2) The simulation for the second time
The emitter threat degree obtained by the proposed algorithm and BP neural network are shown in table 3.

Table 3. Radiator threat degree value secondly

| Threat degree | Radiator x₁ | Radiator x₂ | Radiator x₃ | Radiator x₄ |
|---------------|-------------|-------------|-------------|-------------|
| Ideal value   | -0.3941     | 0.3204      | 0.2105      | -0.1090     |
| MEA-BP        | -0.3816     | 0.2829      | 0.2088      | -0.1058     |
| BP            | -0.3531     | 0.2253      | 0.2112      | -0.1408     |

(3) The simulation for the third time
The emitter threat degree obtained by the proposed algorithm and BP neural network are shown in table 4.

Table 4. Radiator threat degree value thirdly

| Threat degree | Radiator x₁ | Radiator x₂ | Radiator x₃ | Radiator x₄ |
|---------------|-------------|-------------|-------------|-------------|
| Ideal value   | -0.3941     | 0.3204      | 0.2105      | -0.1090     |
| MEA-BP        | -0.3816     | 0.2829      | 0.2088      | -0.1058     |
| BP            | -0.3531     | 0.2253      | 0.2112      | -0.1408     |
IWAACE 2020
Journal of Physics: Conference Series 1550 (2020) 032107 doi:10.1088/1742-6596/1550/3/032107

(4) The simulation for the fourth time
The emitter threat degree obtained by the proposed algorithm and BP neural network are shown in table 5.

| Threat degree | Radiator $x_1$ | Radiator $x_2$ | Radiator $x_3$ | Radiator $x_4$ | Radiator $x_5$ |
|---------------|----------------|----------------|----------------|----------------|----------------|
| Ideal value   | -0.1708        | 0.3005         | -0.1695        | 0.4386         | -0.1620        |
| MEA-BP        | -0.1703        | 0.3292         | -0.1706        | 0.4307         | -0.1597        |
| BP            | -0.2794        | 0.3813         | -0.2874        | 0.3798         | -0.2709        |

(5) The simulation for the fifth time
The emitter threat degree obtained by the proposed algorithm and BP neural network are shown in table 6.

| Threat degree | Radiator $x_1$ | Radiator $x_2$ | Radiator $x_3$ | Radiator $x_4$ | Radiator $x_5$ |
|---------------|----------------|----------------|----------------|----------------|----------------|
| Ideal value   | -0.0483        | 0.2105         | 0.3024         | -0.1695        | 0.4386         |
| MEA-BP        | -0.0329        | 0.2759         | 0.2963         | -0.1703        | 0.3434         |
| BP            | -0.0825        | 0.0863         | 0.2227         | -0.1696        | 0.3332         |

Calculating threat degree of MEA-BP and BP neural network, the actual value and the ideal value of mean square error results are as follows:

| Threat degree | mse firstly | mse secondly | mse thirdly | mse fourthly | mse fifthly |
|---------------|-------------|--------------|-------------|--------------|-------------|
| MEA-BP        | 0.00059     | 0.00085      | 0.00063     | 0.00014      | 0.0027      |
| BP            | 0.00230     | 0.00650      | 0.02330     | 0.00870      | 0.0068      |

By above knowable, MEA-BP neural network and BP neural network can realize the threat level estimation of radiator. By calculating mean square error, evaluation error of MEA-BP neural network less than BP neural network not optimized. Proving validity and superiority of the proposed algorithm in this paper. The training set and testing set are selected randomly, furtherly proving the reliability of the proposed algorithm.

6. conclusion
According to the characteristics of radiator threat assessment and the existing literature radiator threat assessment index system, this paper introduces the applications of mind evolutionary algorithm (MEA). For the selection of initial weights and threshold optimization in BP neural network, this paper optimizes the values. It can improve the integrity of the model. The simulation results show that the proposed MEA-BP algorithm is lower than not optimized BP neural network for error, and it proves the validity and superiority of the model. The training set and test set in simulation are randomly selected, and the great evaluation results can prove the reliability and the generalization of the model.

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