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TARGET THREAT ASSESSMENT BASED ON FUZZY RECURRENT WAVELET NEURAL NETWORK

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Abstract. *In this paper, according to the problem of target threat assessment, a fuzzy recurrent wavelet neural network (FRWNN) is proposed, which combined the good performance of fuzzy neural network in approximating nonlinear functions with the prominent analysis ability of wavelet transform in time-frequency two-dimensional signal domains. Firstly, the structure of FRWNN and the influence of activation function on network performance are analyzed. Then, the main factors affecting target threat assessment are analyzed, and training algorithms and processes of the FRWNN are introduced. Finally, in order to demonstrate the efficiency of the proposed model, several banks of threat assessment techniques are compared by simulation results. It is shown that the mean square error (MSE) of this method is obviously less than that of the PSO-BP neural network method and the MPSO-BP neural network assessment method. In short, the obtained MSE is presented to confirm the validity of our proposed strategy.*

Keywords: Threat assessment, Particle swarm optimization (PSO), Modified PSO optimization BP neural networks (MPSO-BP), FRWNN

1. **Introduction.** With the rapid development of information and intelligence, the air raid environment is becoming more and more complicated. Therefore, the demand for real-time and precision is very important for the collaborative attack in modern warfare. Threat assessment can not only provide reasonable decision-making basis for the modern warfare, but also enhance overall effectiveness of the air defense combat by improving the killing probability. So, the research of threat assessment is one of the most important topics in modern warfare, which has important theoretical and practical significance.

Threat assessment can be executed by using several conventional approaches, such as Bayesian network [1,2], multi-attribute decision-making method [3], analytic hierarchy process [4], information fusion theory [5], and fuzzy logic theory [6,7]. However, for the aforementioned threat assessment approaches, the reasoning methods must rely on experts' knowledge to set weight vector, which increase subjective and ill-defined factors of the target threat assessment. In addition, the evaluations are independent of each other so that complex relationship among threat factors cannot be effectively and unambiguously reflected. Especially, the aforementioned methods have not the self-learning and self-adaptive capabilities, so it is hard to meet the changes of enemy tactical means and weapons performance in the aspect of real-time. Consequently, the aforementioned approaches cannot appropriately learn the intricate behavior of input/output mapping. Artificial neural networks have a strong self-learning and adaptive capacity. On the contrary, the general neural network cannot be described by a uniform architecture of networks. Moreover, the training process can be easy to possess the drawback of over learning and poor generalization capability. Wang et al. [8] studied threat assessment using glowworm swarm optimization algorithm to optimize the BP neural network, and achieved satisfactory result in some way. However, the performance of the neural network is dependent on the dimension of training data. With the dimension increasing, the deterioration of network performance is unavoidable, such as premature convergence and slow convergence speed. Furthermore, the choice of network structure is so difficult and the training process is easy to converge to local minimum.

In recent years, it has become a hot spot that the wavelet neural network (WNN) is applied to the target threat assessment [9]. Compared with BP neural networks, the WNN has a strong nonlinear mapping ability, adaptive organization capacity and adaptive learning capacity, as well as generalization ability. However, due to its feed-forward network architecture, it cannot offer dynamic mapping capabilities to the nonlinear complex problem and there were also some irreconcilable contradictions in the practical application.

To remedy the above phenomenon, the superiority of fuzzy neural network (FNN) in dealing with nonlinear function approximation [10], and the advantages of wavelet function with good time-frequency two-dimensional analysis abilities were considered. The FRWNN inherits the advantages of WNN and FNN in this paper. Moreover, the proposed model is different from a fuzzy wavelet neural network (FWNN) [11], that is, a single neuron used in consequent part of FRWNN is capable of capturing the previous information of the networks instead of the consequent part of conventional TSK fuzzy model [12]. As a result, the FRWNN substantially reduces the number of rules compared with the FNN, converges in low number of iterations and is more reliable, reasonable and efficient than FNN and WNN. In addition, dynamic approximation capability reduces the increasing number of dimension and parameter generated by the use of a large number of neurons, owing to a single neuron consequent part storing the past data of the network.

The main contributions of the present paper are highlighted as follows.

- Taking into consideration the disadvantages of the feed-forward network architecture in approximating a complex dynamic system [11], we propose to use a single neuron with the ability to record the previous data of the network as the consequent part of each fuzzy rule of FRWNN.
- We use fuzzy recurrent wavelet neural network to model threat degree; FRWNN with low computational burden, high flexibility and adaptive learning capacity can adapt to the target complexity of battlefield and the requirements for quickly processing information in the modern war.

The remaining sections of the paper are organized as follows. Section 2 describes the architecture of fuzzy recurrent wavelet neural network. Influencing factors analysis of target threat assessment is given in Section 3. The learning algorithm for the FRWNN is introduced in Section 4. Construction and validation of assessment model based on FRWNN are provided in Section 5. Finally, the conclusions and future work are presented in Section 6.

2. **FRWNN.** Architecture of FRWNN is shown in Figure 1, which is a five-layer structure including a single hidden layer with recurrent wavelet structure used as a consequent part based on the TSK [13]. The modified consequent part is constructed by a single neuron that can record the past useful information. Meanwhile, wavelet function is selected as the activation function, which reduces computation burden and improves generalization capability. Here, a single hidden layer stores the data of the past state of the network. At the next time interval, the previous data stored by a single neuron is multiplied by a feedback gain and then re-input to the neuron of a single hidden layer. As a result, the characteristics of recurrent memory of a single hidden layer make the network enhance the prediction accuracy by improving the dynamic approximation capability.

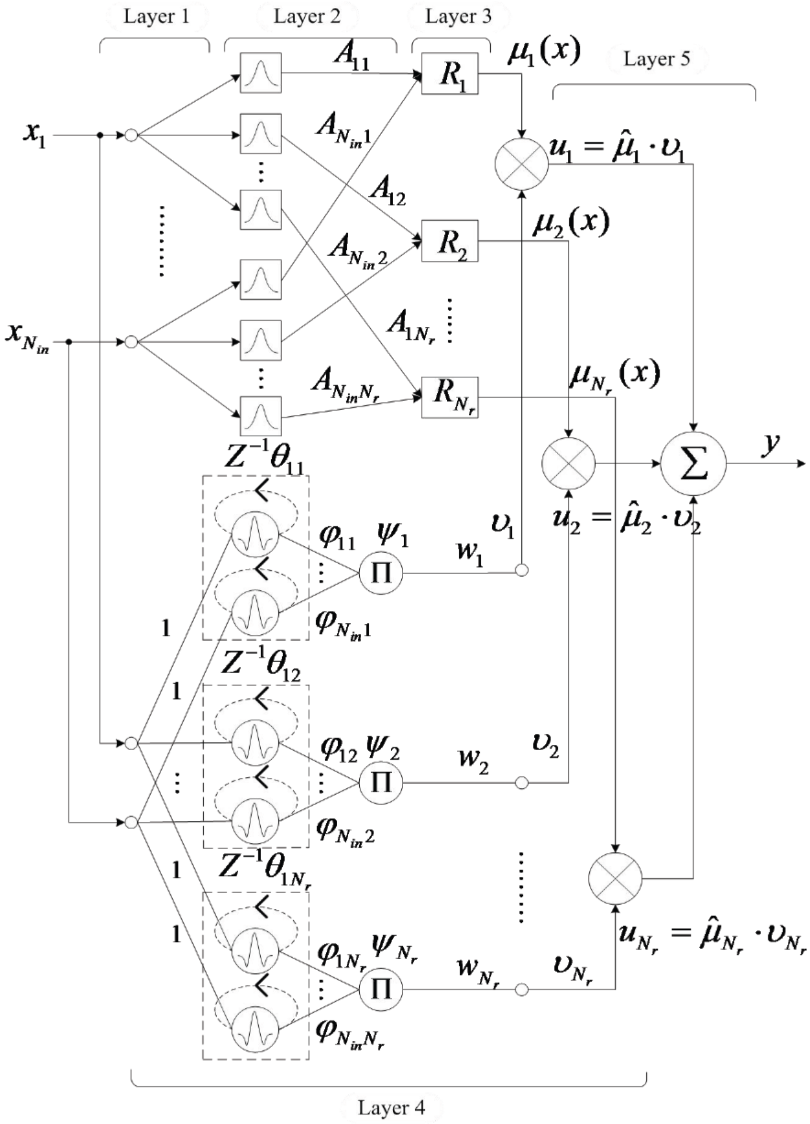

FIGURE 1. Architecture of the proposed FRWNN

The first layer is responsible for accepting and transmitting input vector $x = \{x_1, x_2, \ldots, x_{N_{in}}\}$. Now, suppose that x_i is the i-th external input variable of the system, so $i = 1 : N_{in}$. In second layer each node represents one linguistic term, and A_{ij} is a linguistic term characterized by a fuzzy membership function $\mu_{A_{ij}}(x_i)$ for $j = 1 : N_r$. Here Gaussian membership functions are adopted as activation function of the second layer, and the output of each node is computed as follows:

$$\mu_{A_{ij}}(x_i) = \exp\left(-(x_i - c_{ij})^2/\sigma_{ij}^2\right), \quad \forall i = 1 : N_{in};\ j = 1 : N_r \tag{1}$$

where the adjustable parameters c_{ij} and σ_{ij} represent the center and scaling for the membership function associated with rule j, respectively. In the third layer R_j denotes the fuzzy rule of node j, and the activation strength of each rule is calculated; the output of this layer is calculated as follows:

$$\mu_j(x) = \prod_i \mu_{A_{ij}}(x_i), \quad i = 1 : N_{in},\ j = 1 : N_r \text{ and } 0 < \mu_j \le 1 \tag{2}$$

As consequent part of the fuzzy rules, the fourth layer is constructed by a single hidden layer which uses Gaussian wavelet activation function in neurons. Four kinds of wavelet functions frequently used are introduced as follows:

1) Haar wavelet function:

The Haar wavelet has the characteristics of close support and orthogonality. It is the simplest wavelet function in the early application of wavelet analysis. Moreover, Haar wavelet is not continuous in time domain. Haar function is defined as follows:

$$\varphi(t) = \begin{cases} 1 & 0 \leq t \leq 1/2 \\ -1 & 1/2 \leq t \leq 1 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Its curves can be seen from Figure 2.

2) Mexican Hat wavelet function:

Mexican Hat wavelet has good localization properties in time-frequency two-dimensional domains. It cannot offer the orthogonality, due to the fact that it does not have the scaling function. Although its convergence rate is fast, sometimes it cannot escape getting into local minima. Mexican Hat is defined as follows:

$$\varphi(t) = c\left(1 - t^2\right)\exp\left(t^2/2\right) \tag{4}$$

where $c = \frac{2}{\sqrt{3}}\pi^{-\frac{1}{4}}$, and its curves can be seen from Figure 3.

3) Gaussian wavelet function:

Gaussian wavelet has global mapping generalization capabilities and also has an efficiency in terms of local details. Mexican Hat wavelet is the second derivative of the Gaussian function, and the derivative of Gaussian wavelet is infinitely smooth. Not only the convergence rate of Gaussian wavelet is faster, but also it can avoid the phenomenon of over-fitting. Its expression is as follows:

$$\varphi(t) = t \cdot \exp\left(-t^2/2\right) \tag{5}$$

Its curves can be seen from Figure 4.

4) Morlet wavelet function:

Morlet wavelet has no scaling function and cannot do orthogonal decomposition. When it was selected as an activation function, the convergence rate of the network is relatively slow and sometimes it is prone to have poor fitting. Its expression is defined as follows:

$$\varphi(t) = C \cdot \cos(5t) \cdot \exp\left(-t^2/2\right) \tag{6}$$

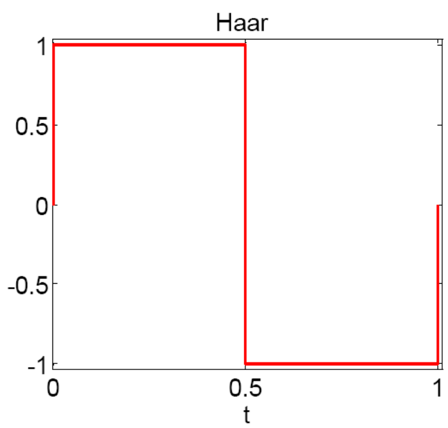

FIGURE 2. Haar

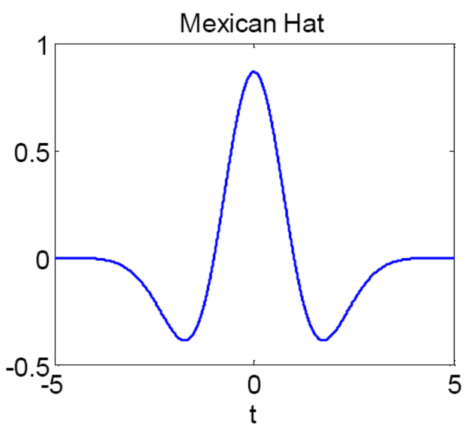

FIGURE 3. Mexican Hat

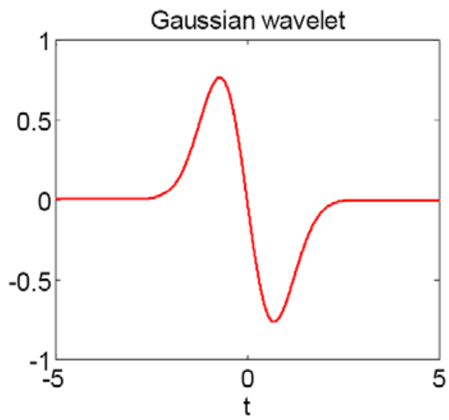

FIGURE 4. Gaussian wavelet

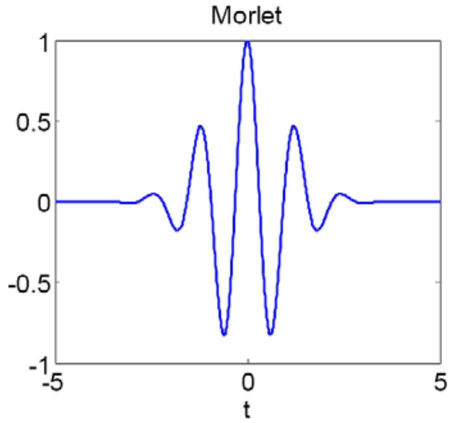

FIGURE 5. Morlet wavelet

where C is its normalized constant after reconstruction, and its curves can be seen from Figure 5.

In this paper Gaussian wavelet function was chosen as the activation function, and the output of each wavelet of the fourth layer is described as:

$$\varphi_{ij} \triangleq \varphi_{ij}\left(z_{ij}(k)\right) = \varphi_{ij}\left(\left(u_{ij}(k) - t_{ij}(k)\right)/d_{ij}(k)\right), \quad \forall i = 1 : N_{in};\ j = 1 : N_r \tag{7}$$

where, at the discrete time k, the inputs of this layer can be expressed as:

$$u_{ij}(k) = x_i(k) + \varphi_{ij}(k-1) \cdot \theta_{ij}(k), \quad \forall i = 1 : N_{in};\ j = 1 : N_r \tag{8}$$

In (7) and (8), t_{ij} and d_{ij} are defined as translation and dilation parameters, respectively; θ_{ij} is a feed-back factor to describe the rate of data storage. The subscript ij denotes i-th external input term of the j-th rule. In addition, the input of the layer includes the memory term $\varphi_{ij}(k-1)$, which can capture the previous information of the networks.

The sub-wavelet function of fourth layer is denoted as follows:

$$\psi_j\left(z_{ij}\right) = \prod_{i=1}^{N_{in}} \varphi_{ij}\left(\left(u_{ij} - t_{ij}\right)/d_{ij}\right), \quad \forall i = 1 : N_{in};\ j = 1 : N_r \tag{9}$$

The corresponding output of fourth layer is described as follows:

$$\upsilon_j(k) = w_j \cdot \psi_j, \quad j = 1 : N_r \tag{10}$$

where w_j stands for connection weight between the product and the output layers.

The product of the fourth layer and the node outputs of the third layer is computed as follows:

$$u_j(x) = \hat{\mu}_j(x) \cdot \upsilon_j, \quad j = 1 : N_r \tag{11}$$

where $\hat{\mu}_j(x)$ is described as follows:

$$\hat{\mu}_j(x) = \mu_j(x) \Big/ \sum_{j=1}^{N_r} \mu_j(x) \tag{12}$$

The fifth layer as the output layer of the proposed network, its output is computed as follows:

$$y(k) = \sum_{j=1}^{N_r} \hat{\mu}_j(x) \cdot \upsilon_j = \sum_{j=1}^{N_r} u_j \tag{13}$$

3. **Influencing Factors Analysis of Target Threat Assessment.** Target threat assessment needs to consider different types of factors. It is also not a simple linear combination between various factors, so it can hardly be created the explicit functional relationship between the various factors and the target threat value. Many factors and relationships between them should be taken into account such as target type, target speed, target interference capability, target heading angle, target height and target distance. According to G. A. Miller's nine levels quantitative theory [14], main factors are analyzed as follows.

3.1. **Target type.** Different types of target have different flight speed and attack ability, and the threat level to protected target is also different. In this paper, the target type is divided into three kinds, reconnaissance plane, small target (such as tactical ballistic missiles, stealth aircraft) and large target (such as bomber, fighter bomber). In general, the threat degree of small target is the biggest, and the threat degree of reconnaissance plane is the least. In order to facilitate quantitative study, in this paper, the target threat attribute is quantified using G. A. Miller's nine levels quantitative theory; the reconnaissance plane, small target and large target were quantified for 3, 5 and 8.

3.2. **Target speed.** The velocity of the target is the vector synthesis of its approximation rate and its lateral velocity, directly affecting the target threat assessment. Even if the same type of target, if the flight speed is different, their threat degree is also not the same. In general, the faster the flight speed, the greater the threat degree.

3.3. **Target interference capability.** Target interference capability is one of the typical counter measures of enemy air raid formation, and it can be divided into four kinds: very weak, weak, medium and strong. Generally, the stronger the target interference capability is, the greater the threat degree is. In this paper, this index is quantified by G. A. Miller's nine levels quantitative theory; the very weak, weak, medium, strong was quantified for 2, 4, 6 and 8.

3.4. **Target heading angle.** Heading angle of target is the angle between the target advancing direction and the direction of target's position to the protected target's position. In general, the smaller the heading angle, the more possible that the target suddenly appeared, and the threat is also greater.

3.5. **Target height.** When the target is far, the threat of flying height to our side is not obvious, but the target that suddenly appeared in low altitude will be a great threat to us. In this paper, the index is quantified by G. A. Miller's nine levels quantitative theory; the ultralow altitude, low altitude, medium altitude and high altitude were quantified for 2, 4, 6 and 8.

3.6. **Target distance.** The closer the distance between the incoming target and the protected target, the shorter the defense time, and the greater the incoming target threat level. Contrariwise, the farther the distance between the incoming target and the protected target, the attack intent of incoming target is not more obvious, and the threat level is lower.

4. **The Learning Algorithm for the FRWNN.** All parameters need to be automatically adjusted in the consequent part of the fuzzy rules, during the training process of the proposed networks. In this paper, the back propagation algorithm is used to adjust the consequent parameters.

The quadratic objective performance function of FRWNN is denoted as follows:

$$E(k) = \frac{1}{2}\left[\left(y^d(k) - y(k)\right)^2\right] = \frac{1}{2}e^2(k) \tag{14}$$

where $y^d(k)$ is the desired output values and $y(k)$ is the current output values at discrete time k, $e(k)$ is the estimation error of FRWNN.

The weight vector is $W = [w_j\ t_{ij}\ d_{ij}\ \theta_{ij}]^{\mathrm{T}}$ in the consequent part of FRWNN, and it was updated by using the following equations:

$$w_j(k+1) = w_j(k) - \overline{\eta}^w(k) \cdot \frac{\partial E(k)}{\partial w_j(k)} \tag{15}$$

$$t_{ij}(k+1) = t_{ij}(k) - \overline{\eta}^t(k) \cdot \frac{\partial E(k)}{\partial t_{ij}(k)} \tag{16}$$

$$d_{ij}(k+1) = d_{ij}(k) - \overline{\eta}^d(k) \cdot \frac{\partial E(k)}{\partial d_{ij}(k)} \tag{17}$$

$$\theta_{ij}(k+1) = \theta_{ij}(k) - \overline{\eta}^\theta(k) \cdot \frac{\partial E(k)}{\partial \theta_{ij}(k)} \tag{18}$$

where $\eta = diag\left\{\overline{\eta}^w, \overline{\eta}^t, \overline{\eta}^d, \overline{\eta}^\theta\right\}$ denotes the matrix of learning rates for the weight of FRWNN, $diag\left\{\cdot\right\}$ is denoted as diagonal matrix.

By differentiating $E(k)$ with respect to $y(k)$, $y(k)$ with respect to $\upsilon_j(k)$ and $\psi_j(k)$ with respect to $z_{ij}(k)$, it gives as follows:

$$\frac{\partial E(k)}{\partial y(k)} = y(k) - y^d(k) \tag{19}$$

$$\frac{\partial y(k)}{\partial \upsilon_j(k)} = \frac{\mu_j(x)}{\sum\limits_{j=1}^{N_r} \mu(x)} \tag{20}$$

$$\frac{\partial \psi_j(k)}{\partial z_{ij}(k)} = \left(\frac{1}{z_{ij}} - z_{ij}\right)\psi_j \tag{21}$$

Now, differentiating $\upsilon_j(k)$ with respect to $w_j(k)$ and $\psi_j(k)$, it gives as follows:

$$\frac{\partial \upsilon_j(k)}{\partial w_j(k)} = \psi_j \tag{22}$$

$$\frac{\partial \upsilon_j(k)}{\partial \psi_j(k)} = w_j \tag{23}$$

By differentiating $z_{ij}(k)$ with respect to $t_{ij}(k)$, $d_{ij}(k)$ and $u_{ij}(k)$, it gives as follows:

$$\frac{\partial z_{ij}(k)}{\partial t_{ij}(k)} = -\frac{1}{d_{ij}(k)} \tag{24}$$

$$\frac{\partial z_{ij}(k)}{\partial d_{ij}(k)} = -\frac{1}{d_{ij}} z_{ij} \tag{25}$$

$$\frac{\partial z_{ij}(k)}{\partial u_{ij}(k)} = \frac{1}{d_{ij}} \tag{26}$$

Now, differentiating $u_{ij}(k)$ with respect to $\theta_{ij}(k)$, it gives as follows:

$$\frac{\partial u_{ij}(k)}{\partial \theta_{ij}(k)} = \varphi_{ij}(k-1) \tag{27}$$

Combining (19) and (20) with (22), the chain rule of calculus can express the gradient of Equation (15) as follows:

$$\frac{\partial E(k)}{\partial w_j(k)} = \big(y(k) - y^d(k)\big) \cdot \psi_j(z) \cdot \frac{\mu_j(x)}{\sum\limits_{j=1}^{N_r} \mu_j(x)} \tag{28}$$

Considering Equations (19)-(21), (23), and (24), we may express the the gradient of Equation (16) as follows:

$$\frac{\partial E(k)}{\partial t_{ij}(k)} = \big(y(k) - y^d(k)\big)\, w_j \cdot \psi_j \left(\frac{-1}{d_{ij}}\right) \cdot \left(\frac{1}{z_{ij}} - z_{ij}\right) \cdot \frac{\mu_j(x)}{\sum\limits_{j=1}^{N_r} \mu_j(x)} \tag{29}$$

Combining (19)-(21), (23) and (25), the gradient of the Equation (17) is denoted as follows:

$$\frac{\partial E(k)}{\partial d_{ij}(k)} = z_{ij} \cdot \frac{\partial E(k)}{\partial t_{ij}(k)} \tag{30}$$

Considering Equations (19)-(21), (23), (26) and (27), the gradient of the Equation (18) is written as follows:

$$\frac{\partial E(k)}{\partial \theta_{ij}(k)} = -\varphi_{ij}(k-1) \cdot \frac{\partial E(k)}{\partial t_{ij}(k)} \tag{31}$$

5. **Construction and Validation of Assessment Model Based on FRWNN.** Our goal is to build the relationship between threat degree and the influencing factors; meanwhile, the relationship is nonlinear. As mentioned in Section 3, six factors are mainly considered as external inputs including the target's type, speed, interference, heading angle, height and distance. The performance of FRWNN is tested by these factors. After acquired data normalization, part of the data used to validate the proposed model is presented in Table 1. Large target, reconnaissance plane, and small target are listed in the form of six groups, respectively. The input data is six-dimensional, while the output data is one-dimensional.

5.1. **The flow chart and the training process of target threat assessment.** In this paper, we select 60 groups of combat situation data including 45 group data as a training set to train FRWNN, and then the target threat value of the rest of situation data are predicted by using the trained network. Target threat algorithm flow chart based on FRWNN is shown in Figure 6.

The process of training FRWNN is as follows.

(1) Data preprocessing. First, the acquired data is quantified and normalized [9], and the data set was divided into training data set and testing data set, respectively.

(2) Initialization of the FRWNN. Connection weights, storage factors, center and scaling parameters, translation and dilation parameters of the FRWNN are initialized.

(3) Training FRWNN: The FRWNN was trained using training test and then the error indexes between the output and the expected value were calculated.

(4) Updating the weights. Based on the prediction error, the parameters and the connection weights of FRWNN are updated in order to make the predictive value as close to the actual value as possible.

(5) When the results meet the given criteria, testing set is used to test the FRWNN. Otherwise, go back to Step 3 and repeat this cycle.

Table 1. Part of the data

No.	Type	Velocity (m/s)	Inference	Heading angle ($\circ$)	Height	Distance (km)	*Threat value*
1	8	460	6	9	6	310	0.5939
2	8	500	6	17	8	210	0.6031
3	8	400	8	5	2	110	0.5869
4	8	580	6	9	6	160	0.5888
5	8	800	2	8	4	100	0.5763
6	8	600	6	16	6	200	0.5661
7	5	190	2	4	4	120	0.4302
8	5	90	4	11	8	100	0.4013
9	5	80	8	9	4	160	0.3639
10	5	200	4	14	8	160	0.4692
11	5	120	2	15	6	100	0.3906
12	5	260	6	7	6	160	0.4968
13	3	630	8	7	4	210	0.6083
14	3	600	8	9	4	260	0.6485
15	3	610	6	17	8	310	0.6451
16	3	760	6	15	8	490	0.7078
17	3	400	2	8	6	170	0.4906
18	3	550	4	7	2	290	0.6039

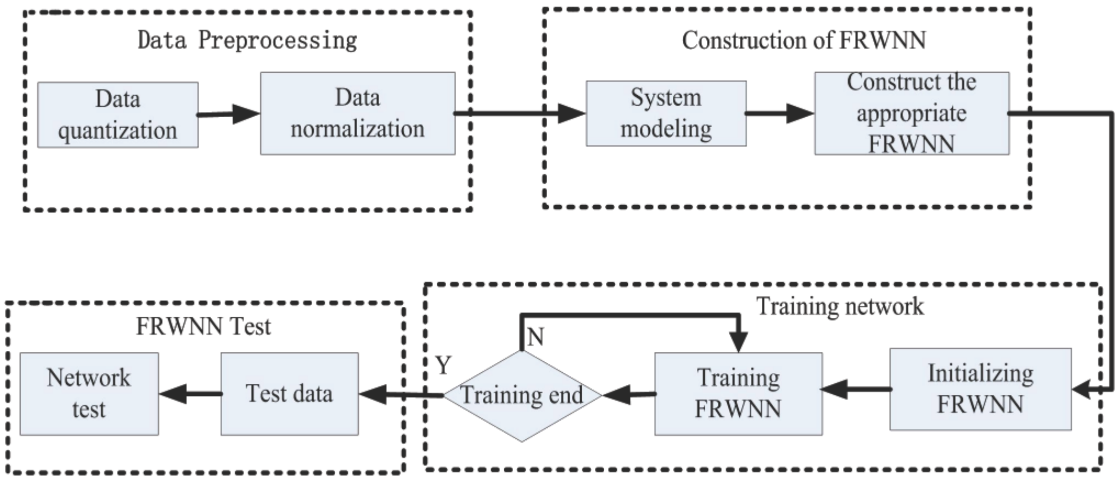

Figure 6. Target threat algorithm flow chart based on FRWNN

5.2. **Model validation and simulation.** To verify the efficiency of the FRWNN, it is compared with PSO-BP and MPSO-BP target threat assessment techniques under MATLAB. The obtained results confirm the validity of developed approach for Figures 7-13.

The predicted results of the target threat based on PSO-BP, MPSO-BP and FRWNN are shown in Figure 7. It can be seen that the prediction result based on FRWNN provides a higher accuracy than PSO-BP and MPSO-BP. In the following paragraphs, the other performance indexes such as error, relative error and mean square error (MSE) are analyzed to demonstrate the effectiveness and feasibility of proposed FRWNN further.

The iterative curve of FRWNN is shown in Figure 8. It can be seen from the graph that the network realizes the best training condition at 121 iterations, which indicates

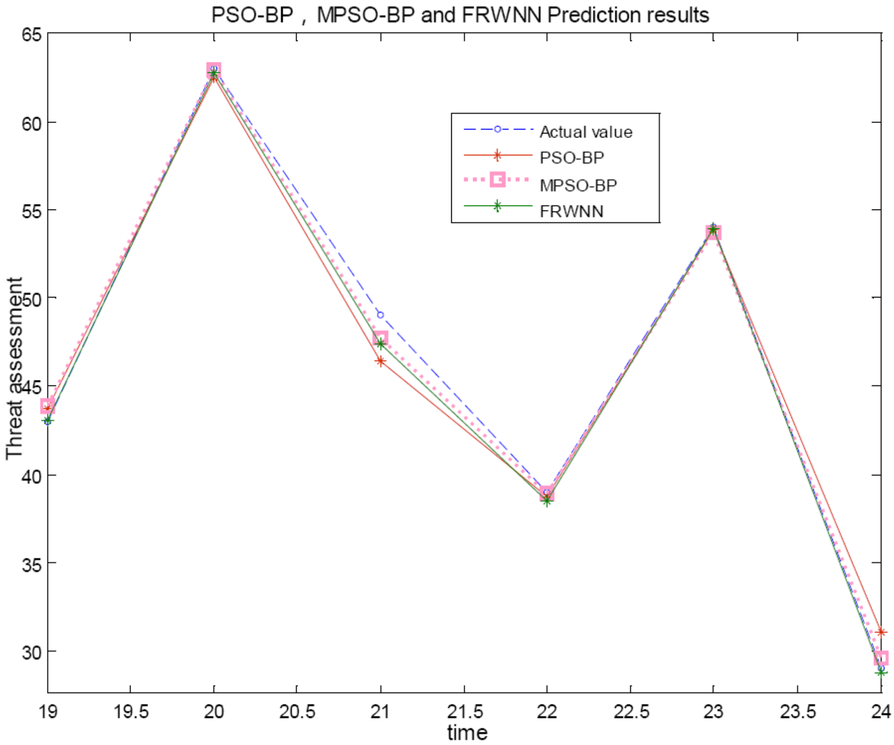

FIGURE 7. PSO-BP, MPSO-BP and FRWNN prediction results

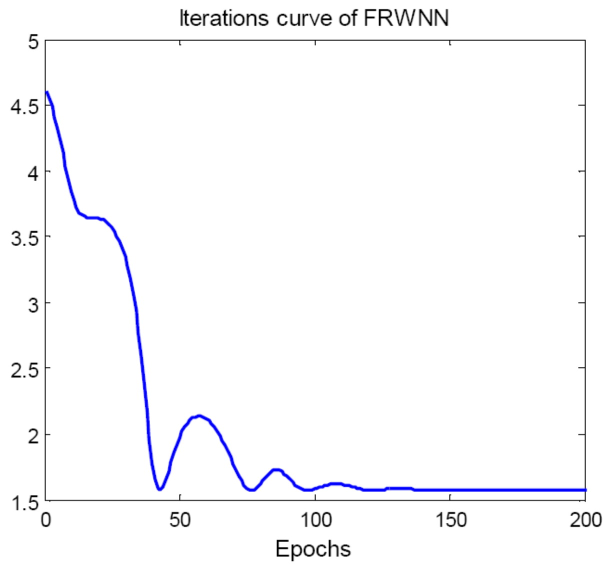

FIGURE 8. Iterations curve

that the proposed FRWNN has faster convergence speed and converges in a small number of iterations.

The network performance curves of FRWNN are shown in Figure 9. From the picture, the network performance obtains a reasonable and good verification; meanwhile, the FRWNN has the best validation performance at 121 epochs and gets very small MSE.

The training state curves of FRWNN are shown in Figure 10. It can be seen that the FRWNN has faster convergence rate, better adaptive learning rate and better validation performance.

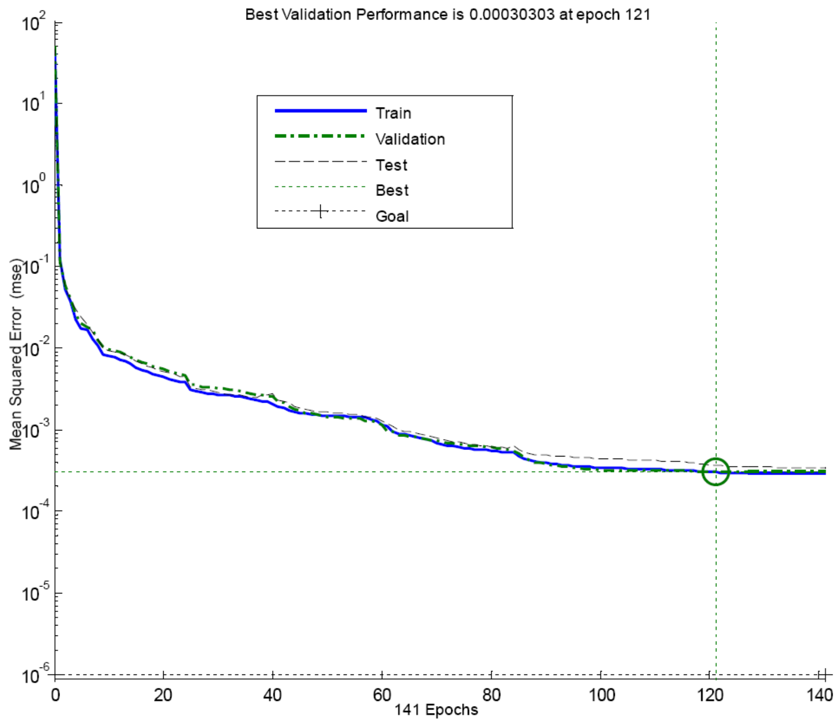

FIGURE 9. The network performance curves

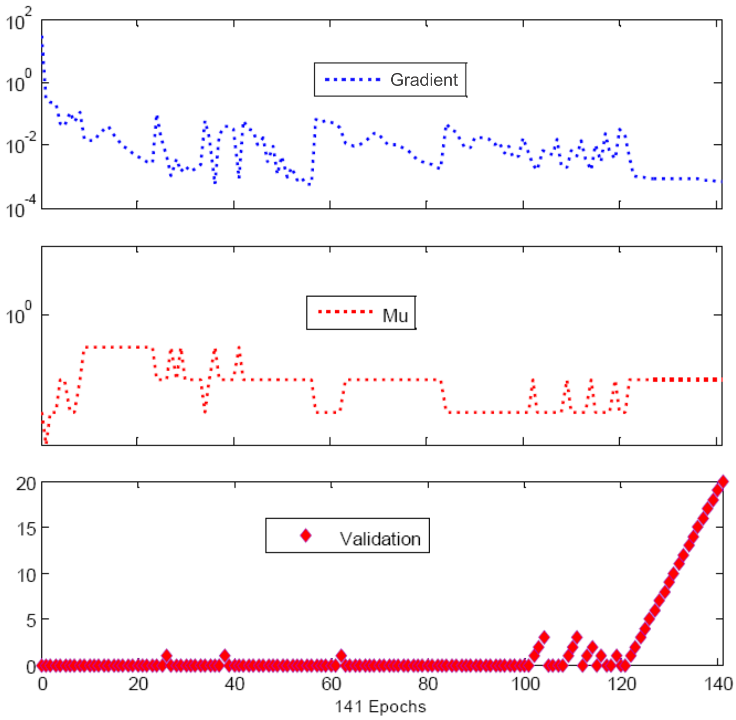

FIGURE 10. Training state curves

The linear regression state of the FRWNN is shown in Figure 11. As can be seen from pictures, the FRWNN has achieved a satisfactory linear regression state. The proposed model gives the more precise prediction results, which is attributed to possess higher R-value (close to 1) and lower MSE.

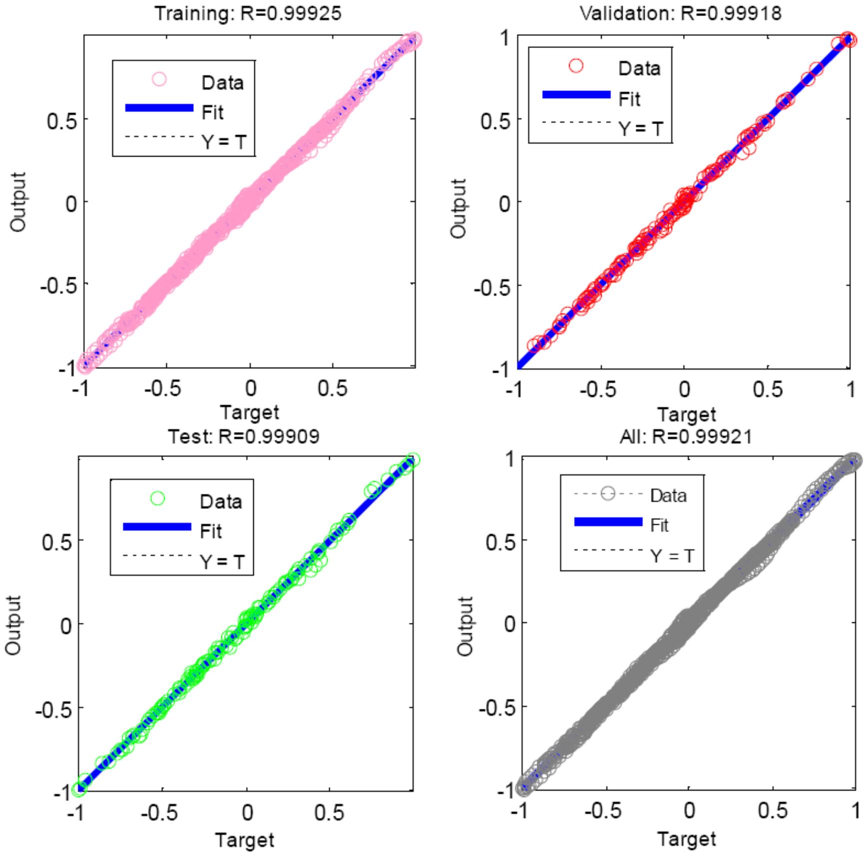

FIGURE 11. Linear regression state

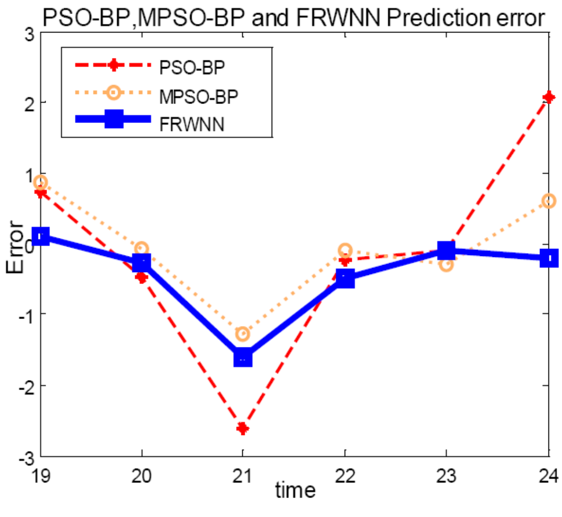

FIGURE 12. Assessment error curve

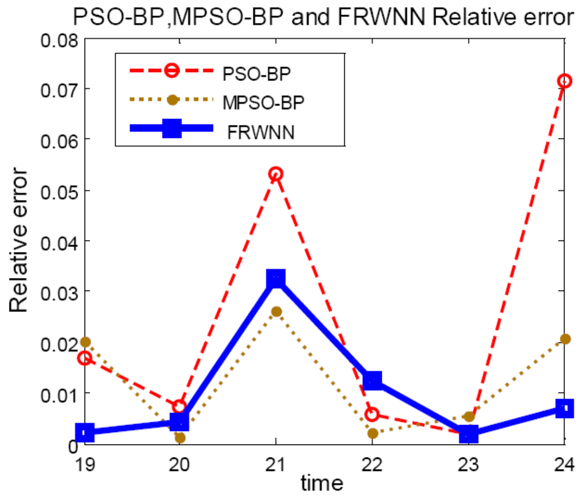

FIGURE 13. Relative error curve

By comparing and analyzing the real threat value and evaluation value of three kinds of neural networks mentioned above, we got the actual error curve and relative error curve and shown in Figures 12 and 13. In general, the actual error and relative error of the proposed FRWNN achieve satisfactory results compared with other models. Meanwhile, the error is further evaluated by MSE, which is shown in Table 2.

TABLE 2. Error analysis

Network	PSO-BP	MPSO-BP	FRWNN
MSE	1.685×10^{-2}	1.305×10^{-2}	9.5×10^{-3}
Running times (s)	4	4	4

The simulation results show that the MSE of the FRWNN is 9.5×10^{-3}, which is superior to the PSO-BP (1.685×10^{-2}) and the MPSO-BP (1.305×10^{-2}) neural network. And the efficiency of the FRWNN algorithm is improved and has better performance in achieving the global optimum. The assessment accuracy of the FRWNN is better than the PSO-BP and the MPSO-BP neural network. The FRWNN has a competitive degree of prediction ability, which provides a new method for the threat assessment.

6. **Conclusions.** In this paper, we developed a novel assessment modeling methodology based on the FRWNN on target threat. The relationship between influencing factors and target threat value is a very complicated non-linear model. The FRWNN with the ability of capturing the dynamic data, can significantly reduce the computational cost and enhance generalization capability. The assessment modeling was used to fit the non-linear relationship between input and output in modern warfare. Because of the dynamic ability to store history data, the FRWNN based prediction model can flexibly adapt to the complex modern warfare. Moreover, the proposed network can effectively overcome defects of BP with PSO. Through the analysis of examples, it can be seen that the proposed method has better evaluation ability, and can quickly and accurately evaluate the target threat, and provide support for the task allocation and tactical decision. The performance of the proposed FRWNN is evaluated in the prediction of the system problems, so it can be further examined to solve other problems such as system identification, function approximation, signal processing and attitude control subsystem.

By observing type-2 fuzzy systems [15,16], it is noteworthy that type-2 ones are extensions of type-1. Thus, in our future work, using the type-2 fuzzy membership function in the antecedent part of the FRWNN can be further considered. Meanwhile, to better realize the algorithm in aspect of real-time and on-line, the improved algorithm and the choice of the initial values of FRWNN are becoming challenges.

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REFERENCES

[1] J. Yang, W. Y. Gao and J. Liu, Threat assessment method based on Bayesian network, *Journal of PLA University of Science and Technology*, vol.11, no.1, pp.43-48, 2010.

[2] Y. Wang, Y. Sun, J. Y. Li and S. T. Xia, Air defense threat assessment based on dynamic Bayesian network, *International Conference on Systems and Informatics*, pp.721-724, 2012.

[3] M. Cheng, D. Y. Zhou and K. Zhang, Threat assessment of target based on a hybrid multi-attribute decision-making method, *Electronic Optics & Control*, vol.17, no.1, 2010.

[4] S. H. Yan, H. Liu and T. F. Tu, A threat sequencing method for aerial infrared multi-target, *Fire Control & Command Control*, vol.39, no.6, 2014.

[5] K. Sycara, R. Glinton, B. Yu et al., An integrated approach to high-level information fusion, *Information Fusion*, vol.10, no.1, pp.25-50, 2009.

[6] J. Gao, W. T. Liang and J. P. Yang, Application of fuzzy beliefs in threat assessment of aerial targets, *International Conference on Intelligent Human-Machine Systems and Cybernetics*, vol.2, pp.87-92, 2013.
[7] Y. L. Lu, Y. N. Wang and Y. J. Lei, Air targets threat assessment based on fuzzy rough reasoning, *IEEE Conference on Control and Decision*, pp.885-890, 2015.
[8] G. G. Wang, L. H. Guo, H. Duan and L. Liu, Target threat assessment using glowworm swarm optimization and BP neural network, *Journal of Jilin University*, vol.43, no.4, pp.1064-1069, 2013.
[9] G. G. Wang, L. H. Guo and H. Duan, Wavelet neural network using multiple wavelet functions in target threat assessment, *The Scientific World Journal*, vol.2013, Article ID 632437, 2013.
[10] C. M. He, *The Performance and Learning Algorithm of Fuzzy Neural Network*, Ph.D. Thesis, Nanjing University of Science & Technology, Nanjing, 2010.
[11] N. Noroozi, A. A. Safavi and S. H. Mousavi, New fuzzy wavelet network for modeling and control: The modeling approach, *Communications in Nonlinear Science and Numerical Simulation*, vol.16, no.8, pp.3385-3396, 2011.
[12] H. K. Lam and J. Lauber, Membership function dependent stability analysis of fuzzy model-based control systems using fuzzy Lyapunov functions, *Information Sciences*, vol.232, pp.253-266, 2013.
[13] X. Wen and X. Lin, Observer design for the single hidden layer fuzzy recurrent wavelet neural network, *Chinese Journal of Radio Science*, vol.30, no.6, pp.1197-1204, 2015.
[14] S. X. Wei and X. Z. Zhou, *Multiple Attribute Decision Theoretic Method and Its Application in C3I System*, National Defend Industry Press, Peking, 1998.
[15] A. E. Ougli and B. Tidhaf, Optimal type-2 fuzzy adaptive control for a class of uncertain nonlinear systems using an LMI approach, *International Journal of Innovative Computing, Information and Control*, vol.11, no.3, pp.851-863, 2015.
[16] B. Q. Hu and C. K. Kwong, On type-2 fuzzy sets and their t-norm operations, *Information Sciences*, vol.255, pp.58-81, 2014.