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TARGET THREAT ASSESSMENT BASED ON MODIFIED PARTICLE SWARM OPTIMIZED FUZZY RECURRENT WAVELET NEURAL NETWORK

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Abstract. *In this research paper, a practical novel hybrid model to assess the value of target threat degree was proposed. The model was based on modified particle swarm optimization (MPSO) in combination with fuzzy recurrent wavelet neural network (FRWNN), namely MPSO optimized fuzzy recurrent wavelet neural network (MPSO-FRWNN). Moreover, a single neuron employed in consequent part of each fuzzy rule of FRWNN is capable of storing the previous data of the networks instead of conventional Takagi-Sugeno-Kang (TSK) fuzzy model. This optimization mechanism involved a hybrid training procedure integrating MPSO and gradient descent algorithm (GDA), which significantly enhances the prediction or assessment accuracy. To locate a reasonably good region in the continuous search space, a new adjustment scheme named MPSO algorithm is developed, which includes two inline-PSO processes, and thus it can fit well with the consequent forecasting learning based gradient descent optimization. Finally, conclusions of this study are exposed by three comparative threat assessment experiments.*

Keywords: Particle swarm optimization, Takagi-Sugeno-Kang fuzzy model, Gradient descent algorithm, Threat assessment

1. **Introduction.** Target threat assessment is becoming an increasingly active area of research in collaboration attack with the rapid development of science and technology. Target threat assessment belongs to the third level information fusion model with a high level, and thus its significance cannot be ignored. Threat assessment can judge our threat degree according to the disposition of enemy's forces or the weapons and equipment system of the enemy as well as the possible action intentions of the enemy. Accurately evaluating the enemy's target is the essential prerequisite of exerting our operational effectiveness for not only improving battlefield gains in modern warfare, but also plays an effective role in monitoring modern warfare environmental as well as investigating allocation of force and fire and providing relevant support for the task allocation and tactical decision.

In order to solve the problem of target threat assessment, there are several conventional methods such as Bayesian network [1-3], intuitionistic fuzzy reasoning [4], multi-attribute decision making [5-7], analytic hierarchy process [8], plan recognition [9], fuzzy logic theory [10,11], support vector machine (SVM) [12], fuzzy neural network [13], radial basis function (RBF) neural network [14], and wavelet neural network (WNN) [15]. Due to the use of constant weight vector or/and experience of experts in these models, [1-9] increase ill-defined and subjective factors of the threat assessment significantly. Moreover, these methods can yield inaccurate results and lead to large errors in explaining and reflecting the complex relationship between evaluation metrics. Especially, the aforementioned models cannot appropriately learn the intricate input/output mapping, because they lack self-learning and self-adaptive capabilities. Fuzzy logic theory uses human-like reasoning and expert knowledge, which is an effective treatment process for nonlinear systems characterized with uncertain and ill-defined information [10,11], but it cannot meet the real-time requirement effectively. To overcome the limitation of statistical models and learning ability and adapting capability, SVM [12] and artificial neural networks (ANNs) [13,14] have attracted more attention for threat assessment. However, neural networks revealed a number of drawbacks in the course of the use of the system model including slow convergence rate and local minima easily in large-scale training epochs, as well as difficulty to accurately describe the mapping rules which make it impossible to employ them in real-time systems. Based on the wavelet transform, the threat assessment model is constructed using WNN, in which wavelet functions are acted as activation functions of the hidden neurons in the structure [15]. Wavelet functions are powerful tools for complex nonlinear systems due to its excellent time-frequency two-dimensional analysis capability or more accurate time-scale localization properties. The integration of the localization properties of wavelet functions and flexibility of ANNs results in the merit of WNN [15] over the ordinary ANNs and SVM [12].

Based on the TSK fuzzy model [16-18], researchers have proposed various architectures for modeling and control of nonlinear systems. However, the major shortcoming of such fuzzy model is that it cannot provide complete mapping capabilities to the nonlinear complex systems and hence a considerable number of rules in consequence part are desperately needed to acquire the desired connecting mapping between inputs and outputs. Additionally or alternatively, many researchers have proposed to substitute a WNN for the consequent part of the TSK model. The obtained neural network is a fuzzy wavelet neural network (FWNN), which inherits the advantages of WNNs and fuzzy logic and ANNs. To enhance the function approximation and computation power as well as the generalization ability in the complex processes, FWNN approach is proposed for forecasting long term electricity consumption in a high energy consumption city [19]. However, the adjustment for initialization of parameters of FWNN is unreasonable which lead to unsatisfactory convergence rate. Furthermore, due to its feed-forward network architecture, it cannot offer dynamic full mapping capabilities in dealing with the dynamic systems. In view of the demerits of the feed-forward network architecture, the problem can be solved by constructing a recurrent wavelet neural network (RWNN) in the consequent part of the FWNN architecture which can capture the past dynamic behavior of the system [20,21]. For example, an FRWNN was applied to solving such problem as forecasting, function approximation with system identification and control problems [22-24]. In [22], an FRWNN is proposed to solve threat assessment, but its convergence rate enormously rests on the choice of the initial values of the network parameters to be optimized.

In 1995, Dr. Eberhart and Dr. Kennedy first proposed particle swarm optimization (PSO), one of the stochastic search optimization algorithms, which was inspired by social behavior of bird flocking, bee swarming and fish schooling, with self-adaptive characteristic [25,26]. As demonstrated in the literature, the PSO and its modified optimization techniques have successfully attracted more and more attention to achieve high efficiency solver for global optimization problems in sundry scientific and engineering domains such as artificial network training, and function optimization [27-29]. The above methods lighten the need for easy implementation under the absence of sufficient gradient information. However, some demerits of PSO are unavoidable: analogous to other heuristic algorithms, it takes such a long computation time compared with conventional gradient descent method when a considerable accuracy was required; it is apt to sink into local optimal solution at times, and the convergence speed dropped significantly during the posterior evolving process of algorithm; the algorithm sometimes does not continue to optimize while finding a near-optimum solution, and thus the flawed algorithm leads to a restricted accuracy.

The aim of this paper is to propose a novel MPSO-FRWNN hybrid model for target threat assessment, and in FRWNN we employed the concepts of fuzzy logic in combination with a single neuron with the capability to capture the previous information of the network in the consequent part. In our proposed FRWNN, the consequent of a conventional TSK fuzzy model is substituted with a WNN consisting of a large number of neurons resulting in the decrease of the reaction speed of the TSK fuzzy model to external input changes. We have taken a hybrid learning algorithm lest the trial-and-error course and the negative effect caused by random initialization of unknown parameters. Firstly, an MPSO algorithm is developed to search a relatively good selection of the initial values of the unknown parameters that need to be optimized. The two-layer inline-PSO stages of MPSO algorithm demonstrate a faster convergence speed compared to the basic PSO, and meanwhile the updating plan of the velocity and position of each particle gets a more coordinated approach by using the following forecasting learning based gradient descent algorithm. Secondly, the GDA is utilized to perform parameters adjustment of the proposed FRWNN. By investigating the performance criterion of training and testing signals during learning, a more reasonably good model is obtained in this research.

In brief, the main merits of the present paper are highlighted as follows.

(i) Compared to the basic PSO algorithm, MPSO is capable of optimizing high dimension complex problems with a relatively fast convergence speed and avoiding the phenomenon of premature convergence, which can guarantee unknown parameters to obtain a reasonable optimal value.

(ii) Owing to the two layers adjustment plan, MPSO algorithm makes particles keep some diversity along with the cramped search space in the surrounding global best position. Parameters in particles of MPSO fit well with the consequent gradient descent optimization and arrive in the optimal solution promptly.

(iii) We develop a new threat assessment model based on MPSO-FRWNN. A hybrid training algorithm which combined MPSO with GDA is applied to optimizing and training the proposed FRWNN. As a result, the novel assessment model with more reasonable optimization parameters, lower computational cost, high flexibility, strong robust performance as well as adaptive learning capacity can adapt relatively fast to sudden changes from input variables of the system and meet the increasing requirements for quickly processing information in complex combat environment.

The brief outline of the remaining sections is organized as follows. Section 2 introduces the structure of FRWNN. Hybrid learning algorithm to optimize FRWNN is described in Section 3. Target threat assessment using MPSO-FRWNN is given in Section 4. Model simulation is provided in Section 5. Finally, the conclusions and future work are drawn in Section 6.

2. **Fuzzy Recurrent Wavelet Neural Network.** The structure of FRWNN has been shown in [22], which is a five-layer structure including a single hidden layer, where we use a recurrent wavelet neural network structure as a consequent part based on the TSK fuzzy model. In modified consequent part, the consequent part of each fuzzy rule is constructed

by a single neuron that can capture the previous useful information of the network. Meanwhile, wavelet function is chosen as the activation function owing to its time-frequency two-dimensional localization properties. In a single hidden layer, the previous data stored by a single neuron is multiplied by a feedback factor and then re-input to the neuron of a single hidden layer. Due to having the recurrent memory characteristics of a single hidden layer, the proposed network can evidently enhance the prediction accuracy to solve complex dynamic problem.

The first layer is the input layer; neurons pass the input vector $x = \{x_1, x_2, \ldots, x_{N_{in}}\}$ to the next layer, which assumes that x_i is the i-th input variable for $i = 1 : N_{in}$. The second layer selects the Gauss membership function as the activation function, and the A_{ij} is a linguistic term represented by a fuzzy membership function $\mu_{A_{ij}}(x_i)$ for $j = 1 : N_r$. And the second layer contains the input membership function of the system, and the output of each node is expressed as:

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

where c_{ij} denotes the center parameters and σ_{ij} represents scaling parameters for the membership function associated with rule j. In the third layer each node denotes a fuzzy rule, where R_j is given rule for $j = 1 : N_r$; the number of nodes is equivalent to the total number of rules R_1 to R_{Nr}. Each node output of the layer can be computed as:

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

where $\prod$ stands for AND or min operation. The fourth layer is consequent part of the fuzzy rules, and it is constructed by using a single hidden layer which utilizes wavelet activation function in neurons of hidden layer, where Gaussian wavelet function was chosen as the activation function. The each wavelet φ_{ij} of the fourth layer is represented as:

$$\varphi_{ij} \triangleq \varphi_{ij}(z_{ij}(k)) = \varphi_{ij}\left((u_{ij}(k) - t_{ij}(k))/d_{ij}(k)\right), \quad \forall i = 1 : N_{in}; \quad j = 1 : N_r \tag{3}$$

where for the discrete time k

$$u_{ij}(k) = x_i(k) + \varphi_{ij}(k-1) \cdot \theta_{ij}(k), \quad \forall i = 1 : N_{in}; \quad j = 1 : N_r \tag{4}$$

where t_{ij} is defined as translation parameter and d_{ij} stands for dilation parameter in each wavelet; θ_{ij} is the weight of self-feedback loop described as the data storage rate. The subscript ij describes the i-th input term of the j-th rule. Moreover, the input of the layer consists of the memory term $\varphi_{ij}(k-1)$, which can record the past data of the networks.

In the product layer, the product of each wavelet function is then calculated as follows:

$$\psi_j(z_{ij}) = \prod_{i=1}^{N_{in}} \varphi_{ij}\left((u_{ij} - t_{ij})/d_{ij}\right), \quad \forall i = 1 : N_{in}; \quad j = 1 : N_r \tag{5}$$

The output of the fourth layer can be described as:

$$\upsilon_j(k) = w_j \cdot \psi_j, \quad j = 1 : N_r \tag{6}$$

where parameter w_j denotes connection weight between the product and the output layers.

The outputs of the fourth layer are multiplied by the node outputs of the third layer. The product of each node of this layer can be computed as follows:

$$u_j(x) = \hat{\mu}_j(x) \cdot \upsilon_j, \quad j = 1 : N_r \tag{7}$$

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

$$\hat{\mu}_j(x) = \mu_j(x) \Bigg/ \sum_{j=1}^{N_r} \mu_j(x) \tag{8}$$

The fifth layer is the output layer of the FRWNN, and its overall output contributed from each rule can be calculated as follows:

$$y(k) = \sum_{j=1}^{N_r} \hat{\mu}_j(x) \cdot v_j = \sum_{j=1}^{N_r} u_j \tag{9}$$

3. **Hybrid Learning Algorithm to Optimize FRWNN.** This section discusses how the proposed FWNN model is executed by the MPSO-FRWNN approach. It is well known that the convergence rate of the GDA strongly depends on the selection of the initial values of the unknown parameters to be optimized; thus, an MPSO approach is proposed for the initialization of the FRWNN. In dealing with the continuous search space, the parameter vector in proposed-FRWNN that needs to be adjusted is $\Theta = (c_{ij}, \sigma_{ij}, w_j, t_{ij}, d_{ij}, \theta_{ij})$. All of the parameters are considered to be adjusted by using a hybrid algorithm which combines initialization by a modified PSO algorithm with updating by gradient descent algorithm.

3.1. **Basic PSO algorithm.** PSO is an evolutionary population-based algorithm by mimicking birds' feeding behavior, which was proposed to solve the global optimization problem. How to maintain the optimal distances between each particle and its neighbors is one of the main factors in PSO algorithm. Each particle's position needs to be optimized by renovating their position as devised for the objective performance function in the search area. The fitness value of each particle position can be evaluated by the fitness function to be optimized, which indicates the pros and cons of the particles as well as velocities that direct the flying of the particles. A particle's velocity represents the important characteristic of PSO, which is optimized by comparing the former one to guide the particle to reach its best position in every iteration. Initializing the algorithm by a population of random solutions, then the system seeks out optimal by adjusting generations. In each iteration, the basic PSO algorithm adjusts the velocity and positions of all of particles having the form of expression (10) and (11) [25,26]:

$$v_{id}^{k+1} = \omega v_{id}^k + c_1 r_1 \left(pbest_{id}^k - x_{id}^k\right) + c_2 r_2 \left(gbest_d^k - x_{id}^k\right) \tag{10}$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \tag{11}$$

where c_1 and c_2 stand for the positive constants described as acceleration factors; r_1 and r_2 stand for two independent random numbers identically distributed in $[0, 1]$; ω stands for the inertia weight coefficient considered as one variable or one constant of iteration. Theoretical and empirical studies of inertia weight have demonstrated that a relatively large ω makes the algorithm keep more global exploring ability; meanwhile, a relatively small ω improves the convergence performance of PSO. In addition, along the dth dimension of the ith particle at the iteration k, $pbest_{id}^k$ is the best previous position, x_{id}^{k+1} is new position based on the previous x_{id}^k, and v_{id}^{k+1} is the new velocity based on previous v_{id}^k. Meanwhile, along the dth dimension of the iteration k, $gbest_d^k$ is the best previous position among all particles in the swarm.

3.2. **The modified PSO (MPSO) algorithm.** In this paper, we adopt MPSO with the strategy of two-layer inline-PSO process to improve the basic PSO algorithm which can overcome some defects of basic PSO algorithm such as the demerit of taking more calculation time to get a relatively high accuracy. A good initialization of the proposed FRWNN can be got by MPSO with relatively small population size and few number of iterations, and then a GDA is utilized to acquired the final values of parameters which make the model achieve the optimal satisfactory solution of the problem.

The merits of the hybrid learning algorithm to optimize FRWNN are clear to see. Firstly, the neural network training by the use of hybrid learning algorithm to optimize FRWNN features a rapid and steady training process than that adopting uniquely one optimization algorithm, namely, PSO or GDA, which is apt to be influenced by the stochastic factors of training. Secondly, it may lead to a very slow convergence rate because of the "similarity" deficiencies of particles in the course of the optimization procedure of PSO. We can accelerate the convergence of process of training evolution by the combination of MPSO and GDA.

The adjustment strategy of parameters within forecasting learning based gradient descent, which renews the parameters after every investigation (x_l, y_l^d) for $l = 1 : K$ in the opposite direction of the quadratic gradient function is described as follows:

$$E\left(\Theta, x_l, y_l^d\right) = \frac{1}{2}\left(y_l(\Theta, x_l) - y_l^d\right)^2 \tag{12}$$

MPSO algorithm using two layers inline-PSO process including two fitness functions is proposed. where y_l corresponds to the output values of the network in the light of multidimensional input variables x_l and network parameter vector Θ. As mentioned above, constrained optimization plan is constructed by two layers named the outer and inner layers. Here in the outer layer, the velocity and position of particles are renewed in the light of fitness values described by the performance metric of root mean square error (RMSE) expressed as (13):

$$RMSE\left(\Theta, \tilde{x}, y_l^d\right) = \sqrt{\frac{1}{K}\sum\nolimits_{l=1}^{K}\left(y_l - y_l^d\right)^2} \tag{13}$$

The objective is to minimize the fitness value of Equation (13), where $\tilde{x} = \{x_1, x_2, \ldots, x_K\}$, $y^d = \left\{y_1^d, y_2^d, \ldots, y_K^d\right\}$. Within the inner layer based on fitness values described by (12), the velocity and position of particles are updated to optimize.

The detailed optimization strategy of two layers inline-PSO is as follows:

1) Initialization. The population size (*psize*) and the termination iterative number (*Maxgen*) of evolution were set respectively. Initialize particle velocity and position for every particle randomly and set the iterative number $k = 1$.

2) Compute the fitness value of each particle according to Equation (13) and denote it by $fitness_i$ $(i = 1 : psize)$; meanwhile search the best known position $pbest_i^k$ of the i-th particle and select the best known position $gbest^k$ among all the particles in the swarm.

3) Renew particle velocity and position for each particle according to Equations (10) and (11).

S3.1: We randomly sort the input vectors and then record the new obtained input order described as $\{\hat{x}_l\}_{l=1}^K$. Let $l = 1$.

S3.2: Compute the fitness value $\left(E\left(\Theta, \hat{x}_l, y_l^d\right)\right)$ of every particle by means of Equation (12) and denote it by $Infitness_i$, $\forall i = 1 : psize$. Search the best known position $Inpbest_i^k$ of the i-th particle and select the best known position $Ingbest^k$ among all of the particles.

S3.3: Renew the particles' velocity and position by

$$v_{id}^{k+1} = \omega v_{id}^k + c_1 r_1\left(Inpbest_{id}^k - x_{id}^k\right) + c_2 r_2\left(Ingbest_d^k - x_{id}^k\right), \quad x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1}$$

S3.4: Let $l = l + 1$. If $l < K + 1$, go to S3.2; otherwise go back to Step 4.

4) Let $k = k + 1$. Compute the fitness value $fitness_i$ of every particle, and then search the best known position $pbest_i^k$ of the i-th particle and select the best known position $gbest^k$ among all of the particles. If $k > Maxgen$, suspend and choose $gbest^k$; otherwise go back to Step 3.

Additionally, the linear decreasing inertia weight $\omega(k) = \omega_{start} - (\omega_{start} - \omega_{end}) * k/Maxgen$ is adopted here similarly to [30,31], which demonstrates a satisfactory convergence performance. Here $\omega_{start} = 0.9$ and $\omega_{end} = 0.4$ are set respectively.

3.3. **Gradient descent algorithm following the MPSO of FRWNN.** After parameters initialization by MPSO, all parameters need to be automatically updated in the consequent part of the fuzzy rules during the training process of the neural networks. In this paper, the gradient descent algorithm (GDA) is used to train the consequent parameters of the networks. As a result, parameters are renewed in the opposite direction of the gradient of quadratic objective performance function.

For forecasting, the quadratic objective performance function of FRWNN is denoted as follows:

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

where $y^d(k)$ and $y(k)$ are the expected output and the actual output values of the FRWNN at discrete time k respectively, and $e(k)$ is the output error of FRWNN.

$W = [w_j\ t_{ij}\ d_{ij}\ \theta_{ij}]^{\mathrm{T}}$ is the weighting vector for the consequent part of fuzzy rules, and it was updated by taking advantage of the gradient descent algorithm as follows:

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

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

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

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

where $\eta = diag\left\{\overline{\eta}^w, \overline{\eta}^t, \overline{\eta}^d, \overline{\eta}^\theta\right\}$ stands for the learning rates matrix for the weights of FRWNN, and $diag\left\{\cdot\right\}$ stands for diagonal matrix.

The chain rule of calculus can express the values of derivations in (15)-(18) as follows:

$$\frac{\partial E(k)}{\partial w_j(k)} = \frac{\partial E(k)}{\partial y(k)} \cdot \frac{\partial y(k)}{\partial \upsilon_j(k)} \cdot \frac{\partial \upsilon_j(k)}{\partial w_j(k)} = \left(y(k) - y^d(k)\right) \cdot \psi_j(z) \cdot \frac{\mu_j(x)}{\sum_{j=1}^{N_r} \mu_j(x)} \tag{19}$$

$$\begin{aligned} \frac{\partial E(k)}{\partial t_{ij}(k)} &= \frac{\partial E(k)}{\partial y(k)} \cdot \frac{\partial y(k)}{\partial \upsilon_j(k)} \cdot \frac{\partial \upsilon_j(k)}{\partial \psi_j(k)} \cdot \frac{\partial \psi_j(k)}{\partial z_{ij}(k)} \cdot \frac{\partial z_{ij}(k)}{\partial t_{ij}(k)} \\ &= \left(y(k) - y^d(k)\right) w_j \cdot \psi_j \left(\frac{-1}{d_{ij}}\right) \cdot \left(\frac{1}{z_{ij}} - z_{ij}\right) \cdot \frac{\mu_j(x)}{\sum_{j=1}^{N_r} \mu_j(x)} \end{aligned} \tag{20}$$

$$\frac{\partial E(k)}{\partial d_{ij}(k)} = \frac{\partial E(k)}{\partial y(k)} \cdot \frac{\partial y(k)}{\partial \upsilon_j(k)} \cdot \frac{\partial \upsilon_j(k)}{\partial \psi_j(k)} \cdot \frac{\partial \psi_j(k)}{\partial z_{ij}(k)} \cdot \frac{\partial z_{ij}(k)}{\partial d_{ij}(k)} = z_{ij} \cdot \frac{\partial E(k)}{\partial t_{ij}(k)} \tag{21}$$

$$\frac{\partial E(k)}{\partial \theta_{ij}(k)} = \frac{\partial E(k)}{\partial y(k)} \cdot \frac{\partial y(k)}{\partial \upsilon_j(k)} \cdot \frac{\partial \upsilon_j(k)}{\partial \psi_j(k)} \cdot \frac{\partial \psi_j(k)}{\partial z_{ij}(k)} \cdot \frac{\partial z_{ij}(k)}{\partial u_{ij}(k)} \cdot \frac{\partial u_{ij}(k)}{\partial \theta_{ij}(k)} = -\varphi_{ij}(k-1) \cdot \frac{\partial E(k)}{\partial t_{ij}(k)} \tag{22}$$

4. **Target Threat Assessment Using MPSO Optimized Fuzzy Recurrent Wavelet Neural Network.** Target threat assessment requires considering many different kinds of factors (such as geography, weather, and enemy). It is also not a pure linear combination between various factors and threat degree; thus, the explicit functional relationship between the various factors and the target threat value can hardly be created. By considering comprehensively various factors, we selected the influencing factors associated with threat degree, which were systematically elaborated in Section 4.1.

4.1. **Influencing factors of target threat assessment.** Through considering synthetically various factors, we selected target type, target speed, target interference capability, target heading angle, target height and target distance as main influencing factors of threat degree. Under G. A. Miller's nine levels quantitative theory [32], the six input variables applied in this innovative research work were as follows.

• Target type (K): the target type is split into three kinds consisting of reconnaissance plane, small target (such as tactical ballistic missiles, and stealth aircraft) and large target (such as bomber, and fighter bomber). For the sake of facilitating quantitative study, the reconnaissance plane, small target and large target were quantified for 3, 5 and 8, respectively.

• Target speed (V): the target speed is the vector composite of approach velocity and transverse velocity. Under different flight speeds, the same type of target has a different threat level. Generally, a greater value of threat degree is associated with faster flight speed.

• Target interference capability (C): target interference capability, as an important method of electronic countermeasure, can be divided into four kinds: strong, medium, weak and very weak. Generally, a greater value of threat degree is associated with stronger capability of target interference capability. The strong, medium, weak and very weak are quantified for 8, 6, 4 and 2, respectively.

• Target heading angle (θ): target heading angle is the angle between the target advancing direction and the actual position of the target to the defended target. Speaking generally, the small heading angle means big possible that the target appeared; a greater value of threat degree is associated with smaller heading angle of target.

• Target height (H): in the case of the target away from our side, the flight altitude of the target is not obvious to our threat. However, it will be a great threat degree to us when the target crops up and hits us in low altitude. The ultralow altitude, low altitude, medium altitude and high altitude were respectively quantified for 2, 4, 6 and 8.

• Target distance (D): the closer the distance between the incoming target and the protected target is, the greater the target threat degree is. Contrariwise, the farther the distance between the incoming target and the protected target is, the lower the threat degree is.

4.2. **The flow chart and the training process of target threat assessment.** In this section, we discuss the detailed threat degree model for influencing factors provided by combat situation data. We choose 60 pairs of combat situation data containing 45 pairs data as a training set to train MPSO optimized FRWNN, and then the target threat value of the rest of situation data is assessed by using the trained network. Based on MPSO optimized FRWNN, the flow chart of target threat assessment algorithm is shown in Figure 1.

The detailed training process of MPSO optimized FRWNN is as follows.

1) Data preprocessing. First, the raw data is quantified and normalized, and then the data set was split into training data set and testing data set, respectively.

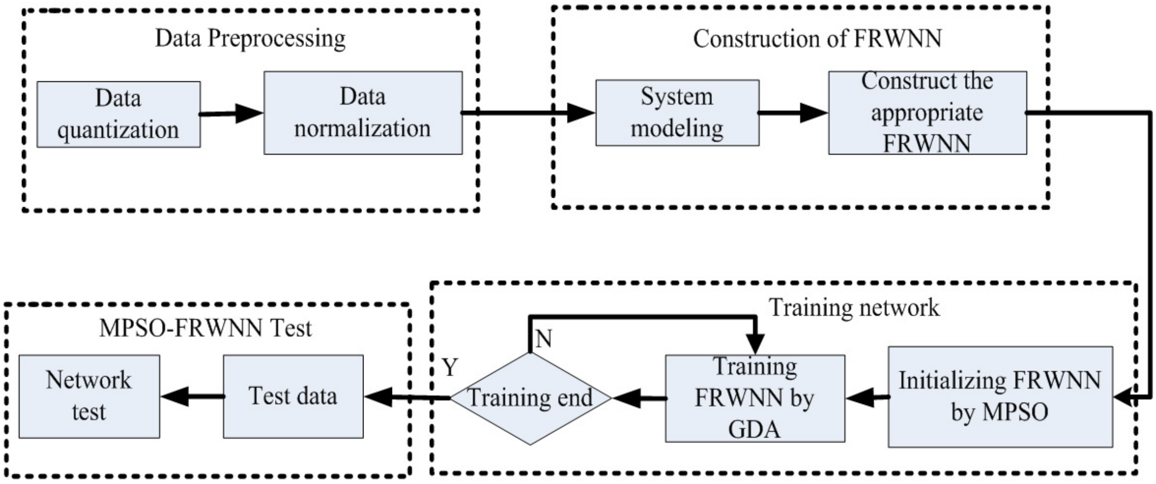

Figure 1. Target threat algorithm flow chart based on MPSO optimized FRWNN

2) Initialization of the MPSO optimized FRWNN. By using MPSO in Section 3.2, we initialize the important parameters of MPSO-FRWNN such as center parameters, scaling parameters, translation parameters, dilation parameters and weights as well as storage factor.

3) Training MPSO-FRWNN by GDA. Train the consequent part of the proposed MPSO-FRWNN by Equations (15)-(18) as noted previously in Section 3.3.

4) Updating the network parameters. In the light of the prediction error indicator, the parameters and the connection weights of MPSO optimized FRWNN are renewed in order to make the assessment value as close to the actual value as possible.

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

5. **Model Simulation.** The main idea of the threat assessment is to extract target's combat situation metrics related to threat degree (T) and build the relationship between threat degree and these metrics. As mentioned in Section 4, we selected six influence factors of target threat values as input variables and the target threat values as output variable. The performance of MPSO-FRWNN is tested by these factors. Part of the data used to validate the proposed model is presented in Table 1, where large target, reconnaissance plane, and small target are listed in nine pairs, respectively.

5.1. **Analysis of simulation results.** In order to demonstrate the efficiency of the MPSO-FRWNN, it was then compared with the known architectures using different models named PSO-FRWNN and FRWNN.

Three rules ($Nr = 3$) are employed in our three experiments, so the number of network parameters is 93. The population size $psize = 57$, and the termination iterative number $Maxgen = 50$, which are constructed comparatively small to cut down the running time and prevent over-training of the training signal which may result in reducing search scope of testing signal. The acceleration coefficients c_1 and c_2 in MPSO and basic PSO are all set to 2, and the linear decreasing inertia weight is utilized here. Initialize the proposed FRWNN by using MPSO, PSO and a random generation of network parameters, which corresponds to the MPSO-FRWNN, PSO-FRWNN and FRWNN models respectively. The three different ANN assessment models (for FRWNN, PSO-FRWNN and MPSO-FRWNN) are trained and tested for the above-mentioned combat situation data

TABLE 1. Part of the data

No.	K	V (m/s)	C	θ (°)	H (km)	D (km)	T
1	8	560	6	10	6	150	0.5828
2	8	700	6	17	8	310	0.5580
3	8	760	8	4	8	120	0.6235
4	8	430	8	11	4	130	0.5841
5	8	740	6	6	4	110	0.6473
6	8	730	8	16	2	260	0.6574
7	8	460	6	8	4	200	0.5784
8	8	400	8	5	8	140	0.5056
9	8	620	8	13	2	320	0.6302
10	5	1250	6	13	4	190	0.8789
11	5	660	8	17	6	270	0.6424
12	5	970	8	3	6	310	0.8253
13	5	1080	8	8	6	270	0.8306
14	5	830	8	12	8	160	0.7285
15	5	630	6	5	8	160	0.5943
16	5	900	8	17	8	310	0.7052
17	5	720	8	7	4	300	0.7336
18	5	1010	8	5	8	190	0.8078
19	3	109	4	13	4	270	0.3623
20	3	100	4	13	4	220	0.3624
21	3	100	2	8	6	250	0.3462
22	3	95	4	9	4	190	0.3781
23	3	105	2	17	2	140	0.3605
24	3	90	4	17	4	180	0.3504
25	3	96	4	10	6	310	0.3427
26	3	90	4	2	8	220	0.3581
27	3	105	4	4	8	160	0.3706

by using the MATLAB. Then the researchers compared the MPSO-FRWNN algorithm with the PSO-FRWNN and FRWNN neural network models.

All three predicted results are shown in Figure 2. Compared to other models, a higher accuracy was provided by the prediction result based on MPSO-FRWNN. However, the partial detail of predicted results cannot be unambiguously illustrated by Figure 2. As a result, the other performance metrics such as error, relative error and root mean square error (RMSE) are analyzed to further investigate the effectiveness and feasibility of developed MPSO-FRWNN.

In Figure 3, the research results of MPSO and PSO optimization mechanisms are shown and illustrated; it revealed that the fitness value of MPSO improves more rapidly in the early evolution. The fitness values of MPSO after 23 iterations have been better than those of basic PSO after 32 iterations. When the fitness value does not decrease any more with time, it implies that the proposed optimization mechanism reaches the best solution of the problem. As shown in Figure 3, the optimization mechanisms of MPSO and PSO reach the fitness values of 0.0120 and 0.0196 after the same iteration steps respectively, which demonstrates that the convergence speed of the MPSO algorithm is faster than that of PSO.

For the consequent part of MPSO-FRWNN hybrid algorithm, the RMSE diminution curve at the time of training and testing of GDA is illustrated in Figure 4. As shown

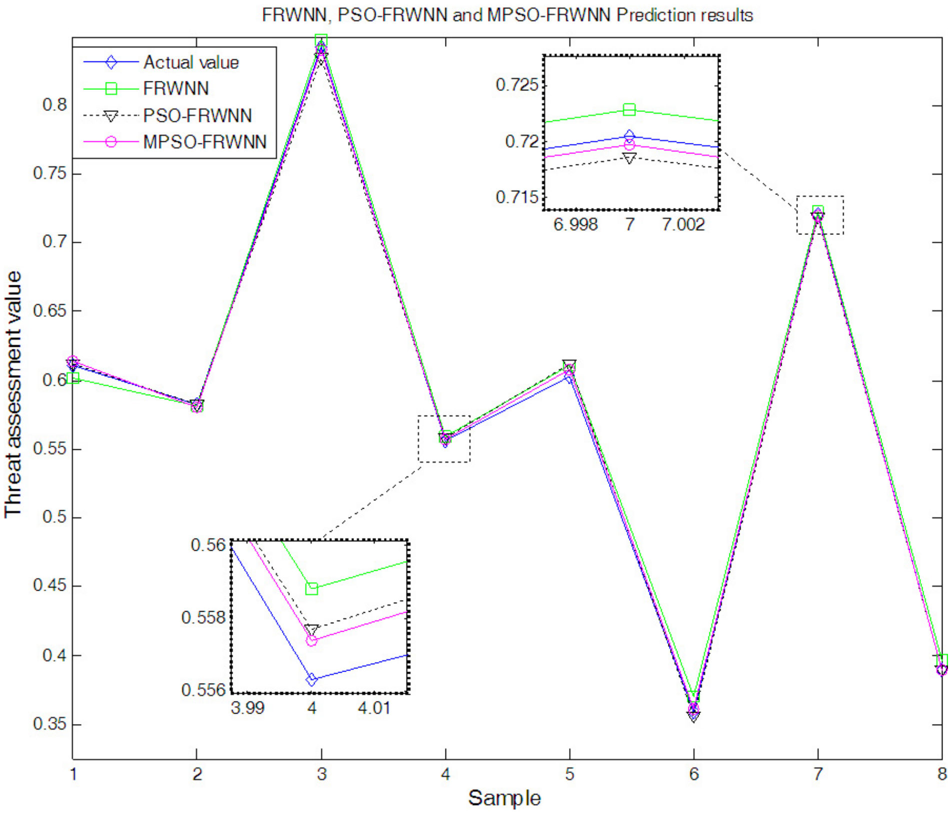

FIGURE 2. FRWNN, PSO-FRWNN and MPSO-FRWNN prediction results

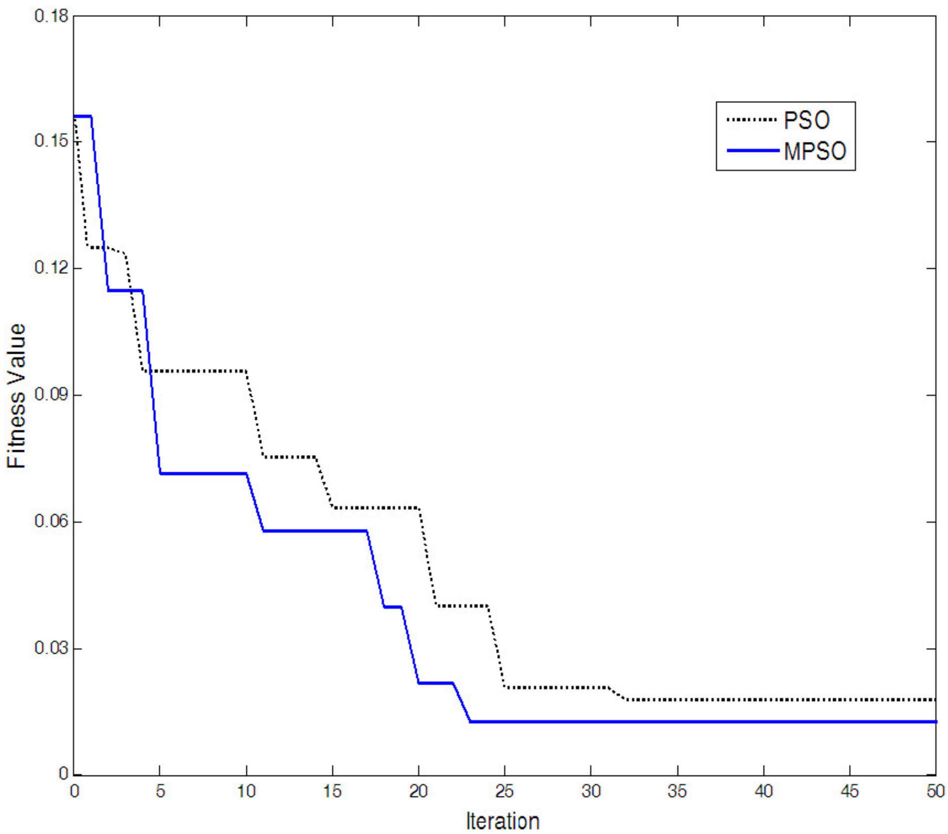

FIGURE 3. Fitness value of two PSO

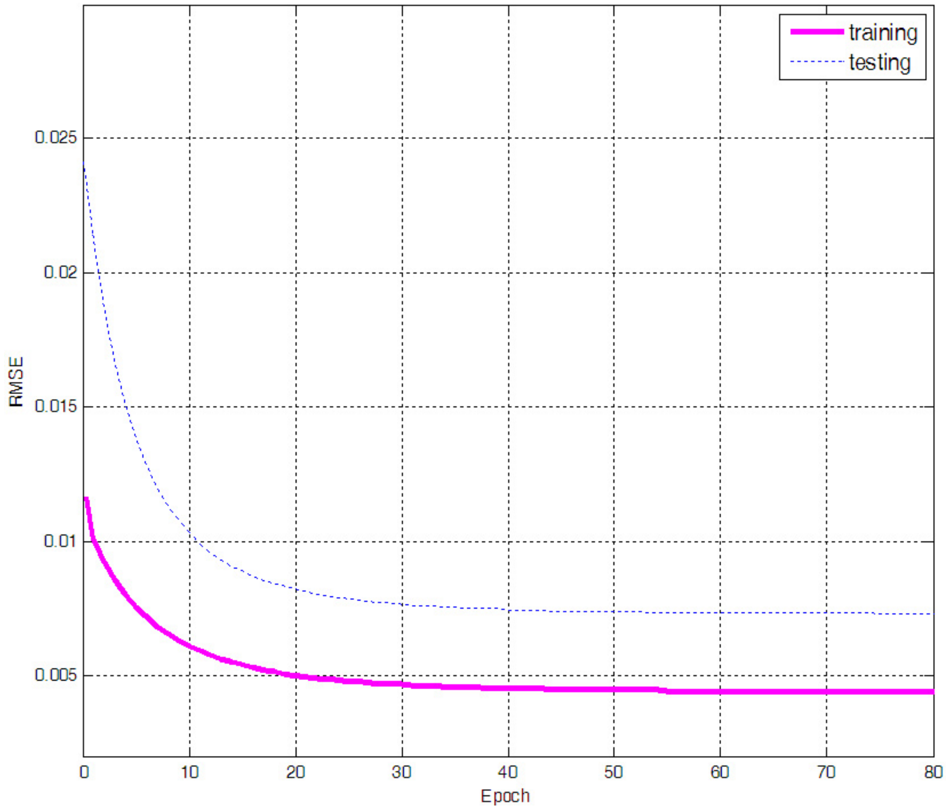

FIGURE 4. RMSE value for MPSO-FRWNN

in Figure 4, owing to the appropriate initialization parameters for FRWNN obtained by two-layer inline stage of MPSO, whose adjustment plan can be in harmony with gradient descent, the RMSE values can decrease moderately with iteration at the time of training and testing for the hybrid model, while small learning rates are employed. The dashed line corresponding to the RMSE values obtained for testing curve reveals the reasonableness of the hybrid algorithm.

To better compare and investigate the relation between the real threat value and the evaluation value of all three kinds of assessment models, the error curve and relative error curve are shown in Figures 5 and 6. In terms of overall trend of error curve, the prediction error of MPSO-FRWNN shows the smallest fluctuation around zero, which indicates that a small matching error between the real threat value and the evaluation value is obtained. Comparing the overall change trend, relative error curve from the hybrid algorithm is closer to zero than that of others, demonstrating the low error of the proposed scheme further in Figure 6. Generally, the error and relative error of the proposed MPSO-FRWNN achieve minimum errors compared to the PSO-FRWNN and FRWNN models.

The performance of the MPSO-FRWNN is elaborately investigated to identify the model's threat assessment capabilities by considering the same criterion. The RMSE values of the proposed FRWNN based target threat assessment system for training and testing data are compared and illustrated in Table 2, which describes the simulation results of other two models as well. As shown in Table 2, the RMSE values of training and testing of MPSO-FRWNN (0.004150, 0.006901) are all lower than PSO-FRWNN (0.009279, 0.012086) and FRWNN (0.018198, 0.020292). So it can be seen that the proposed MPSO-FRWNN model shows better performance than the other models for target threat assessment when the three rule numbers are employed.

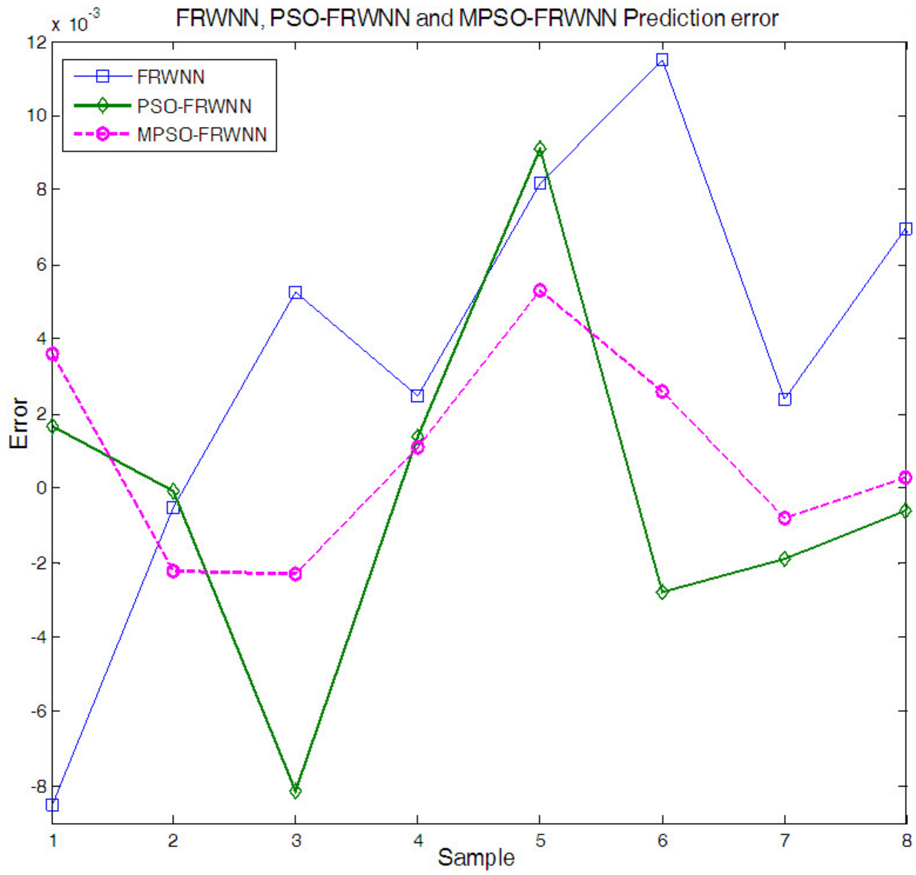

FIGURE 5. Assessment error curve

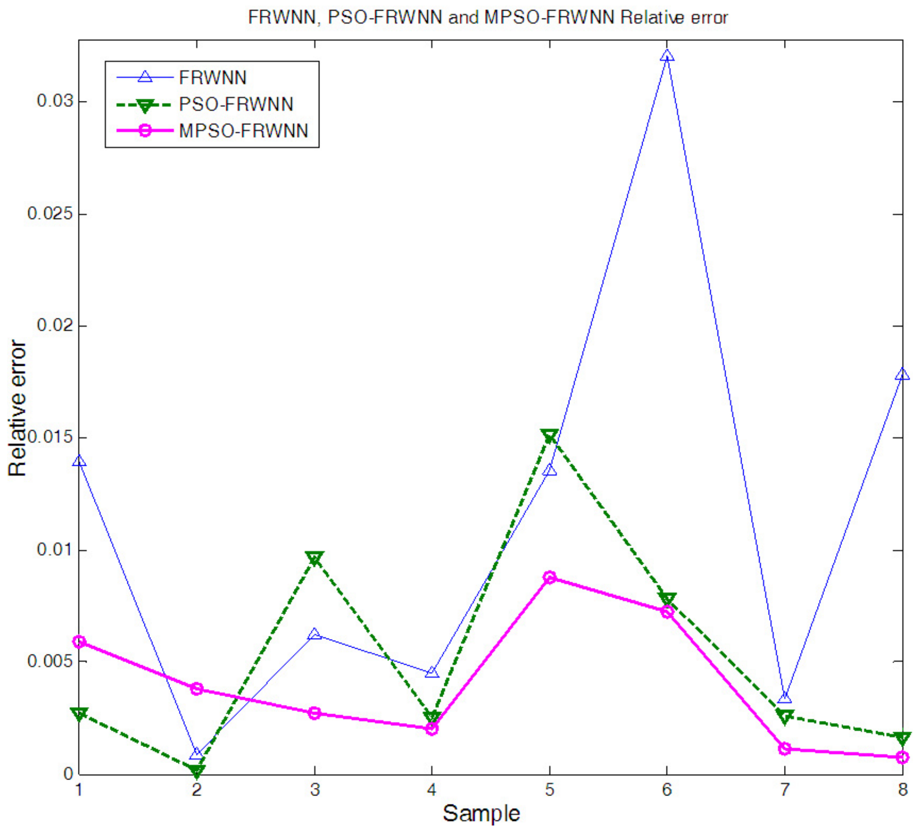

FIGURE 6. Relative error curve

Table 2. Comparison of all three simulation results for threat assessment

Model	RMSE of training	RMSE of testing	Rule number	Network parameters
FRWNN	0.018198	0.020292	3	93
PSO-FRWNN	0.009279	0.012086	3	93
MPSO-FRWNN	0.004150	0.006901	3	93

The analyzed results manifest that the error, relative error and RMSE of the MPSO-FRWNN are all superior to the PSO-FRWNN and the FRWNN assessment models. A better prediction result is gained compared to other models, and the defect of PSO falling into local optimal solution is overcome; meanwhile, the training rate of MPSO-FRWNN network makes better cooperation with GDA on the basis of the optimal solution offered by the MPSO. As a result, studies demonstrate promising results and show that the obtained error analysis successfully confirms the validity of our proposed strategy, which provides a novel model for the threat assessment.

6. Conclusions.

In the light of the increasing sundry challenges such as high fluctuations of battlefield environment, the uncertainty and sudden changes of the target situation as well as the requirements for quickly processing information in modern war, in some ways FRWNN can solve the target threat assessment by synthetical consideration of various factors which influence the target threat degree [22]. However, there are two main concerns for the FRWNN and PSO-FRWNN assessment models when we use GDA to train two kinds of models. Firstly, the convergence rate of GDA depends on the initial values of unknown parameters for FRWNN. Secondly, non-stable training process may occur caused by the large learning rate due to an unsatisfactory optimization solution for PSO-FRWNN. The two concerns can be resolved by MPSO-FRWNN assessment model which combines MPSO with GDA. To situate a more reasonable region in the search space, MPSO with two-layer inline-PSO can hunt for the optimal solution by updating parameters after each measurement and that contains all vectors, which is in correspondence to the adjustment plan of the consequent part gradient descent algorithm and can result in a faster convergence speed. GDA can be taken advantage for coordinating the optimal solution, which can accelerate the convergence performance of the training process.

Ultimately, MPSO-FRWNN can deal with the uncertainty and sudden changes of the target situation by both the concepts of fuzzy logic and the flexible consequent part while the local details of non stationary and high dimension of external input variables can be decomposed in the light of the translation and dilation parameters of the proposed consequent part. The assessment modeling was used to learn the non-linear relationship between influencing factors and target threat value. The characteristics of the proposed MPSO-FRWNN demonstrated its promising characteristics like dynamic approximation capability, excellent convergence performance and strong online adapting capacity as well as its good coordination ability with GDA are also highlighted. By the comparative analysis of evaluation model, it can be observed that the proposed method has more competitive evaluation ability and can quickly and accurately evaluate the target threat as well as provides support for the tactical decision and task allocation.

The use of type-2 fuzzy systems can be further considered as the antecedent part of the MPSO-FRWNN to deal with the uncertainties and to handle uncertain information in our future work by observing type-2 fuzzy wavelet neural network [33,34]. To further overcome the disadvantage of the GDA, the initialization of FRWNN by evolutionary population-based algorithms such as genetic algorithm could be considered and compared. Moreover, the future work will further consider the changes in the learning algorithm including both initialization and new updating rules.

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