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RESEARCH ARTICLE

A Radar TR Component Electromagnetic Interference Signal Strength Prediction Model Based on IGWO-SVR

JINGYANG WANG [1], **JIN LI** [1], **LIYUN MA** [2], **AND YUMING WANG** [2]

[1] Hebei University of Science and Technology, Shijiazhuang, Hebei 050018, China
[2] Army Engineering University, Shijiazhuang Campus, Shijiazhuang, Hebei 050003, China

Corresponding authors: Liyun Ma (maliyun@aeu.edu.cn) and Yuming Wang (wangyuming@aeu.edu.cn)

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ABSTRACT As a key sensor, radar plays an important role in obtaining war information. However, radar will be affected by the deteriorating electromagnetic environment on the battlefield. Therefore, it is necessary to carry out electromagnetic interference effect experiments to improve the anti-interference ability. In the electromagnetic interference experiment of the radar TR component, the signal output from the signal generator passes through the power amplifier, the transmitting antenna and the receiving antenna, and then is applied to the TR component. In the experiment, to obtain a certain size of interference signal acting on the TR component, it is often necessary to manually adjust the output signal strength of the signal generator repeatedly through human experience. The experimental process is complicated, and the experimental error is large. Therefore, it will make the experiment more convenient and accurate to achieve the desired interference signal size on the TR component by accurately predicting the output signal strength value of the signal generator, which has important practical significance. This paper proposes an IGWO-SVR based signal generator output signal strength prediction model, which includes Improved Grey Wolf Optimizer (IGWO) and Support Vector Regression (SVR) algorithms. IGWO is a new swarm optimization algorithm proposed in this paper. By improving the convergence factor a and the final position of ω wolf, IGWO solves the problems that the traditional GWO algorithm easily falls into local optimum and the convergence speed is slow. IGWO is used to optimize two hyperparameters of SVR (penalty coefficient C and kernel parameter γ). SVR is used to predict the output signal strength value of the signal generator. To prove the validity of the IGWO-SVR, comparison experiments are made between the IGWO-SVR and 20 other models. The real data obtained from the experiments of electromagnetic interference effect by irradiation method are selected as the experimental data. Mean Absolute Error (MAE), Mean Squared Error (MSE), and Fitting Degree R Squared (R^2) are used to evaluate the overall performance of the models. Through comparative experiments, the MAE of the IGWO-SVR model is 1.1481, MSE is 2.6679, R^2 is 0.9430, and its performance in various evaluation indexes is better than other models.

INDEX TERMS Signal strength, IGWO, SVR, prediction, electromagnetic interference.

I. INTRODUCTION

In the modern high-tech war, whether to obtain information effectively has become the key to getting the first combat opportunity. Radar plays an important role as a key information acquisition sensor. However, with the escalation of electronic warfare, the radar must deal with the deterioration of the electromagnetic environment on the battlefield. Therefore, we must conduct experimental research on the electromagnetic interference effect to improve the anti-interference ability of radar [1]. The electromagnetic interference effect experiment of the TR component includes two parts: the electromagnetic interference experiment and the effect analysis experiment. The electromagnetic interference experiment

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applies electromagnetic interference to the TR component, and the effect analysis experiment analyzes the effect of the TR component after being interfered with. This paper studies the electromagnetic interference effect experiment of the TR component, as shown in Figure 1.

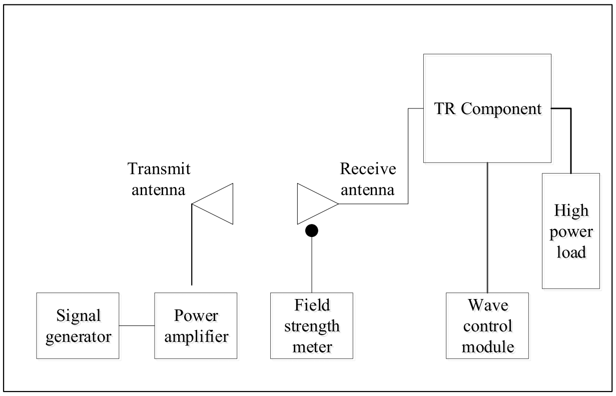

FIGURE 1. Electromagnetic interference effect experiment of TR component.

The signal generated by the signal generator passes through the power amplifier, the transmitting antenna, and the receiving antenna and is applied to the TR component. The field strength meter measures the interference signal acting on the TR component. The wave control module sets the transmitting/receiving state of the TR component. The size of the interference signal applied to the TR component is an important index in the experiment of the electromagnetic interference effect, which affects the TR component's working state and transmitting/receiving performance. However, the power amplifier, transmitting antenna, and receiving antenna are all nonlinear devices, so it is difficult to directly calculate the signal strength value of the signal generator by the interference signal preloaded on the TR component. In the experimental process, it is usually necessary to manually adjust the output signal of the signal generator repeatedly with the help of personal experience to achieve the interference intensity required by the TR component, which is cumbersome and easily produces large errors. Therefore, it will be more convenient and accurate to achieve the desired interference signal size on the TR component by accurately predicting the output signal strength value of the signal generator. This measure has significant practical significance.

Machine learning uses computers to learn the laws and patterns existing in data and deeply mines the potential information existing in data. Machine learning can deal with classification and regression problems [2]. Traditional mathematical methods cannot model complex relationships, while machine learning suits complex problems. With the development of electronic warfare, machine learning has been widely used in the military field.

As a kind of machine learning, SVR has some advantages in prediction. It can effectively deal with nonlinear problems and map data to high-dimensional space using a kernel function to achieve higher prediction accuracy. It has better processing ability for small samples and nonlinearity [3]. In practical application, the prediction accuracy can be improved by combining it with other algorithms. So, we introduce GWO to combine with SVR.

GWO is a global optimization swarm intelligence search algorithm proposed by Australian scholar Mirialili et al., which simulates the predator-prey pattern of grey wolves in nature. It uses the hunting process of wolves to optimize the search for the optimal solution [4]. GWO has low complexity, simple principle, few adjustable parameters, and easy implementation, and shows strong global search ability [5]. Because of its good convergence speed and solution accuracy, GWO has been verified to have better optimization performance than many current intelligent optimization algorithms and has been widely used by many scholars in recent years [6].

This paper proposes a new combined model IGWO-SVR to predict the output signal strength of the signal generator. IGWO is a new swarm optimization algorithm proposed in this paper. By improving the convergence factor a and final position of ω Wolf, IGWO solves the problems that the traditional GWO algorithm easily falls into the local optimum and has a slow convergence speed. IGWO is used to optimize the penalty coefficient C and kernel parameter γ of the SVR. SVR is used to predict the output signal strength value of the signal generator. To verify the validity of IGWO-SVR, the prediction results of IGWO-SVR are compared with those of 20 other models.

The following are the innovations and main contributions of this paper:

(1) This paper proposes a new grey wolf optimization algorithm, IGWO, which uses an exponential nonlinear convergence method to replace the original linear convergence method. This nonlinear convergence factor not only ensures the ability to expand the search range of the algorithm but also balances the conflict between global search and local optimization and further enhances the ability of global optimization of the algorithm, so it is more in line with the actual convergence process.

(2) In this paper, by combining self-organized criticality theory, the Evolutionary Population Dynamics (EPD) is fused into the population updating process of the GWO algorithm. In this way, the search range of wolves can be extended to the whole solution space, thus increasing the probability of obtaining the global optimal solution.

(3) This paper proposes a new prediction model based on IGWO-SVR for the signal generator's output signal strength. Under the same data set and experimental conditions, the prediction results of the IGWO-SVR model are better than other models.

II. RELATED WORK

In 2008, Xu et al. used the numerical calculation method in the electromagnetic field to study the electromagnetic environment prediction and utilized the moment method to predict the electromagnetic environment effect [7]. The predicted field strength of the equipment based on the moment method is in good agreement with the measured field strength in the space area within 45 degrees of the caliber plane of the equipment. However, there are certain restrictions on the caliber surface of the equipment. In 2014, Guo et al. used the parabola equation to predict electromagnetic environmental effects [8]. The parabolic equation model calculates the propagation process of radio waves, and the electromagnetic environment intensity at a specific geographical position in the sea battlefield is predicted. It provides a basis for battlefield commanders to deploy quickly, but it is easily affected by radiation sources, environment, and other factors. In 2017, Hu et al. used a Bayesian network to predict and analyze complex electromagnetic environments and solved the problem of uncertain decision-making [9].

Han et al. [10] put forward AdaBoost for power load forecasting. However, it is easily affected by noise and redundancy in eigenvalues. Xu et al. [11] found that MLP is superior to other Antarctic dynamic models in predicting tropical cyclone intensity, but this only applies to the Atlantic Ocean, not the whole world. Wu et al. [12] applied RF to short-term load forecasting of power systems. At the same time, the grey relational projection method was used to select similar days to simplify the model training and improve the prediction accuracy. However, the generalization error is uncontrollable. Aiming at the problems of low prediction accuracy and too many input variables in the existing temperature prediction method of grain storage, Guo and Wang [13] constructed a grain temperature prediction model combining Bayesian with XGBoost. However, there are many super parameters of XGBoost, which are difficult to choose reasonably. In 2016, Anicici et al. [14] utilized the SVR method to predict noise levels in wind turbines. The experiments show that the accuracy of SVR using radial basis function is significantly higher than that using polynomial basis function.

In 2016, Chen et al. applied GWO to turbine parameter optimization. The results show that GWO has better robustness and stronger generalization ability, but there is still the problem of premature convergence [15]. In 2017, Duca et al. applied Particle Swarm Optimization (PSO) to optimize electromagnetic field devices, suggesting that using one thread per block is the most efficient approach. This method is four times faster than sequential implementations on hardware architectures [16]. In 2019, Najimi, et al. applied an Artificial Bee Colony (ABC) combined with artificial neural network and applied it to predict the direction of chloride ion penetration. The experimental results show that the model has higher reliability [17]. Demirdelen et al. applied the Firefly Algorithm (FA) combined with artificial neural network and applied it to characteristics for wind turbines prediction. The experimental results show that the prediction effect is improved [18]. Holzinger et al. used the Ant Colony Optimization (ACO) algorithm to conduct the shortest path in a snake-like game, and the experimental results show that the algorithm achieves good results [19]. In 2019, Santra et al. applied Genetic Algorithms (GA) to power load forecasting, enhancing the robustness of short-term load forecasting. The results demonstrate that this method yields a small average absolute percentage error in the test data [20]. In 2020, Tao et al. used the PSO-RF combined model to predict wind speed, and the results showed that the PSO-RF model has significant performance [21]. In 2021, Li et al. established a new pavement performance prediction model based on PSO-SVR to solve the problem of low prediction accuracy of asphalt pavement performance at present. The research results show that the generalization effect is good and the prediction accuracy is high [22]. In 2022, Zhu et al. established a production prediction model of coalbed methane Wells based on GA-RF, and the results had high accuracy [23]. In 2022, Wang et al. proposed a new GA-SVR-GRNN combined model for predicting future oil prices. The experimental results show that this is an accurate and effective method for predicting oil futures prices [24]. In 2022, Chen et al. proposed the IGWO-SVR combined model and applied the model to the cold load prediction of ice storage air conditioners. This model is named IGWO1-SVR for the convenience of later expression. The prediction accuracy is improved by changing the convergence factor into a piecewise function and using a random walk to change the position. However, it lacks in balancing local search and global search [25]. In 2022, Bi et al. proposed a combined prediction model of the IGWO-SVR algorithm and applied it to predict coal mine gas emission. This model is named IGWO2-SVR for the convenience of later expression. The prediction accuracy is improved by improving the convergence factor and using the DLH search strategy to update the location of the grey wolf population. Still, the convergence rate of convergence factors is slow [26]. We will conduct comparative experiments on IGWO1-SVR, IGWO2-SVR, and IGWO-SVR to illustrate this paper's contribution further.

III. MODELS

A. SVR

SVR aims to find an optimal hyperplane and minimize the deviation between all sample points and the optimal hyperplane [27].

Given the data sample set $X = \{(x_i, y_i) \mid i = 1,2,\cdots,n\}$, where $x_i = [x_i^1, x_i^2, \cdots, x_i^d]^T$, $y_i \in R$, a regression function is established as shown in formula 1.

$$f(x) = w \cdot \varphi(x) + b \quad x \in X \tag{1}$$

where $\varphi(x)$ is a nonlinear mapping function; $b \in R$ denotes the threshold; w is the feature weight vector.

Reference a linear insensitive loss function ξ:

$$\xi(f(x), y) = \begin{cases} 0, & |y - f(x)| \le \theta \\ |y - f(x)| - \theta, & |y - f(x)| > \theta \end{cases} \tag{2}$$

where $f(x)$ is the predicted value of the fitting function; y is the corresponding actual value. θ is the maximum deviation we can tolerate.

The meaning of the reference of the insensitive loss function ξ is that if the difference between $f(x)$ and y is within the allowable error range, then $f(x)$ has no loss.

Introducing the relaxation variables ξ_i, ξ_i^*, the following constraint conditions are established:

$$min\frac{\| w \|^2}{2}+C\sum_{i=1}^{n}\left(\xi_i+\xi_i^*\right) \tag{3}$$

$$s.t.\begin{cases} y_i-w\cdot\varphi\left(x_i\right)-b\leq\theta+\xi_i \\ -y_i+w\cdot\varphi\left(x_i\right)+b\leq\theta+\xi_i^* \\ \xi_i\geq 0,\ \xi_i^*\geq 0,\ i=1,2,\cdots,n \end{cases} \tag{4}$$

The Lagrange coefficient is introduced and transformed into the dual form:

$$\begin{aligned} max&\left[-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left(\alpha_i-\alpha_i^*\right)\left(\alpha_j-\alpha_j^*\right)K\left(x_i,x_j\right)\right. \\ &\left.-\sum_{i=1}^{n}\left(\alpha_i+\alpha_i^*\right)+\sum_{i=1}^{n}\left(\alpha_i-\alpha_i^*\right)y_i\right] \end{aligned} \tag{5}$$

$$s.t.\begin{cases} \sum_{i=1}^{n}\left(\alpha_i-\alpha_i^*\right)=0 \\ 0\leq\alpha_i\leq C \\ 0\leq\alpha_i^*\leq C \end{cases} \tag{6}$$

where $K\left(x_i,x_j\right)=\varphi(x_i)\varphi(x_j)$ is the kernel function.

The optimal solutions α and α^* of this programming problem are solved. Through Karush-Kuhn-Tucker condition, we can get:

$$\begin{cases} w^*=\sum_{i=1}^{n}\left(\alpha_i-\alpha_i^*\right)\varphi\left(x_i\right) \\ b^*=\frac{1}{N_{nsv}}\begin{Bmatrix} \sum\limits_{0<\alpha_i<C}\left[y_i-\sum\limits_{x_i\in SV}\left(\alpha_i-\alpha_i^*\right)K\left(x_i,x_j\right)-\theta\right] \\ +\sum\limits_{0<\alpha_i<C}\left[y_i-\sum\limits_{x_j\in SV}\left(\alpha_i-\alpha_j^*\right)K\left(x_i,x_j\right)+\theta\right] \end{Bmatrix} \end{cases} \tag{7}$$

where N_{ns} is the number of support vectors, the offset b^* is calculated.

$$\begin{aligned} f\left(x\right)&=w\cdot\varphi\left(x_i\right)+b^* \\ &=\sum_{i=1}^{n}\left(\alpha_i-\alpha_i^*\right)\varphi\left(x_i\right)\varphi\left(x_j\right)+b^* \\ &=\sum_{i=1}^{n}\left(\alpha_i-\alpha_i^*\right)K\left(x_i,x_j\right)+b^* \end{aligned} \tag{8}$$

B. IGWO

In 1986, Craig Reynolds first studied swarm intelligence algorithms and established a simulation model, Boid. By observing the flight behavior of birds, it reconstructed the trajectory of birds and abstracted simulation and finally got a new motion pattern. In 1994, Millonas put forward that swarm intelligence should follow five basic principles [28]. In 1999, Bonabeau et al. wrote "Swarm Intelligence: From Natural to Artistic System," which made swarm intelligence further development [29]. Swarm intelligence algorithms have been applied in many fields. The commonly used swarm intelligence algorithms include the artificial bee colony algorithm, PSO algorithm, ant colony algorithm, and GWO. This paper selects GWO as a swarm intelligence algorithm.

GWO is a global optimization method of swarm intelligence search, and it simulates the hunting process of grey wolf predators. Swarm intelligence is the optimization method of simulating swarm behavior in social organisms [30]. It has strong global search ability and convergence performance, fewer parameters, easy to implement, and other characteristics, making the solution's accuracy higher in function optimization. GWO is widely used in many fields, such as feature subset selection [31], optimal control of DC motor [32], multi-layer sensor training [33], MIMO power system [34], UAV route planning problem [35], and so on. However, there are still some problems in GWO, such as easy falling into local optimum, slow convergence speed in the later iteration, and high algorithm complexity. In this paper, the swarm intelligence algorithm GWO is improved, which makes the algorithm difficult to fall into local optimum and solves the problem of slow convergence speed. It is used to optimize the parameters of SVR and establish a prediction model of signal strength value.

GWO simulates the powerful organization system and perfects the cooperation mode of the grey wolf population in nature. The grey wolf group has a strict social hierarchy. In the hunting process, each order performs its duties and cooperates sincerely until it successfully catches prey. Now, we artificially divide the grades in the wolf pack into four stages, which are named α, β, δ, and ω wolves, and their grades are arranged from high to low. The behavior of grey wolves in hunting can be divided into three stages: dividing grades to determine leadership, tracking prey, and encircling and besieging prey. When the final siege of prey is successful, the position of the α wolf is the optimal value of the super parameter found by GWO for us. Then, from the perspective of mathematical theory, the details of the GWO algorithm in simulating these three stages are as follows.

1) DIVIDING GRADES TO DETERMINE LEADERSHIP

The grey wolf population in nature has a strict social hierarchy. In each hunting process, the order will be divided first, the leadership will be determined, and each individual will find his scale and position and then perform his duties. As shown in Figure 2, the whole wolf pack is divided into

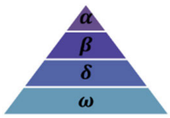

FIGURE 2. Grey Wolf hierarchy.

four grades, namely α, β, δ, and ω wolves, which are arranged from high to low. The first three grades are the three groups with the best fitness, which are located in the leadership of the population. The grey wolves in the administration not only have the strongest fitness but also have the function of leading the grey wolves lower than themselves. However, leadership is only sometimes constant. Through internal competition, better young individual wolf will constantly choose to update the administration to ensure the success of every hunt.

2) TRACKING PREY

After determining the level of each individual in the population, GWO will initialize the positions of α, β, δ, and ω wolves. Its positions and the distances between them will be continuously updated in tracking prey, as shown in Figure 3. Formula 9 represents the distance between grey wolves, and formula 10 represents the update mode of the grey wolf position.

$$D = \left| C \cdot X_p(t) - X(t) \right| \tag{9}$$

$$X(t+1) = X_p(t) - A \cdot D \tag{10}$$

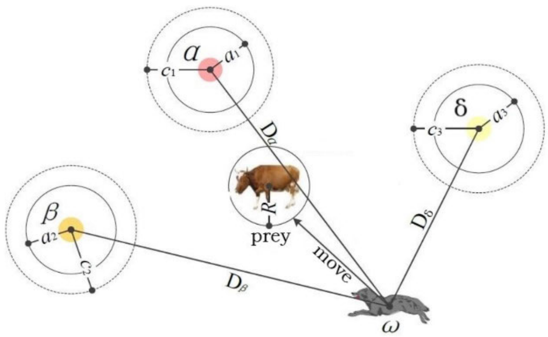

FIGURE 3. Principle of GWO algorithm.

D is the distance between the grey wolf individual and its prey; X_p is the position of the prey; t is the number of iterations; X is the position of the current grey wolf individual; A is a random variable, calculated as shown in formula 11, and C is a disturbance to prey, calculated as shown in formula 12.

$$A = 2a \cdot r_2 - a \tag{11}$$

A controls the increase and decrease of grey wolf individuals in the algorithm. When $|A| > 1$, the grey wolf will expand the search scope and find more possible solutions, which corresponds to the global search. On the contrary, when $|A| < 1$, the grey wolf will narrow the search range and find the possible solutions in the current field more accurately.

$$C = 2r_1 \tag{12}$$

Both r_1 and r_2 are random numbers between [0, 1].

The main control of parameter A is a, named the convergence factor, which decreases linearly from 2 to 0, and the calculation method is shown in formula13. Where t represents the current number of iterations and max represents the maximum number of iterations.

$$a = 2 - 2\left(\frac{t}{max}\right) \tag{13}$$

3) ENCIRCLING AND BESIEGING PREY

In encircling and besieging prey, when the leadership finds the prey position, the α wolf at the top of the pyramid will lead the β and δ wolves to command the whole wolf pack and guide the wolves to move closer to the prey from all directions to surround and besiege the target and finally hunt successfully. Because the positions of α, β and δ wolves must be closest to the prey when finding prey, the positions of these three wolves are used to guide the updated direction and moving step length of other wolves. The mathematical description of the update method is shown in Equations 14 to 16.

$$D_\alpha = |C_1 \cdot X_\alpha(t) - X(t)| \tag{14}$$

$$D_\beta = \left|C_2 \cdot X_\beta(t) - X(t)\right| \tag{15}$$

$$D_\delta = |C_3 \cdot X_\delta(t) - X(t)| \tag{16}$$

where X_α, X_β, and X_δ represent the current position of α, β and δ wolves, respectively, C_1, C_2, and C_3 represent random vectors, and X represents the current position of ω wolf.

Formulas 17-19 define the moving direction and step length of ω wolf to α, β, δ wolves, respectively. Where A_1, A_2, A_3 stand for random vector. Formula 20 determines the final position of the ω wolf.

$$X_1 = X_\alpha - A_1 \cdot D_\alpha \tag{17}$$

$$X_2 = X_\beta - A_2 \cdot D_\beta \tag{18}$$

$$X_3 = X_\delta - A_3 \cdot D_\delta \tag{19}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{20}$$

By studying the principle and structure of GWO, we can see that the dividing line of parameter A is 1, which determines whether the grey wolf should expand its search scope to find more and better food or narrow its encirclement to ensure its hunting success, that is, the balance between global search and local optimum. At the same time, we also know that the value of parameter A is mainly determined by convergence factor a. From formula 13, we can know that a is linearly decreasing in the original GWO algorithm. Still, as we all know, any swarm intelligence algorithm can not be linear in the whole convergence process, and of course, GWO can not be linear convergence. Therefore, the convergence factor based on this linearity does not conform to the actual convergence process of the algorithm. Reference [36] proposes an improved convergence factor a, shown in formula 21.

$$a = 2 - 2\left(2^{\frac{t}{max}} - 1\right) \tag{21}$$

Reference [37] also proposes an improved convergence factor a, as shown in formula 22.

$$a = 2 - 2\sin\left(\frac{t}{max} \cdot \frac{\pi}{2}\right) \tag{22}$$

Inspired by predecessors, another improved convergence factor a is proposed in this paper, as shown in formula 23.

$$a = 2 - 4\left(\frac{3}{2}^{\frac{t}{max}} - 1\right) \tag{23}$$

In formulas 21-23, t is the number of iterations, and max is the maximum number of iterations.

The three improved nonlinear convergence methods are compared with linear convergence, as shown in Figure 4.

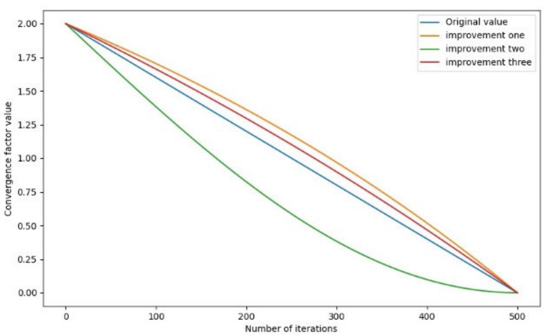

FIGURE 4. Comparison of convergence factors.

The original value represents the convergence factor corresponding to formula 13; the improvement one represents the convergence factor corresponding to formula 21; the improvement two represents the convergence factor corresponding to formula 22; and the improvement three represents the convergence factor proposed in this paper corresponding to formula 23. To prove that the convergence factor proposed in this paper is the most effective, the prediction results are compared with those of other convergence factors. The evaluation indexes of the experiment are MAE, MSE, and R^2. To avoid randomness, the average value of the evaluation index results of three experiments is taken as the final evaluation index experimental results. The forecast results are shown in Table 1.

It can be seen from Table 1 that the R^2 of the improved convergence factor proposed in this paper is larger than that of other models, and the fitting degree is better. At the same time, MAE and MSE are smaller than other models, and the prediction error is smaller. It can be seen from Figure 4, the improved convergence factor proposed in this paper gradually decreases in the form of a convex function, and the attenuation rate falls obviously at the initial stage of iteration,

TABLE 1. Experimental results of different convergence factors.

Convergence factor	R^2	MAE	MSE
$a = 2 - 2\left(\frac{t}{max}\right)$	0.9080	1.6461	4.3052
$a = 2 - 2\left(2^{\frac{t}{max}} - 1\right)$	0.9141	1.5473	4.0207
$a = 2 - 2\,sin\left(\frac{t}{max} \cdot \frac{\pi}{2}\right)$	0.9086	1.6015	4.2745
$a = 2 - 4\left(\frac{3^{\frac{t}{max}}}{2} - 1\right)$	0.9165	1.5139	3.9072

which means that the global search range is wider, and more candidate solutions are found. At the later stage of iteration, the convergence speed of the improved convergence factor proposed in this paper is accelerated, which makes the local optimal solution more accurate. Therefore, this nonlinear convergence factor not only ensures the ability to expand the search range of the algorithm but also balances the conflict between global search and local optimization and further enhances the ability of global optimization, so it is more in line with the actual convergence process.

For the conventional GWO algorithm, the next optimization direction of the grey wolf is determined by formula 20. It can be seen that the optimization direction of ω wolf in the population is guided by high-grade grey wolves (α, β and δ), which makes ω wolf search in the high-grade grey wolves. The found α wolf will fall into the local optimal solution, resulting in low convergence accuracy. In this paper, the EPD operator is integrated into the population renewal process of the GWO algorithm by combining the self-organized criticality theory so that the search range of wolves can be extended to the whole solution space and the probability of obtaining the global optimal solution can be increased. The updated formulas are:

$$X_{11} = X_1 + (ub - lb \cdot r1 + lb) \tag{24}$$
$$X_{22} = X_2 + (ub - lb \cdot r1 + lb) \tag{25}$$
$$X_{33} = X_3 + (ub - lb \cdot r1 + lb) \tag{26}$$
$$X(t+1) = \frac{X_{11} + X_{22} + X_{33}}{3} \tag{27}$$

where ub and lb are the upper and lower bounds of the population search space, respectively, and $r1$ is a random number with a value range between [0, 1]. This method is beneficial to jump out of the local optimum and get the global optimum solution. To prove the effectiveness of the population optimization proposed in this paper, its prediction results are compared with those of the original model. To avoid randomness, the average value of the evaluation index results of three experiments is taken as the final evaluation index experimental results. The forecast results are shown in Table 2.

TABLE 2. Experimental results of ω wolf's final position.

The final position of the ω wolf	R^2	*MAE*	*MSE*
$X(t+1) = \frac{X_1 + X_2 + X_3}{3}$	0.9080	1.6461	4.3052
$X(t+1) = \frac{X_{11} + X_{22} + X_{33}}{3}$	0.9399	1.1898	2.8120

It can be seen from Table 2 that the R^2 of the final position of the improved ω wolf proposed in this paper is larger than that of the original model, and the fitting degree is better. At the same time, MAE and MSE are smaller than the original model, and the prediction result is more accurate.

C. IGWO-SVR

The overall structure of the prediction model of output signal strength of signal generator based on IGWO-SVR is shown in Figure. 5.

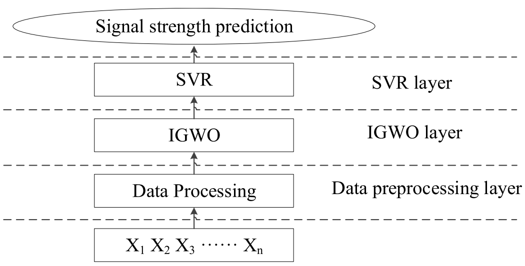

FIGURE 5. IGWO-SVR model structure diagram.

1) DATA PREPROCESSING LAYER

Standardize the data in the dataset by converting the data to similar scales to avoid certain features having too much impact on the model.

2) IGWO LAYER

Initialize IGWO algorithm-related parameters, randomly generate grey wolf individuals, and the position of each grey wolf is composed of SVR parameter penalty coefficient C and kernel parameter γ. Calculate the fitness value of each grey wolf, sort according to the fitness value, and get the top three grey wolves: α wolf, β wolf and δ wolf. The individual position of the grey wolf is updated by the position update formula; a, A, C are updated according to formula 23. The fitness value of the grey wolf is recalculated. The obtained fitness value is compared with the optimal fitness value of the previous iteration to retain the optimal fitness value. According to formula 27, the next generation of grey wolf individual $X(t+1)$ is generated. If t reaches max, the optimization process is terminated, and the optimal penalty coefficient C and kernel parameter γ of global search are obtained. Otherwise, it returns to the front to continue optimization. The IGWO algorithm is used to find the optimal individual position of the grey wolf as the optimal C and γ of the SVR model, and the SVR prediction model is established.

3) SVR LAYER

The SVR model is retrained by using the two optimal solutions found in the previous layer, and the prediction result of signal strength value is obtained.

IV. EXPERIMENT

A. EXPERIMENTAL ENVIRONMENT

The hardware environment and software environment of this experiment are shown in Table 3:

TABLE 3. Experimental environment.

Environment type	Item	Value
Hardware environment	Operating system	Windows 11
	CPU	12th AMD Ryzen 7 6800H with Radeon Graphics 3.20 GHz
	Memory	16GB
	Graphics card	RTX 3060
Software environment	Development tools	PyCharm 2022 2.3
	Programming language	Python3.7.0
	Basic platform	Anaconda4.5.11
	Learning framework	scikit-learn

B. DATA COLLECTION

Irradiation method is used in this experiment. The power amplifier amplifies the output signal of the signal generator, and the interference signal is finally applied to the TR component through the transmitting antenna and the receiving antenna, thus completing the electromagnetic interference experiment. During the experiment, the strength of electromagnetic interference is monitored using a field strength meter. The strength of the interference signal, gain of power amplifier, signal type, frequency of interference signal, and output signal strength of signal generator are taken as experimental data. A total of 1000 pieces of data are collected. Some data are shown in Table 4.

TABLE 4. Partial original experimental data.

Interference signal (dBm)	Gain	Signal type	Frequency (Hz)	Output signal (dBm)
-3.6998	0.8	1	8530000000	-8
-5.5238	0.7	2	9200000000	-12
-14.9555	0.9	3	9220000000	-20
-25.1009	0.8	4	2000000000	-30

In Table 4, the Interference signal (dBm) indicates the strength of the interference signal in dBm; the Gain indicates the gain of the power amplifier; in the Signal type field, 1 stands for continuous wave, 2 for amplitude modulation, 3 for phase modulation, and 4 for frequency modulation;

the Frequency indicates the frequency of the interference signal in Hz; the output signal (dBm) indicates the signal strength of the output of the signal generator in dBm.

C. DATA STANDARDIZATION

In the raw data, the values of different features may have different measurement units and ranges. If it is not standardized, features with a wider range may have a greater impact on the model, which leads to the inability of the model to learn and predict effectively. Many machine learning algorithms are very sensitive to the scale of data. Failure to standardize may lead to performance degradation of the algorithm because the algorithm may not converge or produce inaccurate predictions. Therefore, in this experiment, zero-mean normalization is selected to process the original data. After the standardized data processing, the data has a unified scale and distribution to improve the performance and stability of the machine learning model.

In this experiment, 800 pieces of data are selected as training set, 100 samples are used as verification set, and the remaining 100 are used as test set.

D. MODELS PARAMETERS

In this experiment, the important parameters of the twenty-one models are shown in Table 5.

TABLE 5. Model parameters.

Model	Parameters
DT	max_depth=3.5, random_state=42
AdaBoost	base_estimator=DecisionTreeClassifier (max_depth=2), n_estimators=50, random_state=42
XGBoost	objective=reg:squarederror, eta=0.15, max_depth=1, eval_metric=rmse
MLP	hidden_layer_sizes=(4,4), activation=relu, solver=adam, random_state=42
RF	n_estimators=1, max_depth=8, random_state=42, min_samples_leaf=0.08
SVR	kernel=rbf, C=1, gamma=0.01, epsilon=0.1
GWO- RF	n_estimators=1, max_depth=best_C*100, min_samples_leaf=best_gamma/5, random_state=42
GWO-SVR	kernel=rbf, cache_size=300, C=best_C, gamma=best_gamma
PSO-RF	n_estimators=1, max_depth=int(xopt[0]),min_samples_leaf=int(xopt[1]),random_state=42
PSO-SVR	C=abs(xopt[0]), gamma=abs(xopt[1])
GA-RF	n_estimators=int(best_n_estimators), max_depth=int(best_max_depth)
GA-SVR	C=best_C, epsilon=best_epsilon, gamma=best_gamma
ACO-RF	n_estimators=int(best_params[0]),max_depth=int(best_params[1]),min_samples_leaf=int(best_params[2]),random_state=42
ACO-SVR	C=best_params['C'], gamma=best_params['gamma']
ABC-RF	n_estimators=best_solution['n_estimators'],max_depth=best_solution['max_depth'],min_samples_leaf=best_solution['min_samples_leaf'],random_state=42
ABC-SVR	C=best_solution['C'], gamma=best_solution['gamma']
FA-RF	n_estimators=int(best_firefly['n_estimators']),max_depth=int(best_firefly['max_depth']),min_samples_leaf=int(best_firefly['min_samples_leaf']),random_state=42
FA-SVR	C=best_firefly['C'], gamma=best_firefly['gamma']
IGWO1-SVR	svr_regressor = SVR (kernel='rbf', cache_size=300, C=best_C, gamma=best_gamma)
IGWO2-SVR	svr_regressor = SVR (kernel='rbf', cache_size=300, C=best_C, gamma=best_gamma)
IGWO-SVR	kernel=rbf, cache_size=300, C=best_C, gamma=best_gamma

E. EXPERIMENTAL ANALYSIS

To verify the effectiveness and accuracy of the prediction model of output signal strength of signal generator based on IGWO-SVR, the prediction results of this model are compared with those of other models. R^2, MAE, and MSE are used as evaluation indexes. At the same time, to eliminate the influence of randomness on the results, the average value of the evaluation index results of the three experiments is taken as the final evaluation index experimental results. The experimental results are shown in Table 6. The results show that the IGWO-SVR model is superior to other models in all evaluation indexes.

It can be seen from Table 6 that the fitting degrees of DT, AdaBoost, and XGBoost models in signal strength prediction only reach 0.6392, 0.7174, and 0.7718, respectively, and the fitting degrees are poor compared with other models. The fitting degree of MLP reaches 0.8039, which is improved compared with the first three, but it is easily affected by the amount of data. The fitting degrees of RF and SVR are 0.8130 and 0.8795, respectively. Compared with other single models, RF and SVR have good processing ability for small

TABLE 6. Table of experimental results.

Model	R^2	MAE	MSE
DT	0.6392	3.1000	16.8800
AdaBoost	0.7174	2.9400	13.2200
XGBoost	0.7718	2.7395	10.6733
MLP	0.8039	2.5571	9.1726
RF	0.8130	2.4502	8.7489
SVR	0.8795	1.9413	5.6375
GA-SVR	0.8667	2.0876	6.2373
GA-RF	0.8703	2.0068	6.0661
PSO-RF	0.8714	1.9546	6.0167
GWO-RF	0.8730	1.9515	5.9403
ACO-RF	0.8802	1.9092	5.6030
FA-RF	0.8813	1.8917	5.5548
ACO-SVR	0.8818	1.8790	5.5304
ABC-RF	0.8831	1.8773	5.4710
ABC-SVR	0.8839	1.8623	5.4309
FA-SVR	0.8852	1.8484	5.3727
PSO-SVR	0.8861	1.8365	5.3295
GWO-SVR	0.9080	1.6461	4.3052
IGWO2-SVR	0.9223	1.4046	3.6361
IGWO1-SVR	0.9305	1.3157	3.2493
IGWO-SVR	0.9430	1.1481	2.6679

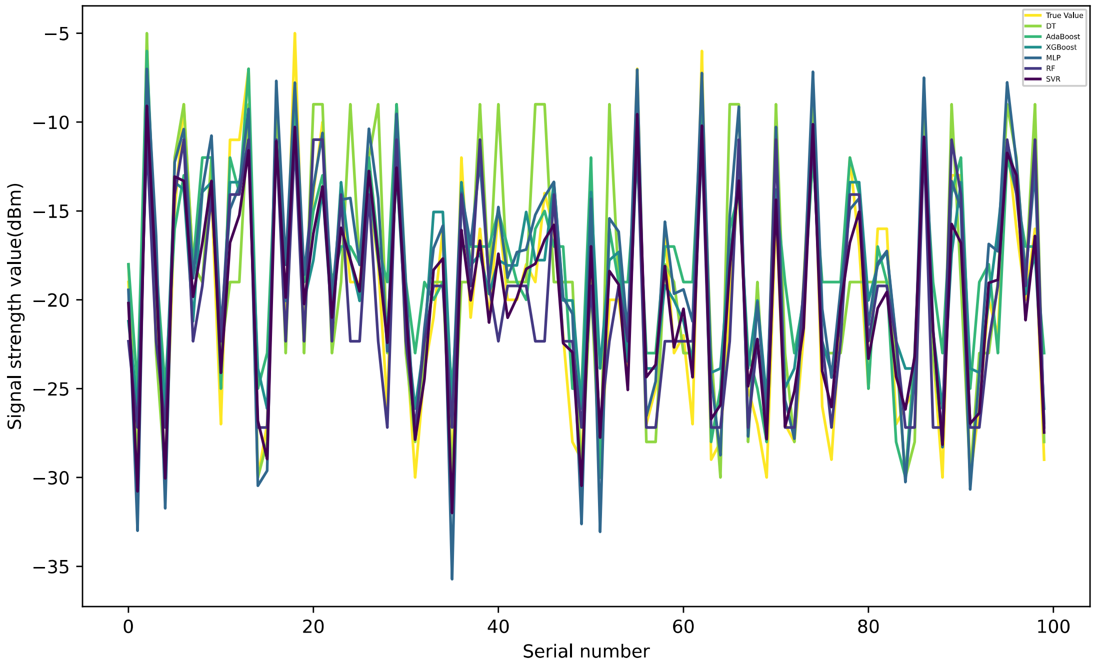

FIGURE 6. Comparison of true values with the predicted results of DT, AdaBoost, XGBoost, MLP, RF, and SVR.

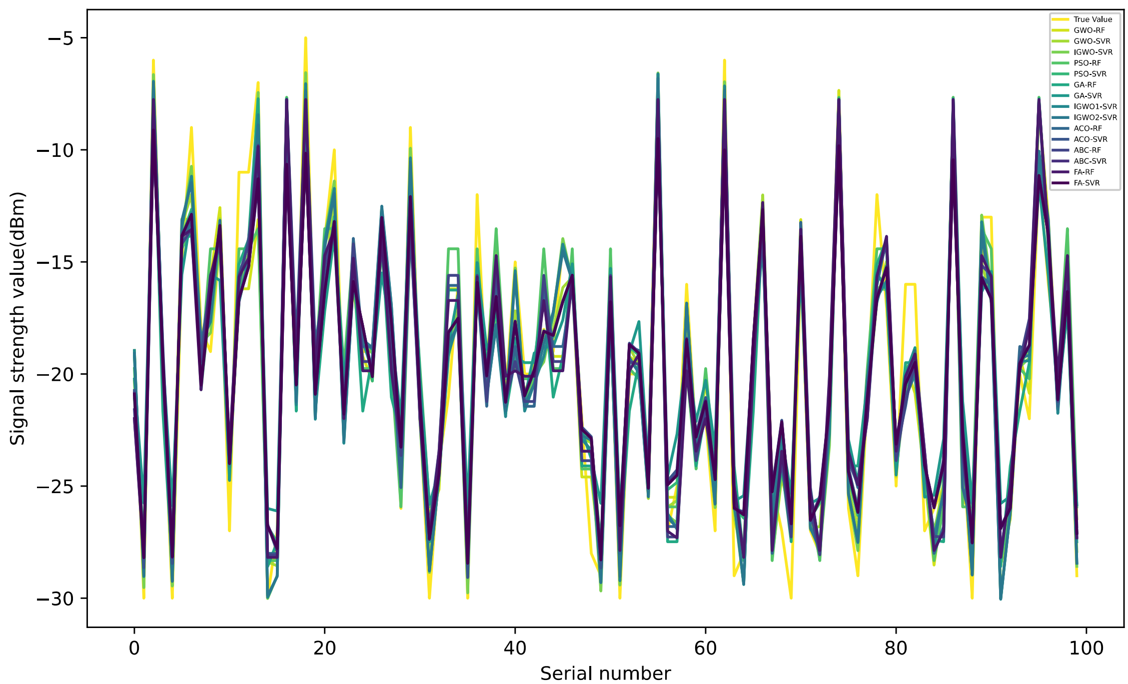

FIGURE 7. Comparison of true values with the predicted results of GWO-RF, GWO-SVR, PSO-RF, PSO-SVR, GA-RF, GA-SVR, ACO-RF, ACO-SVR, ABC-RF, ABC-SVR, FA-RF, FA-SVR, IGWO1-SVR, IGWO2-SVR, and IGWO-SVR.

samples. The comparison between the true value and the predicted results of DT, AdaBoost, XGBoost, MLP, RF, and SVR is shown in Figure 6.

The algorithms of PSO, ACO, ABC, FA, GWO, and GA can optimize the model's hyperparameters well. Since RF and SVR perform well on a single model, PSO, ACO, ABC, FA, GA, and GWO are combined with RF and SVR. It can be seen from Table 6 that the fitting degree of GWO-SVR is 0.9080, which is the highest among the combined models except the models (IGWO2-SVR, IGWO1-SVR, and IGWO-SVR) combined the GWO improved model and SVR, so GWO is the most suitable method for our problem.

Therefore, we combined the improved grey Wolf optimization algorithm IGWO with SVR. It can be seen from Table 6 that the IGWO1-SVR and IGWO2-SVR proposed by predecessors are compared with our proposed IGWO-SVR, and the fitting degree of IGWO-SVR is the highest, reaching 0.9430. The comparison between the true values and predicted results of GWO-RF, GWO-SVR, PSO-RF, PSO-SVR, GA-RF, GA-SVR, ACO-RF, ACO-SVR, ABC-RF, ABC-SVR, FA-RF, FA-SVR, IGWO1-SVR, IGWO2-SVR and IGWO-SVR is shown in Figure 7.

V. CONCLUSION

This paper presents a prediction model of output signal strength of signal generator based on IGWO-SVR in radar TR component electromagnetic interference experiment. By comparing SVR with other single models, it is found that SVR has the best fitting degree. At the same time, the IGWO algorithm enhances traditional grey wolf optimization by introducing an exponential nonlinear convergence factor a, thereby improving search range and global optimization effectiveness, and aligning more closely with actual convergence processes. The IGWO also enhances the GWO algorithm by combining EPD with self-organized criticality theory to update the ω wolf's final position, expanding the search range and improving the likelihood of finding the global optimum. The IGWO improves the optimization of SVR's penalty coefficient C and kernel parameter γ. Therefore, the IGWO-SVR combined model improves the nonlinear fitting ability of the model to the data and enhances the model's prediction accuracy.

Currently, the model is limited to irradiation methods. We plan to add injection methods to enhance the model's capabilities in future studies. In addition, we could explore improving GA or other advanced swarm intelligence algorithms such as PSO.

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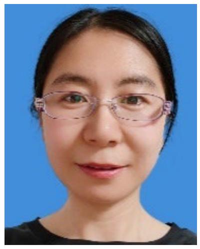
JINGYANG WANG received the B.Eng. degree in computer software from Lanzhou University, China, in 1995, and the M.Sc. degree in software engineering from Beijing University of Technology, China, in 2007. He is currently a Professor with Hebei University of Science and Technology, Shijiazhuang, Hebei, China. His research interests include machine learning, deep learning, natural language processing, and big data processing

JIN LI is currently pursuing the master's degree with Hebei University of Science and Technology. His research interests include machine learning and deep learning.



LIYUN MA received the B.Eng. and M.Eng. degrees from Shanxi University of Science and Technology, Xi'an, China, in 2007 and 2010, respectively. Since 2011, she has been a Researcher with the Army Engineering University, Shijiazhuang Campus, China. Her research interests include machine learning, EMC, and EMP protection techniques.

YUMING WANG received the B.Eng. degree from Hebei University of Science and Technology, Shijiazhuang, China, in 2003, and the M.Eng. and Ph.D. degrees from the Mechanical Engineering College, China, in 2006 and 2009, respectively. Since 2010, she has been a Researcher with the Army Engineering University, Shijiazhuang Campus, China. Her research interests include machine learning, EMC, and EMP protection techniques.