Improved Fruit Fly Optimization Algorithm Based on Simulated Annealing in Neural Network

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***Abstract*—Aiming at the problem that the fruit fly optimization algorithm (FOA) has weak local optimization ability and difficulty in convergence, this paper combines the improved FOA (IFOA) and simulated annealing algorithm (SA) to propose a new optimization algorithm called IFOA-SA algorithm. The IFOA-SA algorithm first modifies the optimization step size of FOA, increases the escape coefficient, and improves the generation mechanism of candidate solutions. At the same time, the concept of three-dimensional search is introduced to expand the search range of fruit flies, and then the FOA solution acceptance mechanism is modified through SA. Finally, the fusion algorithm IFOA-SA is used to optimize the Generalized Regression Neural Network (GRNN) and Back Propagation (BP) Neural Network for freight volume forecasting and nonlinear function fitting. The experimental results show that the total error of the BP neural network optimized by the IFOA-SA algorithm is 37.4903, which achieves better optimization results than other algorithms. In the end, the effectiveness of the algorithm is proved through experiments.**

***Index Terms* — Fruit fly optimization algorithm, Freight volume forecast, Function fitting, Neural network, Simulated annealing algorithm.**

I. INTRODUCTION

Intelligent optimization problems have penetrated into multiple disciplines and correspond to different research topics. How to maximize benefits under limited resource conditions is the focus of the optimization problem, which is also the problem to be solved by intelligent optimization algorithms. With the rapid development of optimization technology, many intelligent optimization algorithms have been developed, such as genetic algorithm [1], [2], ant colony algorithm [3] and particle swarm algorithm [4], [5]. Inspired by the foraging behavior of fruit fly populations, Professor Pan proposed a fruit fly optimization algorithm(FOA) in 2012 [6]. Because of its simple operation and good global optimization ability, it has been successfully applied in many fields, such as traffic flow forecasting [7], Solve the multidimensional knapsack problem and the traveling salesman problem [8], [9], find the best optimal parameters of the least square support vector machine [10], [11], PID parameter tuning [12] and neural network parameter optimization [13], [14].

In order to improve the optimization performance of FOA, many scholars have proposed different improved FOA algorithms. Reference [15] introduces a complex adaptive parameter in the search radius, so that the algorithm can change smoothly with the number of iterations; Reference [16] converts the non-linear generation mechanism of the fruit fly algorithm candidate solution into a linear generation mechanism, one-dimensional coordinate values are used as candidate solutions; Reference [17] proposes a probability-based flight strategy, this method can make fruit fly individuals search for the global optimal solution with a certain probability; Reference [18] expand the population size of the algorithm and obtain the optimal solution of the population through comparison; Reference [19] adds a differential operation to the fruit fly algorithm, and uses a new search strategy instead of random search to generate progeny populations, thereby improving population diversity.

The basic FOA tends to converge prematurely and cause local extremum problems and cannot obtain the global optimal solution. The improved FOA modified the optimization step size, increased the escape coefficient, and the solutions acceptance mechanism of FOA is modified by SA. In addition, the concept of three-dimensional space search was introduced to expand the flight range of individual fruit fly, and the excellent global optimization capabilities of IFOA -SA were used to optimize the parameters of the GRNN and BP neural network, and perform freight volume prediction and nonlinear function fitting. Compared and analyze the prediction effect with the existing optimization algorithm to verify the effectiveness and feasibility of the algorithm.

II. THE BASIC OF FOA AND SA

A. *Overview of FOA*

Fruit fly optimization algorithm (FOA) as a new type of swarm intelligence optimization algorithm, has a wide range of applications in many fields. This algorithm is an optimized algorithm based on the foraging behavior of individual fruit flies that are superior to other species in terms of smell and vision. When looking for food, the individual fruit fly will use its sense of smell and vision to search for food. When a certain fruit fly individual searches for food, it will send food information to other fruit flies and share the food found by other fruit flies. Information is compared to obtain the best food location.

Compared with other swarm intelligence optimization algorithms (such as particle swarm algorithm, genetic algorithm), the fruit fly algorithm has simple calculations, fewer parameter settings, strong robustness, and has good global search and optimization capabilities, but the disadvantage is that there is a local search Insufficient ability and unstable optimization results lead to premature convergence of the algorithm.

B. *Overview of SA*

Simulated annealing algorithm (SA) simulates the cooling process of solids in nature, and is a relatively simple intelligent optimization algorithm. As the temperature decreases in the simulated annealing algorithm, the solution in the algorithm tends to be stable, but such a solution may be a local optimal solution. At this time, the algorithm will use the solution acceptance mechanism to resolve the solution. Make corrections and judge by calculating expressions. If the expression satisfies the condition, the new solution will be accepted, otherwise it will be discarded. So the simulated annealing algorithm is an extension of the local search algorithm, which can effectively avoid the algorithm from falling into the local optimum.

III. THE PROPOSED IFOA-SA ALGORITHM

In view of the problems of the FOA algorithm, this paper improves the generation mechanism of candidate solutions by improving the search step size and adding escape coefficients, and introduces the concept of three-dimensional search space to expand the flight range of fruit flies, and at the same time introduces the SA algorithm to integrate with it New IFOA-SA algorithm, and use this algorithm to optimize neural networks.

A. Step Size Improvement

According to the description and principle of FOA, with the process of individual fruit fly iterative optimization, the individual fruit fly gradually finds the location of food. In the FOA, the search step size is given randomly, and the step size formula is as follows:

$$l = rand \times value \tag{1}$$

where it is called the initial step length is a fixed value, which is a random number on [0,1], and the value range is[0, $value$]. The problem with this setting step length is that the algorithm requires a relatively large optimal step size, and in the later stage, because it is gradually approaching the optimal solution, a relatively small step size is required, so that the algorithm can get the global optimal solution. In order to solve this problem, this article refers to the idea of non-uniform mutation in particle swarm optimization, using the non-uniform mutation strategy to perturb the current model parameters to generate new model parameters, that is, the improved step length formula:

$$L = n \times \left(1-((i-1)/k)^{\alpha}\right) \times \mathrm{sgn}(r-0.5) \tag{2}$$

where n is the initial step size, i is the current iteration number, k is the maximum iteration number, α is the non-uniform variation factor and the value range is [1, 5]. This article has been repeatedly tested as 2, r is a random number on [0, 1], $\mathrm{sgn}()$ is a symbolic function.

It can be seen from the improved step-length formula that this non-uniform disturbance method gradually decreases with the increase of the number of iterations. When it is close to the optimal solution, the amplitude of the disturbance can be reduced correspondingly, thereby avoiding the algorithm step by step. It is too large to miss the global optimal solution. Therefore, the improved step-size formula is suitable for the fruit fly algorithm and is effective, which can meet the needs of searching for the optimal solution.

B. Improvement of the Candidate Solution Generation Mechanism

The candidate solution of the basic FOA algorithm cannot obtain a negative value, which greatly increases the probability of premature convergence of the algorithm. Therefore, the generation mechanism of the candidate solution must be modified to avoid the generation of a local optimal solution. By adding a jump coefficient to improve it, and the generation mechanism of the improved candidate solution is shown in formula (3):

$$\begin{cases} P_i = \dfrac{1}{D_i} + \Delta \\ \Delta = D_i \times (0.5-\beta), 0 \le \beta \le 1 \end{cases} \tag{3}$$

where P_i is the fitness function value, D_i is the distance between the individual fruit fly and the origin, Δ is the jump coefficient and β is a random number on [0, 1].

By increasing the jump coefficient to modify the candidate solution, the candidate solution can obtain a negative value in the optimization process of FOA, and the algorithm can successfully jump out of the local extreme value and obtain the global optimal solution.

C. Introduction of Three-Dimensional Search Space

The basic FOA is to find the optimal value in two-dimensional space, which will not solve the optimization problem in three-dimensional space. Therefore, the concept of three-dimensional search space is introduced to expand the flight distance and flight range of fruit flies, which is more conducive to the FOA algorithm. Global optimal solution, Fig.1 is a schematic diagram of the three-dimensional space iteration optimization of the fruit fly population.

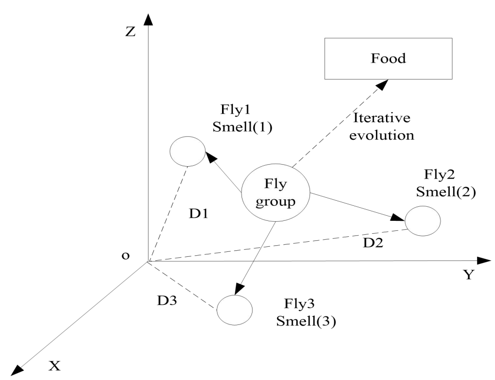

Fig.1. Three dimensional space iterative optimization of fruit fly population

D. Algorithm Steps

The main steps of the IFOA-SA algorithm proposed in this paper for optimizing neural networks are as follows:

Step 1: Initialize the parameters, the initial position of the fruit fly population (X_axis , Y_axis , Z_axis), the population size sizepop, the iteration number k , the initial temperature T of SA, the annealing coefficient and the termination temperature $T_{\min}$;

Step 2: Give the individual fruit flies in the population any direction and distance to find food through smell;

$$\begin{cases} X_i = X\_axis + L \\ Y_i = Y\_axis + L \\ Z_i = Z\_axis + L \end{cases} \tag{4}$$

Step 3: Since the individual fruit fly flies randomly during the optimization process, it is necessary to calculate the distance between the individual fruit fly and the origin of the coordinate, and obtain the fitness function value through the formula;

$$D_i = \sqrt{X_i^2 + Y_i^2 + Z_i^2} \tag{5}$$

$$P_i = \frac{1}{D_i} + \Delta \tag{6}$$

Step 4: Bring the fitness function value into the taste concentration determination function to calculate the taste concentration. This paper uses the mean square error (MSE) of the neural network as the concentration determination function;

$$Smell_i = \frac{1}{N}\sum_{i=1}^{N}(y_i - y)^2 \tag{7}$$

Step 5: Find the fruit fly with the smallest concentration in the fruit fly population and record S_i , S_i is the current model and keep the position coordinates of the model (X_i, Y_i, Z_i);

Step 6: Perform a certain number of disturbances on the position of the previous step to obtain the new position coordinates (X_i', Y_i', Z_i') , and use S_i' to denote the new model;

$$\begin{cases} X_i' = X_i + L' \\ Y_i' = Y_i + L' \\ Z_i' = Z_i + L' \end{cases} \tag{8}$$

Step 7: Use the same method to calculate the taste concentration of the new model and find the concentration difference between the new and the old model and record it as Δs;

If $\Delta s \le 0$, the new position is accepted, if $\Delta s > 0$, it needs to be calculated $p = \exp(-\Delta s / T\lambda)$, if $p > r$ (r is a random number on [0,1]), the new position coordinates are used to continue the optimization, otherwise the original model position coordinates for the next optimization.

Step 8: Save the individual fruit fly with the best odor concentration;

$$[bestSmell\ bestIndex] = \min(Smell) \tag{9}$$

Step 9: Save the fruit fly individual with the best odor concentration value and the position of this fruit fly during the iterative optimization process;

$$\begin{cases} X\_axis = X(bestIndex) \\ Y\_axis = Y(bestIndex) \\ Z\_axis = Z(bestIndex) \end{cases} \tag{10}$$

$$Smellbest = bestSmell \tag{11}$$

Step 10: Repeat steps 2 to 8 to determine the odor concentration value in each generation. If it is better than the previous generation, perform step 9 until the required termination conditions are met or the maximum number of iterations is reached.

IV. Experimental Results and Analysis

A. *Standard Function Test and Analysis*

In order to verify the excellent performance of the IFOA-SA algorithm, this paper selects five commonly used benchmark functions for testing. The function sequence number, function expression, dimension, search interval and theoretical minimum value are shown in TABLE I.

TABLE I. Test Functions

No.	Functions	n	x_i	$f(x^*)$
F1	$f_1(x) = \sum_{i=1}^{n} x_i^2$	30	[-100,100]	0
F2	$f_2(x) = \sum_{i=1}^{n}\left(x_i^2 - 10\cos(2\pi x_i) + 10\right)$	30	[-5.12,5.12]	0
F3	$f_3(x) = 1 - \cos\left(2\pi\sqrt{\sum_{i=1}^{n} x_i^2} + 0.1\sqrt{\sum_{i=1}^{n} x_i^2}\right)$	30	[-100,100]	0
F4	$f_4(x) = \sum_{i=1}^{n}\frac{x_i^2}{4000} - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	30	[-600,600]	0
F5	$f_5(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos 2\pi x_i\right) + 20 + e$	30	[-32,32]	0

These functions have unimodal and multimodal functions, have different heights of hyperplane and have a lot of local minima, so their optimization can well verify the performance of the algorithm. In this paper, we compare the proposed IFOA-SA algorithm with the basic FOA, SA and particle swarm optimization (PSO). At the same time, we set the population number of FOA and PSO as 50 and the number of iterations is 300, in which PSO is $c1 = 1.5$, $c2 = 1.5$, $\omega_{\max} = 0.9$, $\omega_{\min} = 0.4$, the maximum flight distance of particles is 20% of the region, the initial temperature of simulated annealing algorithm is 1000, the annealing coefficient is 0.98, and the termination temperature is 0.001. Use these 4 algorithms to perform 30 independent repeated experiments on the test function to obtain the average and variance. The test results are shown in TABLE II. It can be seen from the results in Table II that the average value of IFOA-SA algorithm is much lower than that of other algorithms, so it is closer to the minimum value of the function.

TABLE II. COMPARISON OF FOA, IFOA-SA, SA AND PSO

No.	Algorithm	Mean	Var
F1	SA	2.873e-01	2.159e-01
	PSO	3.025e-02	3.183e-03
	FOA	8.358e-05	3.629e-10
	IFOA-SA	8.613e-06	1.637e-12
F2	SA	3.873e-01	2.159e-01
	PSO	1.025e-01	1.183e-02
	FOA	1.358e-02	2.629e-06
	IFOA-SA	1.613e-03	7.637e-08
F3	SA	2.873e-01	8.429e-04
	PSO	2.625e-03	4.167e-06
	FOA	1.836e-03	5.163e-07
	IFOA-SA	6.341e-05	2.238e-10
F4	SA	2.323e-04	7.193e-06
	PSO	3.158e-06	1.168e-08
	FOA	2.538e-07	5.216 -10
	IFOA-SA	9.643e-09	1.527e-13
F5	SA	1.253e-02	1.227e-04
	PSO	3.758e-03	1.363e-06
	FOA	1.859e-03	2.209e-07
	IFOA-SA	5.614e-05	1.773e-09

In addition, the variance of IFOA-SA is several orders of magnitude lower than other algorithms, which shows that IFOA-SA has better optimization performance and more stable optimization results. But at the same time, we should also understand that there is a certain distance between the global optimal solutions of the distance function from IFOA-SA, so the algorithm has room for improvemen.

B. *IFOA-SA-GRNN Freight Volume Forecast*

Take China's freight volume as sample data for instance verification, take GDP, gross industrial output, railway transportation line length, proportion of double track mileage, road transportation line length, proportion of graded roads, number of railway trucks and number of civilian trucks, respectively. These 8 index factors are used as the input of the GRNN network, and the total freight volume, railway freight volume and road freight volume are used as the output of the GRNN network to construct the GRNN neural network. Due to the lack of training data, a cross-validation method is adopted to train GRNN. Neural network, and loop to find the best smoothing factor σ .

According to the input and output of the GRNN network determined above, 13 sets of data are randomly selected and the first 12 sets of data are used as the training data of the network, and the remaining set of data is used as the prediction data. The GRNN network, FOA-GRNN and IFOA-SA-GRNN network were used to forecast the freight volume respectively. At the same time, the smoothing factor of the GRNN network is set to 0.6, the initial position of the fruit fly population is [0, 1], and the random direction and distance of the fruit fly individual using smell to search for food is [-1, 1], the population is 50, the number of iterations is 300, the initial temperature of the simulated annealing algorithm is 1000, the annealing coefficient is 0.98, and the termination temperature is 0.001.

The freight volume forecast results of the above three networks are given in Table III, and the mean relative error (MRE) of the pre measurement is also given in the table. The actual value contains three data, which represent the total freight volume, railway freight volume and highway freight volume respectively.

TABLE III. COMPARISON OF PREDICTION RESULTS OF DIFFERENT MODELS

Model	Actual value	Predicted value	MRE/%
GRNN	318454	307419	-3.4652
	160446	158263	-1.3606
	156854	169221	7.8844
FOA-GRNN	318454	328413	3.1273
	160446	162315	1.1649
	156854	146316	-6.7184
IFOA-SA-GRNN	318454	310611	-2.4628
	160446	162100	1.0309
	156854	148276	-5.4688

C. *Nonlinear Function Fitting of IFOA-SA-BP*

In order to verify the prediction accuracy and ability of the prediction model, this section uses the Griewank function to perform nonlinear function fitting, and 2000 groups of sample data are randomly generated. 1900 groups are selected as training samples and the remaining 100 groups are test samples. Meanwhile, in order to verify the effectiveness and feasibility of IFOA-SA-BP, BP, FOA-BP, GA-BP and PSO-BP are compared with each other. Each prediction model is carried out under the same experimental conditions, and the genetic algorithm's The population size is 50, the maximum evolution times is 300, the crossover probability is 0.80, and the mutation probability is 0.05. The initial conditions of other algorithms are the same as the above experiment.

The root mean square error (RMSE), mean absolute error (MAE), and mean absolute error percentage error (MAPE) are used to evaluate how well the network fits the function. The smaller the error, the better the fit of the network and vice versa, the formula of these three errors are as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y - y_i\right)^2} \tag{12}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y - y_i\right| \tag{13}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y - y_i}{y_i}\right| \tag{14}$$

where represents the network prediction value, y_i represents the actual value, and represents the data sample size.

The nonlinear function to be fitted in this section is the Griewank function, and its formula is as follows. The value range of variables and is [-100， 100]. This function is relatively complex and has many local extreme points.

$$f(x,y)=\frac{x^2+y^2}{4000}-\cos x\cos\frac{y}{\sqrt{2}}+1 \tag{15}$$

The result of fitting the function with IFOA-SA-BP network is shown in the figure 2 & figure 3. in which Fig. 2 is the predicted output of the network, and Fig. 3 is the error between the expected output and the predicted output of the network.

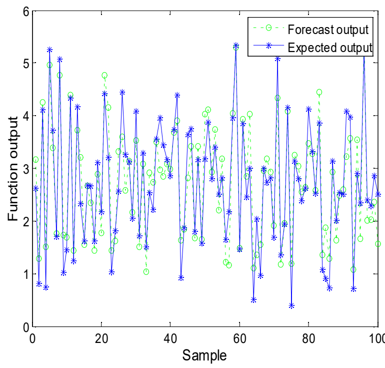

Fig. 2. Predictive output of neural network

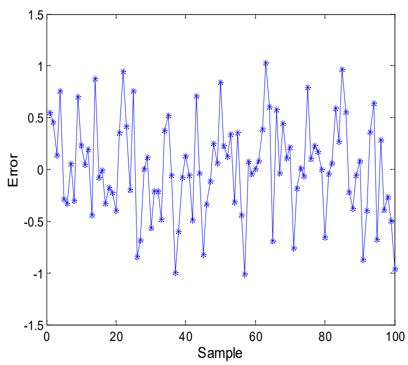

Fig. 3. Predictive output error of neural network

It can be seen from the figure that the BP network trained with this algorithm has smaller errors and better performance when performing nonlinear function fitting. In order to further illustrate the superiority of the algorithm, compare BP, FOA-BP, GA-BP and PSO-BP with it. The detailed comparison results are shown in Table IV.

TABLE IV. COMPARISON OF PREDICTION ERRORS OF DIFFERENT MODELS

Model	Total Error	RMSE	MAE	MAPE
IFOA-SA-BP	37.4903	0.4726	0.3749	0.1840
FOA-BP	41.5233	0.5059	0.4152	0.2056
PSO-BP	44.6155	0.5469	0.4462	0.3574
GA-BP	55.8007	0.6424	0.5580	0.2179
BP	60.0672	0.6923	0.6007	0.2363

It can be seen from the data in Table IV that the total error of IFOA-SA-BP network is the smallest, and the three error indexes used in this paper are also the smallest, so the prediction result is the most accurate and has good robustness. At the same time, it also shows that the optimized network result of fruit fly optimization algorithm is stable, while other algorithms are unsaturated and unstable.

V. CONCLUSION AND FUTURE RESEARCH

In order to solve the problem of weak local optimization ability and premature convergence of FOA algorithm, this paper proposed IFOA-SA algorithm. Through the comparison of benchmark test functions, it shows that foa-sa has good optimization performance in solving high-dimensional function optimization problems.Applied to optimize the relevant parameters of GRNN and BP neural network for freight volume prediction and nonlinear function fitting, and compare the prediction results with the existing optimization algorithms. The simulation results show that the results obtained by the algorithm in this paper are more effective and reliable. The obvious advantage proves the effectiveness and feasibility of the proposed algorithm.

At the same time, it should be noted that although this paper improves FOA and uses SA to integrate with FOA, there are still some limitations. First of all, the improvement of FOA in this paper does not solve its nonlinear iterative characteristics from the root. In future research, this algorithm can be continuously improved to enhance its applicability. The second algorithm proposed in this paper is used to solve simple optimization problems. In the future study and research, we can consider other more complex problems, such as scheduling problems, inventory, location and other problems, and expand the application of algorithms in practical problems.

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REFERENCES

[1] M. Aryanezhad, M. Hemati, “A new genetic algorithm for solving nonconvex nonlinear programming problems,” *Applied Mathematics and Computation*, vol. 199, no. 1, pp. 186-194, 2008.
[2] D. Whitley. “A genetic algorithm tutorial,” *Statistics and Computing*, vol. 4, no. 2, pp. 65-85, 1994.
[3] M. Dorigo, M. Gambardella. “Ant colony system: a cooperative learning approach to the traveling salesman problem,” *IEEE Transaction on Evolutionary Computation*, vol. 1, no. 1, pp. 53-66, 1997.
[4] W. T. Pan. “A new fruit fly optimization algorithm: taking the financial distress model as an example,” *Knowledge-Based Systems*, vol. 26, no. 2, pp. 69-74, 2012.
[5] Y. L. Cong, J. W. Wang, and X. L. L, “Traffic flow forecasting by a least squares support vector machine with a fruit fly optimization algorithm,” *Procedia Engineering*, vol. 137, pp. 59-68, 2016.
[6] M. B. Aryanezhad, M. Hemati, “A new genetic algorithm for solving nonconvex nonlinear programming problems,” *Applied Mathematics & Computation*, vol. 199, no. 1, pp.186-194, 2007.
[7] D. Whitley, “A genetic algorithm tutorial,” *Statistics and Computing*, vol. 4, no. 2, pp. 62-85, 1994.
[8] Y. L. Cong, J. W. Wang, X. L. Li, “Traffic flow forecasting by a least squares support vector machine with a fruit fly optimization algorithm,” *Procedia Engineering*, vol. 137, pp. 59-68, 2016.
[9] Y. Luo, Y. X. Xiang, J. Gao, “A study on intelligent diagnostic method of short-wave receiving system based on SAFOA-LSSVM,” *2018 Chinese Control and Decision Conference (CCDC),* Shenyang, China, pp. 6245-6251, 2018.
[10] L. Si, Z. B. Wang, X. H. Liu, “Identification of shearer cutting patterns using vibration signals based on a least squares support vector machine

with an improved fruit fly optimization algorithm," *Sensors*, vol. 16, no. 1, pp. 1-21, 2016.

[11] X. C. Xie, G. Fu, Y. J. Y. Xue, "Risk prediction and factors risk analysis based on IFOA-GRNN and apriori algorithms: Application of artificial intelligence in accident prevention," *Process Safety and Environmental Protection*, vol. 122, pp. 169-184, 2019.

[12] L. Wang, R. Liu, S. Liu, "An effective and efficient fruit fly optimization algorithm with level probability policy and its applications," *Knowledge-Based Systems*, vol. 97, pp.158-174, 2016.

[13] S. M. Mousavi, M. Tavana, N. Alikar, and M. Zandieh, "A tuned hybrid intelligent fruit fly optimization algorithm for fuzzy rule generation and classification," *Neural Computing & Applications*, vol. 31, no. 3, pp. 873-885, 2019.

[14] S. Sattar, B. Adil, Z. B. Ehsan, "A simulated annealing-based maximum-margin clustering algorithm," *Computational Intelligence*, vol. 35, no. 1, pp. 23-41, 2019.

[15] Y. X. Li, Z. L. Xiang, J. N. Xia, "Dynamical system models and convergence analysis for simulated annealing algorithm," *Chinese Journal of Computers*, vol. 42, no. 6, pp. 1161-1173, 2019.

[16] R. Cheng, Y. C. Jin, "A social learning particle swarm optimization algorithm for scalable optimization," *Information Sciences*, vol. 291, pp. 43-60, 2015.

[17] L. Houcine, M. Bouzbida, A. Chaari, "Improved adaptive particle swarm optimization for optimization functions and clustering fuzzy modeling system," *International Journal of Uncertainty Fuzziness and Knowledge-Based Systems*, vol. 26, no. 5, pp. 717-739, 2018.

[18] A. Ouahab, M. F. Belbachir, "Remote sensing data fusion using fruit fly optimization," *Multimedia Tools and Applications*, no. 10, pp. 1-23, 2020.

[19] X. Yang, W. Li, L. Su, and Y. Wang, "An improved evolution fruit fly optimization algorithm and its application," *Neural Computing and Applications*, vol. 32, no. 14, pp. 9897-9914, 2020.