Journal of Network Intelligence ©2021 ISSN 2414-8105 (Online)
Taiwan Ubiquitous Information Volume **6**, Number **4**, November **2021**

A Routing Optimization in Wireless Sensor Networks Based on Reverse Elite Sparrow Search Algorithm

Chun-Yuan Ning[1a], Lyu-chao Liao[1b], Trong-The Nguyen[2c],
Kuan-Chun Huang[3d], Jeng-Shyang Pan[4*]

[1]Fujian Provincial Key Laboratory of Big Data Mining and Applications
Fujian University of Technology, Fuzhou 350118, China
[2]Multimedia Communications Lab,
University of Information Technology, VNU-HCM, Vietnam
[3]Department of Industrial and Systems Engineering,
Chung Yuan Christian University, Taoyuan 320314, Taiwan
[4]College of Computer Science and Engineering,
Shandong University of Science and Technology, Qingdao 266590, China

[a]ningcy0606@163.com, [b]fjachao@gmail.com, [c]thent@uit.edu.vn, [d]westie888@gmail.com,
Corresponding author: *jengshyangpan@gmail.com

Received April 2021; revised July 2021

Abstract. *This study suggests a solution to the routing optimization insufficiency based on the reverse elite sparrow search algorithm (RESSA) for energy balancing and network lifetime prolonging in wireless sensor networks (WSN). The node's consumption and the remaining energy priority to balance consumption in the data forwarding to the cluster head are considered the optimal path evaluation function. The obtained results of the experimental the suggested scheme are compared with the other methods show that the proposed scheme increases data forwarding round numbers and consumes less energy, the remaining energy more, and higher efficiency of node energy consumption.*

Keywords: Wireless sensor networks, Sparrow search algorithm, Routing optimization, Intelligent algorithms

1. **Introduction.** Due to the limited node energy, difficult positioning, and harsh deployment environment [1], wireless sensor networks (WNS) often leads to node failure [2] or disuse due to power supply [3,4]. Therefore, maximizing the energy of the service life of the network is an important issue in implementing WSN applications [5,6]. The WSN's construction and the application take communication as the center, data as the element, transmission as the purpose, and application as the guide. Unlike traditional computer networks, "small storage space, low computing power, large coverage density, and difficult battery replacement" are the main characteristics of WSN computing nodes [7].

An efficient routing algorithm is crucial for saving energy consumption. The routing problem of deploying WSN application is encountering complication computations whenever using the traditional methods, like gradient and arithmetical algorithms [8]. Metaheuristic algorithm is a promising way to deal with complex problems such as a routing table specifically for deploying WSN applications [9].

Many scholars have studied routing optimization of WSN using swarm intelligence optimization in recent years, such as genetic algorithm (GA) [10], particles swarms optimization algorithm (PSO) [11], Whales optimization algorithm (WOA) [12], sparrow algorithm

(SSA) [13], hybrid particles swarm optimization with bat algorithm (PSO-BA)[14], Sun Wukong evolution (MKE) algorithm [15]. However, these traditional optimization methods have their shortcomings, such as low search efficiency, easy to fall into optimal local solution, difficulty to obtain the optimal global solution, and so on. Besides, most of the above methods only consider the minimum energy consumption of the path as the optimization goal [5,16], without considering the limitations of the remaining energy of a node, which leads to the rapid failure of the node [17].

This paper introduces a WSN routing scheme based on an improved sparrows search routing (ISSR) algorithm. The ISSR is enhanced based on the elite reverse learning strategy and the firefly algorithm (FA) [18], emitting light for balancing energy and prolonging lifetime in WSN. The proposed algorithm has a high convergence speed and considers the balance of the total network energy consumption during routing optimization and improving the network life cycle compared to the other algorithms in the works of literature.

2. **WSN Routing Mathematical Model.** The implementing WSN can be laid out representation by an undirected weighted graph G, $G = \{V, E\}$, where V is the set of network nodes with $\{v_1, v_2, \ldots, v_n\}$ [10,19], E is the inter-node communication link set with $\{e_1, e_2, ..., e_n\}$ [20]. Whether an effective link is formed between node i and j in WSN can be expressed as follows:

$$x_{i,j} = \begin{cases} 1, if Edge\ from\ node\ i\ to\ node\ j\ is\ chosen\ for\ routing \\ 0,\ others \end{cases} \tag{1}$$

The distance from node v_i to v_j is expressed as $d(v_i, v_j)$, and the link length is expressed as: Energy consumption in WSN is a crucial issue to consider. In data transmission by sensor nodes, communication energy consumption is far greater than calculation energy consumption [3], so the influence of calculation energy consumption is ignored. The WSN node's energy consumption model [4] is given as follows.

$$Ec = \lambda d(v_i, v_j)^n \tag{2}$$

Where λ is the energy consumption coefficient, the short-distance multi-hop forwarding mode is adopted between network nodes and $n = 2$. Node routing in WSN is constrained by effective distance, and it is supposed that distance between nodes is considered as an effective transmission way with D_0. Then the effective transmission distance between nodes satisfies the following constraints:

$$d\left(v_i, v_j\right) \leq d_0, and\ v_i, v_j \in V \tag{3}$$

Where v_i, v_j are nodes corresponding to edges.

2.1. **Residual energy model.** The energy consumption efficiency of WSN network nodes is considered in the process of data transmission with saving energy consumption [19,21], that is, the energy consumption of the whole transmission path is the least as possible as the following formulated expression.

$$\min\left(Ec\right) = \sum_{i,j} x_{ij} \lambda d(v_i, v_j)^2 \tag{4}$$

Where x_{ij} is equal to 1. The efficiency of node energy consumption will result only pursuing in a fixed data transmission path of nodes, which will lead to premature failure of nodes in the path of minimum energy consumption. Therefore, to prolong the network lifetime, the balance of energy consumption of network nodes must be considered, that is, the remaining energy of nodes should be considered in the process of routing, and the nodes with more remaining energy should be used to forward data [22]. The residual energy index of the node is defined as.

$$\omega_i = \frac{Er_0}{Er_i} \tag{5}$$

Where Er_0 is the initial node energy consumed, and Er_i is the node's current remaining energy i. It can be seen from Eq. (6) that $\omega_i \geq 1$. Theoretically speaking, when the energy of the node is exhausted until it dies, Er_i is 0 and ω_i has an infinite value [23]. To avoid low energy nodes being selected as routing nodes, in this paper, if the remaining energy is 1/10 of the initial energy, it is regarded as a low energy node [24]. For low-energy nodes, a larger number, maxN, is used to punish them. Then Eq. (6) can be expressed as follows.

$$\omega_i = \begin{cases} \frac{Er_0}{Er_i}, The\ remaining\ energy \geq 1/10\ of\ the\ initial\ energy \\ maxN, The\ remaining\ energy < 1/10\ of\ the\ initial\ energy \end{cases} \tag{6}$$

In the routing process of WSN, considering the balance of energy consumption of nodes, the remaining energy of the entire routing node is required to be the highest. That is, the sum of the remaining energy exponents of the whole routing node is minimized as follows.

$$\min(\omega_s) = \sum_i \omega_i \tag{7}$$

Fitness function of routing optimization can be expressed as.

$$Fitness = \min(\omega_s) \times \min(Ec) \tag{8}$$

The routing optimization fitness function is modeled with considering the balance and effectiveness of energy in network path selection.

3. **Improved Sparrow Search Algorithm.**

This section presents an Improvement version of Sparrow search algorithm (RESSA) based on the opposition based learning (OBL) as elite reverse learning strategy and FA. Before presenting apprach detailly, we review the original algorithm of SSA.

3.1. **SSA algorithm.**

Sparrows search algorithm (SSA) is a kind of swarm-intelligence optimization methods based on the behavior of the sparrows foraging and avoiding predators [13]. Sparrow search algorithm mainly simulates the process of sparrows group foraging processing. The sparrows group foraging process is a finder-follower model with superimposed detection warning mechanism. Among sparrows, individuals who find the food better serve as finders, and other individuals serve as followers. At the same time, a certain proportion of individuals in the population are selected to conduct reconnaissance and early warning (scout). If danger is found, they will give up food, and safety comes first. We use virtual sparrows to search for objects through simulation experiments. And the following matrix is used to represent the position of individual sparrows.

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & \cdots & x_{1,d} \\ x_{2,1} & x_{2,2} & \cdots & \cdots & x_{2,d} \\ \vdots & & \vdots\ \vdots\ \vdots & & \vdots \\ x_{n,1} & x_{n,2} & \cdots & \cdots & x_{n,d} \end{bmatrix} \tag{9}$$

In the formula, n is the sparrows number and d is the variable dimensions. The fitness values of the sparrows can be formulated as vector solution as follows.

$$F(X) = \begin{bmatrix} f([x_{1,1} & x_{1,2} & \cdots & \cdots & x_{1,d}]) \\ f([x_{2,1} & x_{2,2} & \cdots & \cdots & x_{2,d}]) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ f([x_{n,1} & x_{n,2} & \cdots & \cdots & x_{n,d}]) \end{bmatrix} \tag{10}$$

Where $F(X)$ and n are the fitness value of an individual and the sparrows number respectively. In SSA, finders with higher fitness scores were given priority in getting food during the search. Also, because the discoverer is responsible for finding food and guiding the entire population movement. As a result, the discoverers were able to search for food over a much wider area than the participants. According to the rules, the discoverer has a high energy reserve and is responsible for searching the area with rich food in the whole population, providing foraging area and direction for all entrants. Once the sparrow detects a predator, the individual begins to sing as an alarm signal. When the alarm value is greater than the safety value, the finder will take the participants to other safe areas for foraging. In each iteration, the location of the finder is updated as follows:

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t} exp\left(\frac{-i}{\alpha iter_{max}}\right) \ if \ R_2 < ST \\ X_{i,j}^{t} + QL \ if \ R_2 \geq ST \end{cases} \tag{11}$$

Where $X_{i,j}^t$ and t are a solution of representation the $j-th$ dimension value of the $i-th$ sparrow in iteration and the current iteration, with $j = 1, 2, ..., d$; d is dimension of search space. $iter_{max}$ is the constant with the most iterations. $\alpha \in (0, 1]$ is a random number. $R_2 \in [0, 1]$ and $ST \in [0.5, 1]$ represent alarm values and safety thresholds, respectively. Q is a random number that follows a normal distribution. L represents a 1 by D matrix where every entry is 1. There are no predators around if $R_2 < ST$, the finder goes into extensive search mode. Some sparrows have found predators, if $R_2 \geq ST$, all sparrows need to fly to other safe areas quickly. For entrants, the lower their energy, the worse their foraging position in the population as a whole. Some entrants may constantly monitor the finders to increase their predation rate and compete for food resources, during monitoring the finders of some entrants frequently. Once they see that the discoverer has found good food, they will immediately leave their current position for moving to compete for food. If the sparrow is assigned "win", they could get the finder's food immediately that their position could be updated as formula for enrollees is as follows.

$$X_{i,j}^{t+1} = \begin{cases} Qexp\left(\frac{X_{worst}^t - X_{i,j}^t}{i^2}\right) \ if \ i > n/2 \\ X_P^{t+1} + \left|X_{i,j}^t - X_P^{t+1}\right| A^+ L \ otherwise \end{cases} \tag{12}$$

Where X_P and X_{worst} are the best occupied position by the finder and the worst occupied position in the world at the moment respectively. A represents a $1 \times d$ matrix in which each element is randomly assigned 1 or -1, $A^+ = A^T(AA^T)^{-1}$. When $i > n/2$ indicating that the $i-th$ of the entrants with a poor fitness value was most likely to starve without food. Let's assume that 10% to 20% of the sparrow population is aware of the danger. The mathematical model of the scout can be expressed as.

$$X_{i,j}^{t+1} = \begin{cases} X_{best}^t + \beta \left|X_{i,j}^t - X_{best}^t\right| \ if \ f_i > f_g \\ X_{i,j}^t + K\left(\frac{\left|X_{i,j}^t - X_{worst}^t\right|}{(f_i - f_w) + \varepsilon}\right) \ if \ f_i = f_g \end{cases} \tag{13}$$

Where X_{best} is the best obtained solution as the current global optimal location. β is a normal distribution of random numbers with a mean of 0 and a variance of 1 that is as a parameter of step size control. $K \times [-1, 1]$ is a random number. The fitness functions is symbol f is measured with some values, e.g., f_i, f_g and f_w are the current sparrows fitness value, the global best and worst fitness values, respectively. ε is the minimum constant to avoid zero division error. For simplicity, when $f_i > f_g$ means sparrows are at the edge of the group. X_{best} represents the location of a population center around which it is safe. $f_i = f_g$ indicates that sparrows in the middle of the population are aware of the danger and need to be close to other sparrows. K is the sparrow moving direction, which is also the step size control coefficient

Table 1. Selected benchmark functions parameters

No.	Function Name	Functions	Dim	Space	f_{min}
F1	Sphere	$\sum_{i=1}^{n} x_i^2$	30	[-100,100]	0
F2	Schwefel's function 2.21	$\sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	30	[-10,10]	0
F3	Schwefel's function 1.2	$\sum_{i=1}^{n} \left(\sum_{j-1}^{i} x_j \right)^2$	30	[-100,100]	0
F4	Schwefel's function 2.22	$max_i\{\lvert x_i \rvert, 1 \le i \le n\}$	30	[-100,100]	0
F5	Dejong's noisy	$\sum_{i=1}^{n} i x_i^4 + random[0,1)$	30	[-100,100]	0
F6	Schwefel	$\sum_{i=1}^{n} -x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$	30	[-500,500]	- 125969
F7	Rastringin	$\sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	30	[- 5.12,5.12]	0
F8	Ackley	$-20e^{-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}} - e^{\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)} + 20 + e$	30	[-32,32]	0
F9	Griewank	$\frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x[i]}{\sqrt{i}}\right) + 1$	30	[-600,600]	0
F10	Generalized penalized 2	$\left(\frac{1}{500} + \sum_{j=1}^{25}\left(j + \sum_{i=1}^{2}(x_i - a_{ij})^6\right)^{-1}\right)^{-1}$	30	[-50,50]	0
F11	Rosenbrock	$\sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 - (x_i - 1)^2]$	30	[-30,30]	0
F12	Step	$\sum_{i=1}^{n} (x_i + 0.5)^2$	30	[-100,100]	0

3.2. **Improvement SSA.** SSA is one of the most advantageous search algorithms with strong local search ability and faster convergence speed [9], but weak global search capability and jump out of optimal local operation is weak and vulnerable to local optimum, this leads to a basic sparrow optimization search algorithm efficiency is not stable, reverse learning mechanism is optimized by grouping distribution problem effective method [9].

Opposition Based Learning (OBL) is expressed as if x is in the range $[a, b]$, then the opposite particle of x can be expressed as $x = a + b - x$. In D-dimensional space, the concept of reverse learning can still be applied. For D-dimensional search space, let $S(x_1, x_2, .., x_i.., x_D)$, $x_i \in [a_i, b_i](i = 1, 2, ..., D)$ is the forward solution of the problem, and then the corresponding inverse vector can be expressed as $S' \left(x_1', x_2', \ldots, x_D'\right)$, $x_i = a_i + b_i - x_i$. The best fitness value can be selected as a new optimization group through direct screening or other optimization strategies, making the particles in the optimization space quickly converge to the optimal solution's location.

Elite reverse learning strategy is used in the comprehensive collection of the best fitness value to generate new solutions of 20% and 20%, then 20% of the new generation of the total solution to join the original solution and inverse solution set, at this point, to the fitness value reordering of the total in the collection, sorted out 20% of the total worst fitness value from the set of solutions so that we get the new optimization group [9].

In the firefly algorithm, individual fireflies emit light, and the light acts as a signal to attract other individual fireflies [25]. We assume that (1) each firefly will be attracted to all other brighter fireflies and will move to that position without discrimination between genders. (2) In the firefly algorithm, its attractiveness is directly proportional to its brightness. For any two fireflies, one of them will always move towards the one brighter than itself. The brightness of the firefly is constantly changing and decreases with the increase of the distance. (3) If the individual firefly does not find any other firefly that is brighter than the one given to it, it will randomly move to update its position.The optimized mathematical form that produces the new solution X_{inew} is as follows.

$$Q_1 = R_{istar} \times \frac{rand\,(-0.5, 0.5)}{D} \tag{14}$$

$$X_{inew} = X_i \times Q \tag{15}$$

The position update formula of firefly from the FA with $i-th$ attracted to move toward Firefly $j-th$ is given as follows.

$$x_i = x_i + \beta_1{*}\,(x_j - x_i) + \alpha{*}\left(rand - \frac{1}{2}\right) \tag{16}$$

Where x_i, and x_j are the spatial positions of firefly i and j, $\alpha \times [0,1]$ is the step size factor, rand is a uniformly distributed random number on [0,1]. $\beta_1 = \beta_0{*}e^{-\gamma r_{i,j}^2}$, with β_0 is the maximum attraction and $I = I_0{*}e^{-\gamma r_{i,j}^2}$, I_0 is the maximum fluorescence brightness of fireflies. γ is the absorption coefficient of light intensity, and the fluorescence decreases gradually with the increase of distance and the absorption of media. $r_{(i,j)}$ is the spatial distance.

Table 2. A comparison of obtained optimization results of the proposed RESSA with the PSO, GA, SSA algorithms for the benchmark functions.

Algorithms	PSO		GA		SSA		RESSA	
Value	Average	Std.	Average	Std.	Average	Std.	Average	Std.
F1	5.073E+00	1.718E+00	1.626E-02	9.799E-03	3.757E-24	2.058E-23	6.203E-78	3.189E-77
F2	6.920E+00	2.727E+00	2.523E-02	9.803E-03	1.673E-13	7.279E-13	1.767E-40	4.157E-40
F3	1.429E+03	6.541E+02	2.649E+02	2.397E+02	6.526E-14	3.313E-13	3.312E-65	1.312E-64
F4	5.159E+00	1.412E+00	1.498E+00	6.451E-01	6.980E-16	3.278E-15	5.192E-39	2.235E-38
F5	1.271E+01	9.092E+00	1.941E-02	8.228E-03	4.250E-03	4.383E-03	7.235E-04	6.409E-04
F6	−3.211E+03	4.485E+02	−5.459E+03	9.526E+02	−8.513E+03	6.873E+02	−1.113E+04	7.131E+02
F7	1.896E+02	4.051E+01	4.301E+01	1.802E+01	2.266E+02	3.867E+01	0.000E+00	0.000E+00
F8	3.035E+00	3.845E-01	2.561E-02	9.389E-03	1.480E-15	1.885E-15	8.876E-16	0.000E+00
F9	2.977E+01	8.579E+00	2.501E-01	1.227E-01	4.736E+01	5.372E+01	0.000E+00	0.000E+00
F10	3.565E+00	2.217E+00	5.600E+00	4.131E+00	5.552E+00	5.217E+00	1.161E+00	5.273E-01
F11	−3.274E+00	5.924E-02	−3.219E+00	8.396E-02	−3.267E+00	6.033E-02	−3.298E+00	4.123E-02
F12	−8.554E+00	3.376E+00	−9.745E+00	2.232E+00	−7.647E+00	2.738E+00	−1.016E+01	1.292E-05

3.3. **Entrant Location Update.** SSA algorithm can be described as randomly finding a position near the current optimal position. The variance of each dimension away from the optimal position will become smaller, that is, there will not be a big difference between the optimal position and the optimal position in one dimension. In contrast, the difference between other positions is small. Because A^+, A is a matrix of size $1 \times D$ (1 row and D columns).

$$\left(AA^T\right)^{-1} = \left(\begin{pmatrix}-1, & 1, & -1\end{pmatrix}\begin{pmatrix}-1\\ 1\\ -1\end{pmatrix}\right)^{-1} = (3)^{-1} = \begin{pmatrix}\frac{1}{3}\end{pmatrix} \tag{17}$$

$$
\begin{aligned}
& XA^T\left(AA^T\right)^{-1}L = (1,2,3)\begin{pmatrix}-1\\1\\-1\end{pmatrix}\left(\frac{1}{3}\right)(1,1,1) = \frac{1}{3}\left(-11+12+(-1)\,3\right)(1,1,1)\\
& = \left(-\frac{2}{3},-\frac{2}{3},-\frac{2}{3}\right) = \frac{1}{D}\left(L_1x_1+L_2x_2+L_3x_3\right)(1,1,1)\\
& = \frac{1}{D}\left(\sum_{d=1}^{D}\left(rand\left\{-1,1\right\}x_d\right),\sum_{d=1}^{D}\left(rand\left\{-1,1\right\}x_d\right),\sum_{d=1}^{D}\left(rand\left\{-1,1\right\}x_d\right)\right)
\end{aligned} \tag{18}
$$

The position of the participant can be simplified and updated. Formula j should not appear on both sides of the formula, which means that a variable is a number rather than a vector. The details are updated as follows.

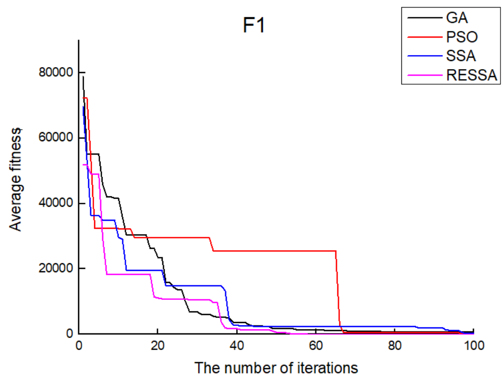
$$
X_{i,j}^{t+1} = \begin{cases} Qexp\left(\frac{X_{worst}^t - X_{i,j}^t}{i^2}\right) \; if \; i > n/2 \\ X_P^{t+1} + \frac{1}{D}\sum\limits_{d=1}^{D}\left(rand\left\{-1,1\right\}\right)\left(\left|X_{i,j}^t - X_P^{t+1}\right|\right) \; if \; i \le n/2 \end{cases} \tag{19}
$$

Where X_{worst} is the worst position of the sparrow in the current population, and X_P is the most position of the sparrow in the population. If $(i > n/2)$, the value of which is the product of a standard normally distributed random number and an exponential function based on the natural logarithm, which corresponds to the standard normally distributed random number when the population converges. If $(i \le n/2)$, the value is the position of the current optimal sparrow plus the random addition and subtraction of each dimension of the distance between the sparrow and the optimal position, and the sum is equally divided into each dimension. The sparrow search algorithm and the firefly algorithm are combined, and the RESSA is proposed to take advantage of the complementary advantages and disadvantages of the two algorithms to carry out the iterative update. If the sparrow is in the current optimal position, it will flee to a position near itself. How close it depends on the ratio of the difference between the distance from the worst position and the difference between the food and the worst food in its position.

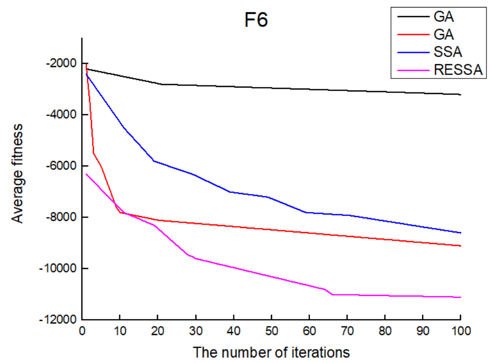
$$
X_{i,j}^{t+1} = \begin{cases} X_{best}^t + \beta_1\left|X_{i,j}^t - X_{best}^t\right| + \alpha\left(rand - \frac{1}{2}\right) \; if \; f_i > f_g \\ X_{i,j}^t + K\left(\frac{\left|X_{i,j}^t - X_{worst}^t\right|}{(f_i - f_w)+\varepsilon}\right) \; if \; f_i = f_g \end{cases} \tag{20}
$$

The reverse elite learning strategy and the group communication in the FA algorithm, the improved spatial search method, according to the new strategy, improves the sparrow search algorithm to fall into the dilemma of local optimal easily and adds the group information exchange function to enhance the global search ability.

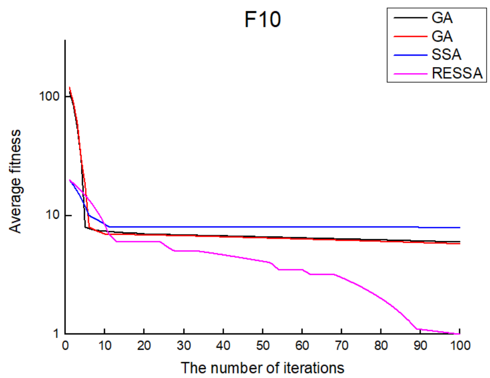
3.4. **Numerical Test Results.** The optimization ability of the RESSA can be fully investigated through various types of benchmark functions. Twelve selected different types functions used to test the proposed FSSSA. Some test function parameters is listed in Table 1. The obtained results of the suggested scheme are compared with PSO [7], GA [6], and SSA [9] algorithms. The setting experiment is detailed as: population size $N = 30$, maximum iteration times $T = 100$, dimension D of the objective function, and upper and lower bounds u_b and l_b of the initial value were selected according to the reference functions in Table 1, the number of finders $pNum$ and the number of sparrows reconnaissance and warning $sNum$ were both 20% of the population size. To avoid the contingency of the optimization results and to prove the stability of RESSA, the experimental results of 30 independent runs of each benchmark function were selected as the experimental data. For



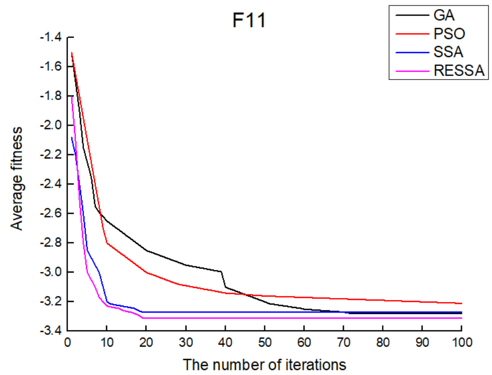
(A) Test function no. 01



(B) Test function no. 06



(C) Test function no. 10



(D) Test function no. 11

FIGURE 1. Comparison of convergence curves of 4 algorithms obtained on the benchmark functions

the 12 benchmark functions, the mean value and standard deviation of each algorithm are taken as the final evaluation indexes. Table 2 lists a comparison of optimization results of the proposed RESSA with PSO, GA, SSA for the benchmark functions.

As seen from the experimental results, the optimization results of the RESSA are better than those of the other three algorithms; In terms of optimization accuracy, the optimization results of F1-F4 and F10-F12 of RESSA are greatly improved compared with the other three algorithms. For functions F7 and F9, RESSA can effectively jump out of the local optimum and stably find the global optimal solution. Figure 2 presents five optimization algorithms. It can be seen from the convergence curve that RESSA is significantly better than the other three algorithms in terms of convergence speed and optimization precision, which indicates that RESSA can fully guarantee the searching ability while ensuring the exploration ability, without losing the diversity of population and optimization stability.

4. Solution WSN Routing Optimization by Applied RESSA.

4.1. Experimental Environment Setting. The proposed RESSA is used to solve the WSN optimization problem, and the sparrow position adopts an integer sequence coding scheme. Assume that the number of nodes in the network is n, and each node in the wireless network built has an independent number corresponding from 1 to n. Assume that the source node is v_s and the destination node is v_d. The possible path from the source node to the destination node is $R_j = (v_s, v_{j2}, v_{j3}.., v_{(jn-1)}, v_d), v_{ji}(i = 1, 2, 3, .., n-1)$ is a random arrangement of other node numbers except source node and destination

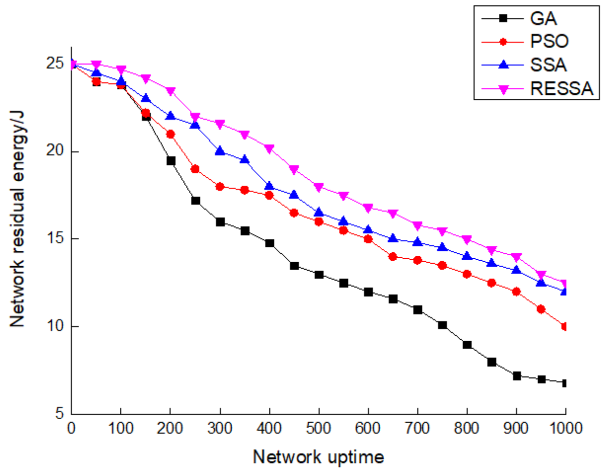


FIGURE 2. Comparison of residual network energy of four algorithms

node, and these node numbers are different from each other. An n-dimensional vector identifies an efficient route satisfying the constraint of Eq. (4) with 0 and 1 elements $X_j = (x_{js}, x_{j2}, x_{j3}, ...x_{(jn-1)}, x_{jd})$. The value of x_{ji} in each dimension is 0 or 1. When the value is 1, it means that the corresponding numbered node is selected as the routing node; if the value is *0*, the corresponding node is not selected as the routing node. Since the source and destination nodes must be in the route, the values of x_{js} and x_{jd} are always *1*. For example, $X = (1, 0, 1, 1, 0, .., 1, 1)$ indicates that $v_s \to v_3 \to v_4 \to v_{(n-1)} \to v_d$ constitutes an efficient route. The effect of particle velocity is to change the position of the particle, which is defined as $S_j = (s_{j1}, s_{j2}, s_{j3}, ..., s_{(jn-1)}, s_{jn})$, and the speed s_{ji} is between $[-4.0, +4.0]$, which represents the possibility that node i is selected as the routing node, that is, the possibility that x_{ji} takes 1. Doing the same with the S function.

4.2. **Algorithm Update Mechanism.** Let the optimal position (global optimum) searched by the whole particle swarm be $R_g = (v_s, v_{g2}, v_{g3}, ..., v_{gn-1}, v_d)$. The current optimal position (individual optimal) found by the *j-th* particle is $R_{pj} = (v_s, v_{p2}, v_{p3}, ..., v_{(pn-1)}, v_d)$, the corresponding routing identification vector for $X_{pj} = (x_{p1}, x_{p2}, x_{p3}, ..., x_{(pn-1)}, x_{pn})$. For a population composed of M particles, the node arrangement vector of individual members is R_j, and the corresponding effective routing identification vector is X_j. The reverse population is $OR_j = (v_s, \bar{v}_{j2}, \bar{v}_{j3}, \ldots, \bar{v}_{jn-1}, v_d), j = 1, \ldots, M$. v_s and v_d are the number of source node and destination node respectively, $v_s, \bar{v}_{j2}, \bar{v}_{j3}, \ldots, \bar{v}_{jn-1}, v_d$ is a permutation of different integers between 1 and n. The inverse component of each dimension is calculated according to the following formula [9].

$$\bar{v}_{ji} = 1 + n - v_{ji} \tag{21}$$

The components of the valid routing identity vector $OX_j = (x_{js}, \tilde{x}_{j2}, \tilde{x}_{j3}, \ldots, \tilde{x}_{jn-1}, x_{jd})$ corresponding to OR_j are assigned as follows: if nodev_{ji} is selected as a route, then the reverse node $\bar{x}_{ji}$ generated by Equation (10) is also selected as a route, then the corresponding value of x_{ji} is 1; On the other hand, if v_{ji} is not selected as a route, then x_{ji} is 0. Similarly, $\tilde{x}_{ji}$ cannot be selected as a route, and $\tilde{x}_{ji}$ is 0.

4.3. **Algorithm Description.** According to the above algorithm ideas and improvement strategies, the specific execution steps of the improved sparrow search algorithm routing optimization method proposed in this paper are as follows.

Step1: Initialize parameters. Including population size M, the number of network nodes n, the proportion of discoverers, the proportion of scouts, and the max-iterations

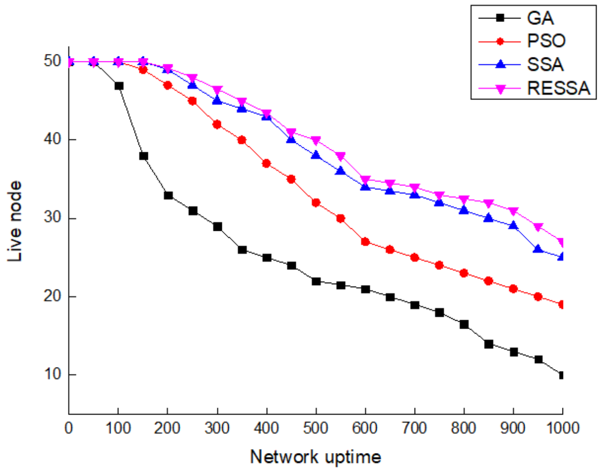


FIGURE 3. Comparison of the network survival times of four algorithms

T_{max}. There is also basic information to determine the routing node, such as effective transmission distance, initial energy, and residual energy, etc.

Step2: Initialize the population. In addition to the starting node and the targeting node, different arrangement of $n-2$ node numbers is randomly generated, namely, R_j is generated. If constraint (4) is satisfied among nodes in R_j, the routing identification of the corresponding node is set to 1, namely, the value of X_j is determined. If the source node and the destination node form a valid communication link, an accurate particle is generated; otherwise, regenerate. After the particle is generated, its initial velocity S_j is randomly set.

Step3: Implement the reverse elite learning strategy. The fitness values of each particle of the current population and reverse population were evaluated. M individuals satisfying the path constraints and having the best fitness values were selected from the current population and reverse population to form the new current population.

Step4: update the historical optimal solution and the global optimal solution of the whole population of sparrows.

Step5: update the population according to the position update formula of the finder, participant, and scout.

Step6: Reevaluate the fitness value of each sparrow agent, update the historical optimal solution of each sparrow agent, and update the global optimal solution of the population.

Step7: If the termination condition of iteration is met, the search will stop and the global optimal solution will be output. Otherwise, return to Step3 and continue to optimize the search.

TABLE 3. Comparison of success rate of algorithm searching optimal solution

Algorithm	Find the optimal number of times	The success rate
PSO [11]	41	82%
GA [10]	36	72%
SSA [13]	43	86%
RESSA	47	94%

4.4. **Simulation Experiment Results and Analysis.** In this experiment, the network covers a rectangular plane area of $100m \times 100m$, 50 sensor nodes are randomly distributed, and nodes are numbered uniformly. The initial energy of nodes is $0.5J$, and the effective transmission distance between nodes is $D_0 = 20m$. Let the population size be 30, the finder ratio be 0.7, the scout ratio is 0.2, the FA $\alpha = 0.2, \beta_0 = 2, \gamma = 1, m = 1$, and the maximum number of iterations T_{max} be 100. The simulation experiment compares genetic algorithm, particle swarm optimization algorithm, sparrow search algorithm, and improved sparrow search algorithm. Under the premise of the same experimental environment parameters, each algorithm was run 10 times, and the average value was taken as the final result. Figure 1 shows the remaining energy wireless sensor network and the network running time (by the number of data sent round) the change of the relationship between, can be seen from the diagram to improve the sparrow search algorithm is superior to genetic algorithm, PSO algorithm and the SSA, the reason is that in this paper, the reconstruction of the algorithm is not the frequent path, is quickly established a better path, data transmission, with less energy consumption you have the most energy left.

The network lifetime is an important indicator to reflect the network performance. In this paper, the number of surviving nodes is used to represent the network. As shown in Figure 2, in the initial stage of the network, the energy of each node is sufficient and there is no dead node. However, with the increase of network running time, as PSO [7], GA [6], and SSA [9] only consider the optimal path without considering the residual energy factor, some nodes are frequently used as routing nodes, which consume a lot of energy and die faster. However, the improved sparrow search algorithm proposed in this paper considers the energy state when choosing the path. It balances the energy consumption of the network, so that there are many surviving nodes, and the network's survival time is significantly improved.

Table 1 compares the success rates of the three algorithms for searching the optimal route in optimization ability of various. Under the premise of the same experimental parameters, the three algorithms were run 50 times respectively, and the success rate of finding the optimal solution in 50 runs was counted. As can be seen from the data in the table, since the algorithm in this paper introduces the reverse learning strategy in the optimization process and considers the mechanism of the firefly algorithm at the same time, it enriches the diversity of the population and increases the probability of the algorithm finding the optimal solution, and its optimization success rate is significantly higher than that of the other two algorithms.

5. **Conclusions.** This paper presented an enhanced sparrow search algorithm with reversing elite learning strategies (called RESSA) the firefly algorithm for the optimal solution to the wireless sensor network (WSN). The improved sparrow search algorithm comprehensively considers the influence of the total energy consumption and the residual energy of nodes on the network lifetime. The increasing group was implemented the diversity of particles update to prevent the algorithm falls into the local optimum and enhance the global search ability of the algorithm. The simulation results show that the RESSA has strong optimization ability, low overall energy consumption, and longer node survival time in prolonging the life cycle of WSN.

REFERENCES

[1] J.-S. Pan, T.-T. Nguyen, S.-C. Chu, T.-K. Dao, and T.-G. Ngo, Network, Diversity Enhanced Ion Motion Optimization for Localization in Wireless Sensor, *Journal of Information Hiding and Multimedia Signal Processing*, vol. 10, no. 1, pp. 221–229, 2019.

[2] S. C. Chu, T. K. Dao, J. S. Pan, and T. T. Nguyen, Identifying Correctness Data Scheme for Aggregating Data in Cluster Heads of Wireless Sensor Network Based on Naive Bayes Classification, *EURASIP Journal on Wireless Communications and Networking,* vol. 2020, no. 1, 52, Dec. 2020.

[3] T. T. Nguyen, J. S. Pan, and T. K. Dao, A Compact Bat Algorithm for Unequal Clustering in Wireless Sensor Networks, *Applied Science,* vol. 9, no. 10, 1973, May, 2019.

[4] J.-N. Chen, Y.-P. Zhou, Z.-J. Huang, T.-Y. Wu, F.-M. Zou, and R. Tso, An Efficient Aggregate Signature Scheme for Healthcare Wireless Sensor Networks, *Journal of Network Intelligence*, vol. 6, no. 1, pp. 1–15, 2021.

[5] J.-S. Pan, T.-T. Nguyen, T.-K. Dao, T.-S. Pan, and S.-C. Chu, Clustering Formation in Wireless Sensor Networks: A Survey, *Journal of Network Intelligence*, vol. 2, no. 4, pp. 287–309, 2017.

[6] J. Zhang, H. Nian, X. Ye, X. Ji, and Y. He, A Spatial Correlation Based Partial Coverage Scheduling Scheme in Wireless Sensor Networks, *Journal of Network Intelligence,* vol. 5, no. 2, pp. 34–43, 2020.

[7] M. F. Othman and K. Shazali, Wireless Sensor Network Applications: A Study in Environment Monitoring System, *Procedia Engineering,* vol. 41, pp. 1204–1210, 2012.

[8] T.-S. Pan, T.-K. Dao, T.-T. Nguyen, and S.-C. Chu, Optimal Base Station Locations in Heterogeneous Wireless Sensor Network Based on Hybrid Particle Swarm Optimization with Bat Algorithm, *Journal of Computers* , vol. 25, no. 4, pp. 14-25, 2015.

[9] J. Yick, B. Mukherjee, and D. Ghosal, Wireless Sensor Network Survey, *Computer Networks*, vol. 52, no. 12, pp. 2292–2330, 2008.

[10] T.-T. Nguyen, C.-S. Shieh, M.-F. Horng, and T.-K. Dao, A Genetic Algorithm with Self-Configuration Chromosome for the Optimization of Wireless Sensor Networks, *Proceedings of the 12th International Conference on Advances in Mobile Computing and Multimedia.* ACM, Kaohsiung, Taiwan, pp. 413–418, 2014.

[11] T.-T. Nguyen, T.-K. Dao, H.-Y. Kao, M.-F. Horng, and C.-S. Shieh, Hybrid Particle Swarm Optimization with Artificial Bee Colony Optimization for Topology Control Scheme in Wireless Sensor Networks, *Journal of Internet Technology*, vol. 18, no. 4, pp. 743–752, 2017.

[12] T. K. Dao, T. S. Pan, and J. S. Pan, A Multi-Objective Optimal Mobile Robot Path Planning Based on Whale Optimization Algorithm, *2016 IEEE 13th International Conference on Signal Processing,* pp. 337–342, 2016.

[13] J. Xue and B. Shen, A Novel Swarm Intelligence Optimization Approach: Sparrow Search Algorithm, *Systems Science and Control Engineering,* vol. 8, no. 1, pp. 22–34, 2020.

[14] T.-T. Nguyen, J.-S. Pan, S.-C. Chu, J. F. Roddick, and T.-K. Dao, Optimization Localization in Wireless Sensor Network Based on Multi-Objective Firefly Algorithm, *Journal of Network Intelligence*, vol. 1, no. 4, pp. 130-138, 2016.

[15] Z. Meng and J.-S. Pan, Monkey King Evolution: A New Memetic Evolutionary Algorithm and its Application in Vehicle Fuel Consumption Optimization, *Knowledge-Based Systems*, vol. 97, pp. 144–157, 2016.

[16] T.-T. Nguyen, J.-S. Pan, T.-Y. Wu, T.-K. Dao, and T.-D. Nguyen, Node Coverage Optimization Strategy Based on Ions Motion Optimization, *Journal of Network Intelligence*, vol. 4, no. 1, pp. 1-9, 2019.

[17] T. T. Nguyen, J. S. Pan, and T. K. Dao, An Improved Flower Pollination Algorithm for Optimizing Layouts of Nodes in Wireless Sensor Network, *IEEE Access*, vol. 7, pp. 75985–75998, 2019.

[18] X.-S. Yang, Firefly Algorithms for Multimodal Optimization, *In International symposium on stochastic algorithms*, pp. 169–178, Springer, Berlin, Heidelberg, 2009.

[19] T.-T. Nguyen, T.-K. Dao, M.-F. Horng, and C.-S. Shieh, An Energy-Based Cluster Head Selection Algorithm to Support Long-Lifetime in Wireless Sensor Networks, *Journal of Network Intelligence*, vol. 1, no. 1, pp. 23–37, 2016.

[20] T.-Y. Wu, L. Yang, Z. Lee, S.-C. Chu, S. Kumari, and S. Kumar, A Provably Secure Three-Factor Authentication Protocol for Wireless Sensor Networks, *Wireless Communications and Mobile Computing*, vol. 2021, 5537018, 2021.

[21] J.-N. Chen, F.-M. Zou, T.-Y. Wu, and Y. Zhou, A New Certificate-Based Aggregate Signature Scheme For Wireless Sensor Networks, *Journal of Information Hiding and Multimedia Signal Processing*, vol. 9, no. 5, pp. 1264-1280, 2018.

[22] K. Renuka, S. Kumar, S. Kumari, and C.-M. Chen, Cryptanalysis and Improvement of a Privacy-Preserving Three-Factor Authentication Protocol for Wireless Sensor Networks, *Sensors*, vol. 19, no. 21, 4625, 2019.

[23] C.-M. Chen, B. Xiang, T.-Y. Wu, and K.-H. Wang, An Anonymous Mutual Authenticated Key Agreement Scheme for Wearable Sensors in Wireless Body Area Networks, *Applied sciences,* vol. 8, no. 7, 1074, 2018.

[24] C.-M. Chen, Y.-H. Lin, Y.-C. Lin, and H.-M. Sun, RCDA: Recoverable Concealed Data Aggregation for Data Integrity in Wireless Sensor Networks, *IEEE Transactions on Parallel and Distributed Systems.* vol. 23, no. 4, pp. 727-734, 2011.
[25] X. S. Yang, Firefly Algorithms for Multimodal Optimization, *Lecture Notes in Computer Science,* vol. 5792, pp. 169-178, 2009.