



Using Simplified Slime Mould Algorithm for Wireless Sensor Network Coverage Problem

Yuanye Wei¹, Yongquan Zhou^{1,2}(✉), Qifang Luo^{1,2}, and Jian Bi¹

¹ College of Artificial Intelligence, Guangxi University for Nationalities,
Nanning 530006, China

zhouyongquan@gxun.edu.cn

² Guangxi Key Laboratories of Hybrid Computation and IC Design Analysis,
Nanning 530006, China

Abstract. Wireless sensor network (WSN) coverage control is a study of how to maximize the network coverage to provide reliable monitoring and tracking services with guaranteed quality of service. The application of optimization algorithm is helpful to effectively control the network nodes energy, improve the perceived quality of services, and extend the network survival time. This paper presents a simplified slime mould algorithm (SSMA) for optimization WSN coverage problem. We mainly conducted thirteen groups of WSNs coverage optimization experiments, and compared with several well-known metaheuristic algorithms. From the experimental results and Wilcoxon rank sum test results demonstrate that SSMA is generally competitive, outstanding performance and effectiveness.

Keywords: WSN · Slime mould algorithm (SMA) · Simplified slime mould algorithm (SSMA) · Effective coverage rate · Metaheuristic

1 Introduction

Wireless sensor network (WSNs) is composed of a large number of densely distributed sensor network node, each node has limited computing, storage and wireless communication capabilities, and can sense the surrounding environment at close range. It has the characteristics of small size, low cost, and low power consumption. It can assist in sensing, collecting and processing the information of the monitored object in real time, so with the rapid development of science and technology in various fields, WSNs has been widely used in military affairs, environmental monitoring, medical and health care, safety monitoring and other fields [1].

In various applications of wireless sensor networks, coverage has always been a crucial issue, which determines the monitoring ability of the target area. An appropriate node deployment strategy can not only improve the service quality of WSNs, but also effectively promote its energy utilization. However, searching for the optimal node deployment scheme is a difficult task, especially for large-scale sensor networks [2]. As this context, scholars choose to focus on meta-heuristic algorithm, which has made a good contribution to the coverage optimization of WSNs. Ref. [3] used PSO Optimized

sink node path location in WSNs; Ref. [4] a novel FFO was introduced to the coverage optimization. Ref. [5] used PSO and Voronoi diagram to optimize sensor coverage in WSNs. Ref. [6] used a novel DE applied to optimize the coverage problem of WSNs. Ref. [7] used ACO based sensor deployment protocol for wireless sensor networks. Ref. [8] proposed a Hybrid Red Deer SSA for Optimal Routing Protocol in Wireless Multimedia Sensor Networks. Ref. [9] proposes FPA to solve MEB problem in WSNs. Ref. [10] used FA for power management in (WSNs) et al.

The Slime Mould Algorithm [11] is a novel metaheuristic algorithm, which was proposed by Seyedali M. et al. in 2020. It to simulate the positive and negative feedback generated by the propagation wave of biological oscillator during the foraging process of Slime mould in nature, and to guide their behavior and morphological changes. Because of its simple concept and strong searching ability, it has been paid attention to and studied by many scholars since it was put forward. Ref. [12] used HSMA_WOA for COVID-19 chest X-ray images; Ref. [13] dynamic structural health monitoring based on SMA; Ref. [14] proposed hybrid ANN model with SMA for Prediction of Urban Stochastic Water Demand; Ref. [15] based on SMA to extract the optimal model parameters of solar PV panel; Ref. [16] SMA for feature selection; Ref. [17] SMA-AGDE for solving various optimization problems; Ref. [18] using SMA to Mitigating the effects of magnetic coupling et al.

In this paper, in order to improve the search accuracy and population diversity of the con SMA in solving the coverage optimization problem of wireless sensor networks, we propose a simplified slime mould algorithm (SSMA). The SSMA has three highlights:

- (1) A simplified slime mould algorithm is proposed to solving WSNs coverage optimization.
- (2) Simplify the position update formula and a new adaptive oscillation factor, for balance the development and exploration capacity, and improve the coverage capacity of WSNs.
- (3) SSMA will be experimentally experimented in a small-scale and large-scale WSNs coverage problems, and comparative analysis of 6 state-of-the-art algorithms.

The rest of this paper is structured as follows: Sect. 2 briefly reviews the original SMA algorithm. Section 3 details the simplified SMA (SSMA). Section 4 gives the practical application of SSMA in solving WSNs coverage optimization problem. Section 5 carries out experimental analysis and discussion. Section 6 provides the conclusions and future directions of this work.

2 Wireless Sensor Network Coverage Optimization

Assumed that the monitoring area of WSNs is a two-dimensional plane, which is digitized into $L \times M$ grids, and the size of each grid is set to unit 1. N homogeneous sensors are deployed in this area, and the node set can be expressed as $Z = \{Z_1, Z_2, Z_3, \dots, Z_N\}$ having the same sensing radius R . In this paper, Boolean model is used as the node sensing model, so long as the target is within the node sensing range, it can be successfully

sensed. Assuming that the coordinates of a node z_i in the detected area are (x_i, y_i) and the position coordinates D_j of the target point are (x_j, y_j) , the distance between the node and the target point is:

$$d(z_i, D_j) = \sqrt{(x_i, y_i)^2 - (x_j, y_j)^2} \quad (2.1)$$

where $p(z_i, D_j)$ represents the perceptual quality of node z_i to D_j . When the position D_j of node z_i is within the circle of perceived range, the perceived quality is 1, otherwise it is 0, and the mathematical expression is:

$$p(Z_i, D_j) = \begin{cases} 1, & \text{if } d(z_i, D_j) \leq R \\ 0, & \text{otherwise} \end{cases} \quad (2.2)$$

Generally, the sensor's perception probability of the target is less than 1. In order to improve the perception probability of the target, multiple sensors need to cooperate to detect, so the sensor's perception probability of a certain target is:

$$p(Z, D_j) = 1 - \prod_{i=1}^N [1 - p(z_i, D_j)] \quad (2.3)$$

The coverage rate of the node set Z over the entire monitoring area is:

$$f = \frac{\sum_{j=1}^{L \times M} p(Z, H_j)}{L \times M} \quad (2.4)$$

Equation (2.4) is the objective function of WSN coverage optimization problem.

3 Slime Mould Algorithm

Slime mould algorithm [11] mainly simulates the behavior and morphological changes of slime mould in the foraging process in nature. SMA can effectively simulate the information transmission mechanism of feeding back the food concentration in the search space through the propagation wave generated by the oscillator, and simulates the threat to the existence in the foraging process with the weight factor, which improves the effectiveness of the algorithm.

Slime mould can judge the position according to the concentration of surrounding food during foraging, and adjust their foraging mode according to the influence of environment.

3.1 Mathematical Model

When slime mould foraging, they can sense the concentration and position of food through odour in the air and then approach it constantly. This process can be expressed by the following equation:

$$\vec{S}(t+1) = \begin{cases} rand * (ub - lb) + lb, rand < pc \\ \vec{S}^*(t) + kb * (\vec{W} * \vec{S}_{R1}(t) - \vec{S}_{R2}(t)), r < q \\ kc * \vec{S}(t), r \geq q \end{cases} \quad (3.1)$$

where ub and lb are represents the upper and lower boundaries of the search space, $rand$ and r are random values between $[0,1]$, and pc is a constant, which is taken same as stander SMA. Parameters kb and kc are oscillation factor, t represents the current iteration times, \vec{S}^* represent the current optimal individual, \vec{S} represent the current individual, \vec{S}_{R1} and \vec{S}_{R2} represents two individuals randomly selected in the slime mould population, \vec{W} represent weight.

The q mathematical formula of is as follows:

$$q = \tanh|f(i) - DF| \quad (3.2)$$

where $i \in 1, 2, \dots, n$, $f(i)$ indicated fitness of individual \vec{S} , DF represents the best fitness value obtained in all iterations. kb and kc mathematical formula as follows:

$$\vec{kb} = [-a, a] \quad (3.3)$$

$$a = \arctan h\left(-\frac{it}{T_{\max}} + 1\right) \quad (3.4)$$

$$\vec{kc} = \left(1 - \frac{it}{T_{\max}}\right) \quad (3.5)$$

\vec{W} mathematical formula as follows:

$$W(smell(i)) = \begin{cases} 1 + r \cdot \log\left(\frac{BF - f(i)}{BF - WF + \varepsilon} + 1\right) \\ 1 - r \cdot \log\left(\frac{BF - f(i)}{BF - WF + \varepsilon} + 1\right), other \end{cases}, i \leq \frac{2}{N} \quad (3.6)$$

$$smell = sort(f) \quad (3.7)$$

where r is a randomly values interval of $[0,1]$, T_{\max} indicates the maximum number of iterations, BF indicates the best fitness in the current iteration, WF indicates the worst fitness in the current iteration, $smell$ represents the corresponding values sorted by fitness values. is the fitness of the whole population.

4 Simplified Slime Mould Algorithm

Since the SMA [11] was put forward, it has been paid attention to and studied by many scholars because of its simple concept and good effect in solving various practical problems. However, like many meta-heuristic algorithms, it also has the disadvantages of premature convergence and easy to fall into local optimum. When solving the coverage optimization problem of wireless sensor networks, the standard shape memory alloy has obvious defects such as local optimum location, low coverage rate and insufficient convergence speed. Therefore, we propose a simplified slime mold optimization algorithm (SSMA) to solve the optimization problem of wireless sensor networks. The position update in Eq. (3.1(3)) of the SMA is that individuals search around themselves, which leads to poor exploration ability. Individuals cannot find the global optimal solution quickly, and easily fall into local optimal solution. The position update in Eq. (3.1(2)), individuals update their position according to the global optimal solution and two random solutions is random choose in the population. This mechanism can balance the exploration and development ability of the algorithm well. In addition, the oscillation factor has a vital impact on the optimization performance of SMA. When the oscillation factor is chosen as trigonometric function, it not only improves the convergence speed of optimization, but also accords with the actual theory of propagation wave. Therefore, we propose a simplified slime mould algorithm (SSMA) to solve the coverage optimization problem of WSNs.

The update formula is as follows:

$$\vec{S}(t+1) = \begin{cases} rand * (ub - lb) + lb, rand < pc \\ S^*(t) + kb * (\vec{W} * S_{R1}^{\vec{}}(t) - S_{R2}^{\vec{}}), otherwise \end{cases} \quad (4.1)$$

The oscillation factor formula is as follows:

$$\vec{kb} = [-a, a] \quad (4.2)$$

$$a = \gamma \left(\cos\left(\pi \cdot \frac{it}{T_{\max}}\right) + \lambda \right) \quad (4.3)$$

where a is the value of the change range of γ , $\gamma = 0.5$; λ is the value step of the slime mould, $\lambda = 1$.

The SSMA mainly depends on the optimal solution and two random solution in the population. Equation (4.1) is the core of the SSMA. When z is less than 0.03, slime mould searches randomly in the whole search space, and Eq. (4.2) is executed; otherwise, Eq. (4.3) is executed. The best individual can lead the development stage of slime mould, while two random individuals in the population mainly dominate the exploration stage of the SSMA. This formula can balance the exploration and development of the algorithm. The pseudo-code of the SMA is shown in Algorithm 1.

Algorithm 1. SSMA pseudo-code

-
1. Initialize the parameter, population, ub , lb , Max_iter ;
 2. Initialize the position of slime mould $S_i(1,2,\dots,n)$;
 3. **While** ($t < Max_iter$)
 4. Calculate the fitness of all slime mould;
 5. Update DF, BF, WF, \vec{S}
 6. Calculate the W by Eq. (3.6);
 7. **for** each search portion
 8. Update q, kb, kc ;
 9. Update position
 10. **If** $rand < pc$
 11. Update position by Eq. (4.1)
 12. **Else**
 13. Update position by Eq. (4. 2)
 14. **End if**
 15. **End for**
 16. $t=t+1$;
 17. **End while**
 18. **Return** DF, \vec{S}
-

5 Simulation Result

5.1 Problem Definition

As mentioned in the second section, we will define it as follows: the coverage of sensor nodes is a circle with a fixed radius. Whether a certain position is in the coverage area of the sensor node can be determined by calculating the distance between the target point and the node. In order to evaluate the coverage of WSNs in two-dimensional area, the whole monitoring area is divided into $L \times M$ grids. If WSNs can cover points, then the coverage rate is 1. In addition, we assume that all sensors are the same monitoring area, and ignore the boundary effect on the sensor network.

During initialization, all sensor nodes are randomly scattered in a given monitoring area, and the initial coordinates of these sensor nodes are the initial input values of the algorithm. Each search agent in the algorithm represents a placement scheme of sensor nodes. In the two-dimensional monitoring area, the dimension of search agent is twice the number of sensor nodes; In other words, the $2x - 1$ dimensional data represents the abscissa of the x -th sensor node, while the $2x$ dimensional data represents its ordinate. The algorithm takes WSNs coverage as the fitness function that is Eq. (2.4), as mentioned in the second section, and maximizes the fitness function as the optimization goal. Finally, the optimized coverage and the positions of all sensor nodes are output.

We compare the experimental results of SSMA with SMA [11], PSO [19], GWO [20], WOA [21], MPA [22] and FPA [23]. Table 1 summarizes the experimental parameter

settings for comparison algorithms. In order to eliminate the experimental error caused by chance, the average value of 20 independent runs is used as the comparison result. We are mainly divided into two kinds of experiments: low dimension and large-scale dimension. Other parameter settings: population size N , maximum iterations T ; The monitoring radius R , the monitoring area $L \times M$, the sensor of node: Node, and the dimension Dim .

Table 1. Parameter settings for each algorithm

Algorithm	Year	Parameters and values
PSO [19]	1995	$C_2 = 1.5, C_2 = 2, W_{\max} = 0.9, W_{\min} = 0.4$
FPA [23]	2012	$p = 0.8$
GWO [20]	2014	$a = [2, 0]$
WOA [21]	2016	$a = [2, 0], b = 1, A = [2, 0]$
MPA [22]	2020	$Fads = 0.2, P = 0.5$
SMA [11]	2020	$z = 0.03$
SSMA	~	$z = 0.03, \lambda = 1, \gamma = 0.5$

5.2 Comparative Analysis of Experiments

In this sector, we compared the SSMA with some competitive MAs on WSNs coverage optimization. Furthermore, all of the experimental series were performed on MATLAB 2017b and were run on a CPU Core i3-6100 v4 (3.70GHz) with 8 GB RAM in this paper.

In the experimental part, we will set up 3 type groups of coverage optimization experiments, among which there are two groups of low-dimensional ones, which are divided into Case1-Case3 and C1-C4, the number of nodes is unequal between 5 to 80 nodes, moreover, there are third groups of large-dimensional experiments, which name C5 to C10, mainly from 100 to 1200 nodes. The parameter settings of three groups of experiments are shown in Table 2. The experiments mainly compared the experimental results of SSMA with six state-of-the-art algorithms to analyze the robustness and convergence speed.

5.2.1 Low-Dimension Experimental Analysis

In this section, we mainly test and analyze the number of nodes in low dimension. There are two types of cases in low dimension: Case1-Cas3; C1-C4. Examples Case1-Case3 come from literature [24], C1-C4 are self-defined cases in this paper, third groups for large dimension. We used the above two types with different radio for experimental comparison. Case 1-Case 3 and C1-C4 compares these two groups of seven cases through Tables 3 and Figs.1 to Fig. 3. Moreover, Tables 3 list results for independent runs for 20 times, where ‘‘Ave’’ and ‘‘Std’’ represent the average coverage and standard deviation,

Table 2. Parameter settings

Case	R(m)	Dim	Node	L*M(m)	Maximum iteration	Population size
Case 1	1	20	10	5*5	250	30
Case 2		40	40	10*10		
Case 3		160	80	15*15		
C 1	10	10	5	50*50	100	30
C 2		40	20	80*80		
C 3		120	60	100*100		
C 4		160	80	150*150		
C5	45	200	100	800*800		
C6	30	600	300			
C7	25	1000	500			
C8	20	1400	700			
C9	18	2000	1000			
C10	15	2400	1200			

respectively. Black bold numbers represent the optimal solution, blue bold represents the secondly best value, and green bold represents the third best.

As Case1 to Case3. It can be clearly seen from Table 3 about the average coverage rate (mean fitness) of SSMA is significantly higher than that of the other six methods. C1 is reached 63.05%, ranking first, which was 1.61%, 4.54%, 0.56%, 3.07%, 1.66% and 10.36% higher than PSO, FPA, GWO, WOA, MPA and SMA, respectively. As C2 is reached 86.43%, which was 13.97%, 15.07%, 2.55%, 11.44%, 7.9% and 19.35% higher than PSO, FPA, GWO, WOA, MPA and SMA respectively. The average coverage rate of SSMA in C3 reaches 99.47%, which is 13.46%, 8.76%, 6.89%, 5.79%, 3.2% and 12.41% higher than PSO, FPA, GWO, WOA, MPA and SMA respectively. The average coverage rate of SSMA in C4 is 85.13%, which is 21.58%, 13%, 10.64%, 9.64%, 4.14% and 15.15% higher than PSO, FPA, GWO, WOA, MPA and SMA respectively. The average coverage rate of C1-C4, SSMA in C1 reached 63.05%, ranking first, which was 1.61%, 4.54%, 0.56%, 3.07%, 1.66% and 10.36% higher than PSO, FPA, GWO, WOA, MPA and SMA respectively. The C2 is reached 86.43%, which was 13.97%, 15.07%, 2.55%, 11.44%, 7.9% and 19.35% higher than PSO, FPA, GWO, WOA, MPA and SMA respectively. Case for C3 reaches 99.47%, which is 13.46%, 8.76%, 6.89%, 5.79%, 3.2% and 12.41% higher than PSO, FPA, GWO, WOA, MPA and SMA respectively. While mean coverage C4 is 85.13%, which is 21.58%, 13%, 10.64%, 9.64%, 4.14% and 15.15% higher than PSO, FPA, GWO, WOA, MPA and SMA respectively. From the above data display and analysis, it can be seen that SSMA has obvious advantages in solving the coverage optimization problem of wireless sensor networks, and has relatively strong robustness and fast convergence speed.

Table 3. Results for low-dimension experimental

Algorithm	PSO	FPA	GWO	WOA	MPA	SMA	SSMA	
case								
Case1	Ave	0.7960	0.97	0.962	0.922	0.962	0.84	0.984
	Std	0.0733	0.0178	0.0275	0.0378	0.0330	0.0486	0.0239
Case2	Ave	0.6815	0.8515	0.8925	0.8405	0.922	0.7685	0.9715
	Std	0.0613	0.0081	0.0481	0.0228	0.0337	0.0157	0.0139
Case3	Ave	0.5842	0.7633	0.7909	0.7507	0.8589	0.7067	0.9044
	Std	0.0514	0.0076	0.0748	0.0254	0.0270	0.0107	0.0193
C1	Ave	0.6144	0.5851	0.6249	0.5998	0.6139	0.5269	0.6305
	Std	0.0343	0.0106	0.0112	0.0135	0.0085	0.0176	0.0039
C2	Ave	0.7246	0.7136	0.8388	0.7499	0.7853	0.6708	0.8643
	Std	0.0383	0.0136	0.0165	0.0230	0.0199	0.0169	0.0124
C3	Ave	0.8601	0.9071	0.9258	0.9368	0.9627	0.8706	0.9947
	Std	0.0427	0.0056	0.0493	0.0115	0.0126	0.0083	0.0025
C4	Ave	0.6355	0.7213	0.7449	0.7549	0.8099	0.6963	0.8513
	Std	0.0196	0.0054	0.0614	0.0124	0.0130	0.0115	0.0068

The convergence curve of Case1 and C2 show in Fig. 1 that the convergence curve of SSMA is much faster than the other six algorithms, and other algorithms are easy to fall into the local optimum, and loss the optimization ability. In Fig. 2, The standard deviation of SSMA is more stable and higher than other algorithms. As can be seen from the coverage in Fig. 3, the coverage of SSMA is a superior than other algorithms. As the dimensionality increases, the coverage performance is stronger.

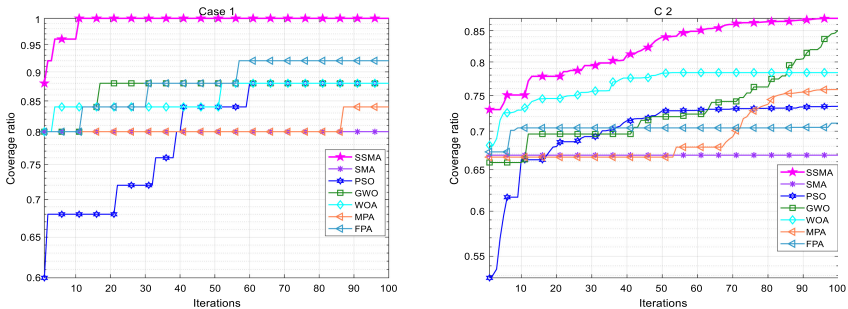


Fig. 1. Coverage curve on case1 and C2

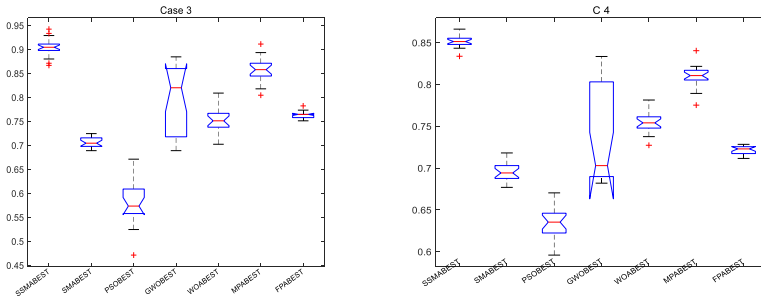


Fig. 2. Box plot on Case3 and C4

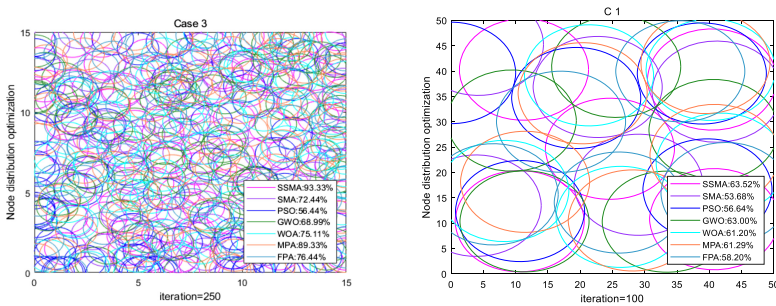


Fig. 3. Nodes distribution optimization on case 3 and C1

5.2.2 Large-Scale Experimental Analysis

In this section, we applied the proposed SSMA on a large-scale wireless sensor node, and compare the results with some methods. The experimental parameters are list in Table 2, which are same as previous mention.

Other algorithms may adapt in low scale dimension problem, but they may lose performance in large-scale dimension. However, the SSMA is still applicable in the large-scale nodes. Results of six large-scale cases show in Table 4. It is obviously that the coverage SSMA of C5, C6, C7 and C9 are ranked first among the six large-scale cases of C5-C10, and the SSMA of C8 and C10 are ranked second. For C8, the coverage rate of SSMA was 0.18% less than that of MPA ranked first, and C10, the coverage rate of SSMA was 0.05% less than that of MPA ranked first. It can be seen that the SSMA ranked second in C8 and C10 is not much different from the MPA ranked first. C5(200 dimensions), the coverage rate of SSMA reached 78.35%, which was 25.44%, 10.89%, 12.87%, 8.39%, 2.82% and 13.41% higher than that of PSO, FPA, GWO, WOA, MPA and SMA. C6(600 dimensions), the coverage rate of SSMA reached 83.32%, which was 29.67%, 6.94%, 8.54%, 5.41%, 0.49% and 8.68% higher than that of PSO, FPA, GWO, WOA, MPA and SMA. In C7(1000 dimensions), the coverage rate of SSMA reached 86.29%, which was 30.44%, 5.46%, 6.95%, 4.32%, 0.21% and 6.92% higher than that of PSO, FPA, GWO, WOA, MPA and SMA. In experiment C8(1400 dimensions), the coverage rate of SSMA reached 81.02%, which was 29.58%, 4.45%, 5.47%, 3.43% and 5.54% higher than that of PSO, FPA, GWO, WOA and SMA. In C9(2000 dimension), the coverage

rate of SSMA reached 85.15%, which was 31.64%, 3.94%, 5%, 0.1%, 3.22% and 4.83% higher than that of PSO, FPA, GWO, WOA, MPA and SMA. In C10(2400 dimensions), the coverage rate of SSMA reached 78.16%, which was 28.21%,3.19%,4.05%,2.82%, and 4.612% higher than that of PSO,FPA,GWO,WOA,SMA.

From the above results and discussions, it shows that SSMA can solve the coverage optimization problem of WSNs. SSMA do still used in large-scale experiments, while other algorithms compared with SSMA have lost their performance. Experiments show that SSMA has superior performance and competitiveness.

Table 4. Average values results on large-scale experimental

Case	PSO	FPA	GWO	WOA	MPA	SMA	SSMA
C5	0.5291	0.6746	0.6548	0.6997	0.7553	0.6494	0.7835
C6	0.5365	0.7638	0.7478	0.7791	0.8283	0.7464	0.8332
C7	0.5585	0.8083	0.7934	0.8197	0.8608	0.7937	0.8629
C8	0.5144	0.7657	0.7555	0.7759	0.8120	0.7548	0.8102
C9	0.5351	0.8123	0.8015	0.8193	0.8505	0.8032	0.8515
C10	0.4995	0.7497	0.7411	0.7534	0.7821	0.7404	0.7816

Figure 4 shows the coverage convergence curve from C7 and C8. We seen that the convergence curve of SSMA is faster than other algorithms, and the optimization speed is stronger. With the increase of dimensions, the ability of optimization is less obvious and the difficulty of optimization increases. Figure 5 shows the graph of standard deviation, from which it can be seen that SSMA is the best, and Fig. 6 shows the optimization of node distribution of randomly selected samples in each case. It can be observed that with the increase of iteration times, the network coverage gradually rises to the optimal value. However, the increase of the dimension of optimization problem brings great challenges to the algorithm. It can be seen that with the increase of dimensions, the performance of optimization becomes a challenge, and the performance of optimization gradually weakens on high-dimensional tasks.

5.3 Analysis of Statistical Significance

Wilcoxon Sum-Rank Test (WSRT), as a non-parameter test, can effectively evaluate the statistically significant difference between the two optimization algorithms. Table 5 shows the P-values of Wilcoxon test [25] obtained by different SSMA for 13 cases, which are statistically significant when the significance level is 0.05. When we calculate the P-value higher than 0.05, it means that there is no significant difference between the two methods. On the contrary, when the P-value is less than 0.05, we can see that there are great differences between them. We use Wilcoxon test to compare the performance difference between the two methods. ‘+’ indicates that SSMA is superior to comparison methods, ‘-’ indicates that SSMA is second only to competitors, and ‘=’ indicates that there is no difference in performance between SSMA and comparison methods for each

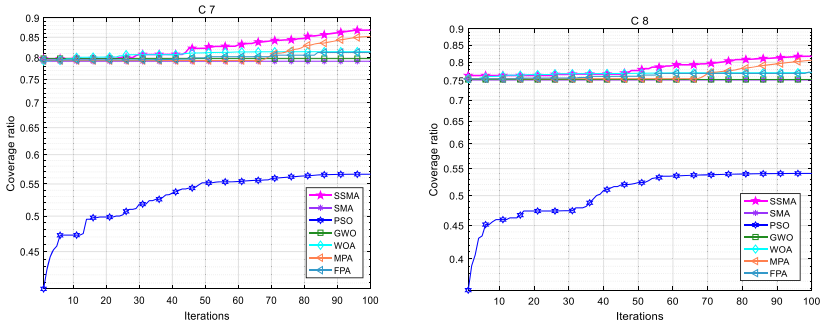


Fig. 4. Coverage curve on C 7 to C 8

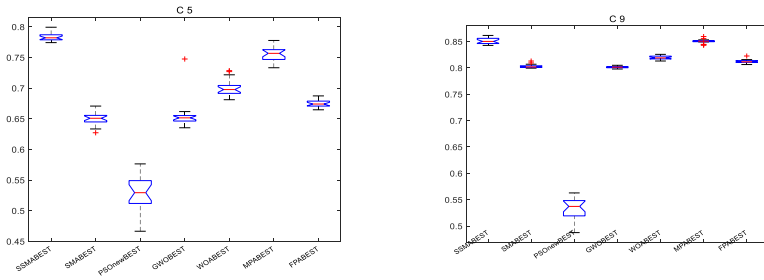


Fig. 5. Box plot on C 5 and C9

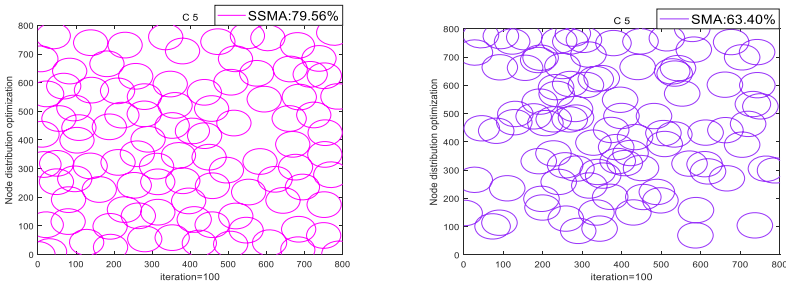


Fig. 6. Node distribution optimization of SSMA and SMA on C 5

example in 20 runs independently. The results highlight the obvious advantages of SSMA over all other competitors in two different dimensional examples.

It can be seen from Table 5 that the performance of our proposed SSMA is better than that of other algorithms. In addition, in Table 6, we use Friedman test [26] to rank several algorithms. According to the Mean rank obtained by Friedman test, the maximum mean rank of SSMA variables is 6.95, which indicates that the overall performance of the proposed SSMA in wireless sensor network coverage optimization is the best. The rank of other test algorithms is $MPA > GWO > FPA > WOA > SMA > PSO$.

Table 5. p-values results of Wilcoxon rank sum test for SSMA vs. PSO, FPA, GWO, WOA, MPA, SMA

Case	SSMA					
	PSO	FPA	GWO	WOA	MPA	SMA
Case1	8.1993e-05	0.1185	0.0239	3.4338e-04	0.0437	7.8386e-05
Case2	8.4627e-05	7.6461e-05	8.6955e-05	8.6584e-05	2.8314e-04	8.4506e-05
Case3	8.7949e-05	8.6461e-05	8.7949e-05	8.7699e-05	1.0078e-04	8.7699e-05
C 1	0.0645	8.8074e-05	8.8575e-05	8.8449e-05	1.1112e-04	8.8324e-05
C 2	8.8575e-05	8.8449e-05	4.4934e-04	8.8575e-05	8.8575e-05	8.8575e-05
C 3	8.8575e-05	8.8575e-05	8.8575e-05	8.8449e-05	8.8575e-05	8.8575e-05
C 4	8.8449e-05	8.8575e-05	8.8575e-05	8.8575e-05	8.8575e-05	8.8575e-05
C 5	8.8575e-05	8.8074e-05	8.8575e-05	8.8449e-05	1.1112e-04	8.8324e-05
C 6	8.8575e-05	8.8449e-05	4.4934e-04	8.8575e-05	8.8575e-05	8.8575e-05
C 7	8.8575e-05	8.8575e-05	8.8575e-05	8.8449e-05	8.8575e-05	8.8575e-05
C 8	8.8575e-05	8.8575e-05	8.8575e-05	8.8575e-05	8.8575e-05	8.8575e-05
C 9	8.8575e-05	8.8575e-05	8.8575e-05	8.8575e-05	0.390	8.8575e-05
C 10	8.8575e-05	8.8575e-05	8.8575e-05	8.8575e-05	0.6813	8.8575e-05

Table 6. Overall wilcoxon sum test rank results and friedman mean rank test results

Result	PSO	FPA	GWO	WOA	MPA	SMA	SSMA
+ / = /-	12/1/0	13/0/0	12/1/0	13/0/0	11/2/0	13/0/0	~
Mean rank	1.20	4.08	4.25	3.65	5.85	2.23	6.95
Over rank	7	4	3	5	2	6	1

6 Conclusions

In this paper, a SSMA is proposed and applied to solve the coverage optimization problem of WSNs. For SSMA, we have mainly made two improvements. To improved update position mathematical formula, mainly to improve the optimization performance of the SSMA hence improve the coverage rate; the second is the improvement of oscillation factor. The second part of the improvement was mainly improved the optimization speed in the early stage of search and the convergence speed. For experimental part, we mainly conducted 13 cases of experiments: low-dimensional experiments and high-dimensional experiments, and compared with six state-of-the-art algorithms. In addition, Wilcoxon rank sum test and Friedman text are used to determine the significant difference between the results of SSMA and other competitors. Experimental results show that these improvements to SSMA can improve search efficiency and speed up convergence. The proposed SSMA was superior to most comparisons methods. For the future work,

first, the proposed SSMA can be applied to other real-world problems, such as route path planning, transportation safety management, job shop scheduling, and graph coloring problem. Second, other versions of SSMA can be extended, such as multi-objective version, complex version, binary version, quantum coding version, etc. Finally, combining SSMA with other algorithms may be a promising aspect. Fourth, the updating formula and parameters of SSMA can be improved, and the correctness can be verified by experiments on benchmark problem.

Acknowledgment. This work is supported by National Science Foundation of China under Grant 62066005, and by the Project of Guangxi Natural Science Foundation under Grants No. 2018GXNSFAA138146.

References

1. Singh, A., Sharma, S., Singh, J.: Nature-inspired algorithms for wireless sensor networks: a comprehensive survey. *Comput. Sci. Rev.* **39**, 100342 (2021)
2. Wang, S., Yang, X., Wang, X., Qian, Z.: A virtual force algorithm-lévy-embedded grey wolf optimization algorithm for wireless sensor network coverage optimization. *Sensors* **19**(12), 2735 (2019)
3. Mendis, C., Guru, S.M., Halgamuge, S., Fernando, S.: Optimized sink node path using particle swarm optimization. In: 20th International Conference on Advanced Information Networking and Applications, 2006, AINA 2006.. IEEE Computer Society (2006)
4. Song, R., Xu, Z., Liu, Y.: Wireless sensor network coverage optimization based on fruit fly algorithm. *Int. J. Online Eng. (Ijoe)* **14**(6), 58–70 (2018)
5. Aziz, N.A., Alias, M.Y., Mohammed, A.W.A.: wireless sensor network coverage optimization algorithm based on particle swarm optimization and Voronoi diagram. In: International Conference on Networking. IEEE (2009)
6. Kuila, P., Jana, P.K.: A novel differential evolution based clustering algorithm for wireless sensor networks. *Appl. Soft Comput. J.* **25**, 414–425 (2014)
7. Liao, W.H., Kao, Y., Wu, R.T.: Ant colony optimization based sensor deployment protocol for wireless sensor networks. *Expert Syst. Appl.* **38**(6), 6599–6605 (2011)
8. Ambareesh, S., Madheswari, A.N.: HRDSS-WMSN: a multi-objective function for optimal routing protocol in wireless multimedia sensor networks using hybrid red deer salp swarm algorithm. *Wireless Pers. Commun.* **119**(1), 117–146 (2021). <https://doi.org/10.1007/s11277-021-08201-z>
9. Rajeswari, M., Thirugnanasambandam, K., Raghav, R.S., Prabu, U., Saravanan, D., Anguraj, D.K.: Flower pollination algorithm with powell's method for the minimum energy broadcast problem in wireless sensor network. *Wireless Pers. Commun.* **119**, 1111–1135 (2021)
10. Pakdel, H., Fotohi, R.: A firefly algorithm for power management in wireless sensor networks (WSNs). *J. Supercomputing* 1–22 (2021). <https://doi.org/10.1007/s11227-021-03639-1>
11. Li, S., Chen, H., Wang, M., Heidari, A.A., Mirjalili, S.: Slime mould algorithm: a new method for stochastic optimization. *Future Gener. Comput. Syst.* **111**, 300–323 (2020) aliasgharheidari.com
12. Abdel-Basset, M., Chang, V., Mohamed, R.: Hsma_woa: a hybrid novel slime mould algorithm with whale optimization algorithm for tackling the image segmentation problem of chest x-ray images. *Appl. Soft Comput.* **95**, 106642 (2020)

13. Tiachacht, S., Khatir, S., Thanh, C.L., Rao, R.V., Mirjalili, S., Wahab, M.A.: Inverse problem for dynamic structural health monitoring based on slime mould algorithm. *Eng. Comput.* 1–24. (2021) <https://doi.org/10.1007/s00366-021-01378-8>
14. Zubaidi, S. L., et al.: Hybridised artificial neural network model with slime mould algorithm: a novel methodology for prediction of urban stochastic water demand. *Water* **12**(10), 2692 (2020)
15. Mostafa, M., Rezk, H., Aly, M., Ahmed, E.M.: A new strategy based on slime mould algorithm to extract the optimal model parameters of solar PV panel. *Sustain. Energ. Technol. Assess.* **42**, 100849 (2020)
16. Abdel-Basset, M., Mohamed, R., Chakraborty, R.K., Ryan, M.J., Mirjalili, S.: An efficient binary slime mould algorithm integrated with a novel attacking-feeding strategy for feature selection. *Comput. Indus. Eng.* **153**, 107078 (2021)
17. Houssein, E.H., Mahdy, M.A., Blondin, M.J., Shebl, D., Mohamed, W.M.: Hybrid slime mould algorithm with adaptive guided differential evolution algorithm for combinatorial and global optimization problems. *Expert Syst. Appl.* **174**, 114689 (2021)
18. Djekidel, R., et al.: Mitigating the effects of magnetic coupling between HV transmission line and metallic pipeline using slime mould algorithm. *J. Magn. Magn. Mater.* **529**, 167865 (2021)
19. Kennedy, J., Eberhart, R.: Particle swarm optimization. In: *Proceedings of IEEE 1995 International Conference on Neural Networks*, vol. 4, pp. 1942–1948 (2002)
20. Mirjalili, S., Mirjalili, S.M., Lewis, A.: Grey wolf optimizer. *Adv. Eng. Softw.* **69**(3), 46–61 (2014)
21. Mirjalili, S., Lewis, A.: The whale optimization algorithm. *Adv. Eng. Softw.* **95**(95), 51–67 (2016)
22. Faramarzi, A., Heidarinejad, M., Mirjalili, S., Gandomi, A.H.: Marine Predators Algorithm: A nature-inspired metaheuristic. *Expert Syst. Appl.* **152**, 113377 (2020)
23. Yang, X.-S.: Flower pollination algorithm for global optimization. In: Durand-Lose, J., Jonoska, N. (eds.) *UCNC 2012. LNCS*, vol. 7445, pp. 240–249. Springer, Heidelberg (2012). https://doi.org/10.1007/978-3-642-32894-7_27
24. Miao, Z., Yuan, X., Zhou, F., Qiu, X., Song, Y., Chen, K.: Grey wolf optimizer with an enhanced hierarchy and its application to the wireless sensor network coverage optimization problem. *Appl. Soft Comput.* **96**, 106602 (2020)
25. Herrmann, D.: *Wahrscheinlichkeitsrechnung und Statistik — 30 BASIC-Programme*. Vieweg+Teubner Verlag, Berlin (1984) https://doi.org/10.1007/978-3-322-96320-8_25
26. Ashcroft, S., Pereira, C.: The friedman test: comparing several matched samples using a non-parametric method. In: Ashcroft, S., Pereira, C. (eds.) *Practical Statistics for the Biological Sciences: Simple Pathways to Statistical Analyses*, pp. 105–108. Macmillan Education, London (2003). https://doi.org/10.1007/978-1-137-04085-5_12