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Deploying charging nodes in wireless rechargeable sensor networks based on improved firefly algorithm☆

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ABSTRACT

A wireless rechargeable sensor network (WRSN) consists of sensor nodes that can harvest energy from the wireless charging nodes (WCNs) for prolonging the network lifetime. This study deals with the WCN deployment optimization problem in WRSNs. We propose an optimization framework that simultaneously maximizes the coverage and the charging efficiency. Moreover, an improved firefly algorithm (IFA) is proposed for solving the WCN deployment optimization problem. IFA adopts a novel adaptive attractiveness factor and introduces a dynamic location update mechanism to enhance the performance of the conventional firefly algorithm (FA). We compare the proposed IFA with several benchmark algorithms in two different scenarios. Simulation results show that the proposed algorithm outperforms other comparative algorithms in both accuracy and convergence rate.

1. Introduction

Wireless sensor networks (WSNs), which are composed of a large number of tiny sensor devices, have been widely used in many applications such as environmental monitoring [1]. As most existing sensor networks are powered by batteries, the lifetime of these sensor nodes are limited [2]. To avoid the high maintenance costs of replacing batteries, some researchers have developed the energy-efficient routing protocols [3,4] to reduce the energy consumption of the sensor nodes and others have used ambient energy, such as light, vibration, heat and wind, to prolong the lifetime of WSNs [5].

A wireless rechargeable sensor network (WRSN) is another promising technology for extending the lifetime of the conventional WSNs. By using the wireless power transmission (WPT), especially the microwave power transmission [6], the batteries of the sensor nodes can be recharged by a mobile charging vehicle or some static charging piles to extend the network lifetime.

WRSN generally consists of two types of devices: normal sensor nodes and wireless charger nodes (WCN). WCN can harvest energy from ambient environment and then emit microwave energy to charge the normal sensor nodes. Since a WCN is much more expensive than a normal sensor node [7], the number of WCN in the monitoring region should be small. At the same time, in order to improve the network lifetime, the limited number of WCN should cover as many sensor

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nodes as possible. Therefore, how to deploy the limited number of WCN to enlarge the coverage and improve the charging efficiency of the whole network becomes a key issue in WRSN.

Several works have been done in the related area. By using the mobile charging nodes, Fu et al. [8] propose a protocol called ESync to simultaneously reduce the charger travel distance and the charging delay. Lin et al. [9] propose two charging algorithms aiming at shortening the charging time as well as the moving distance via merging and splitting charging missions. Wang et al. [10] propose a node deployment mechanism that uses a dedicated data gathering vehicle and multiple charging vehicles to balance the energy consumptions, thereby reducing the transient energy depletion. Shu et al. [11] identify that the velocity of the mobile charger is a key factor of the mobile wireless charging in WRSNs. Thus, they formulate the optimal charger velocity control problem, and propose a heuristic solution for solving the proposed NP-hard problem. For WCN deployment problem in WRCN, Jiang et al. [7] assume that the wireless chargers are equipped with directional antennas and these chargers are deployed on grid points with a fixed height. Then they propose two heuristic algorithms to optimize the charger deployment problem. He et al. [12] propose two energy provisioning problems for WRSN: point provisioning and path provisioning. For the first problem, the authors present how to keep an acceptable charging performance by using the least number of wireless chargers. The second one addresses the same problem but for mobile sensor nodes. Chiu et al. [13] deploy wireless chargers by dividing the sensing areas into grids. The omnidirectional wireless chargers are utilized for the sensor nodes to maximize the survival rate of end-devices.

In this paper, we propose to jointly maximize the charging coverage for the sensor nodes and the charging efficiency, and formulate a multi-objective optimization problem to achieve the goal. Swarm intelligence optimization algorithms [14] are effective in solving the multi-objective optimization problems. The particle swarm optimization (PSO) [15], which is derived from bird flock's foraging behavior, has been used to solve the multi-objective optimization problems. However, its performance is significantly affected by the initial values of the parameters [16]. Ref. [17] proposes the invasive weed optimization (IWO) algorithm. IWO is inspired by a common phenomenon in agriculture that is the colonization of invasive weeds, and is easy to be implemented. However, the performance of IWO is also affected by the parameter selections. Moreover, the convergence rate is slow because less messages are exchanged among the population. The bat algorithm (BA) [18], which is based on the echolocation behavior of the bats, generates new solutions by random flight, thereby improving the ability of local search. However, the accuracy of BA is low for some applications due to that the individuals of BA lack variation mechanism. The grey wolf optimization (GWO) [19] is inspired by the grey wolf hunting for the prey in nature and it simulates the social hierarchy of wolfs to achieve higher convergence rate. However, the global search ability of GWO is weak. Ref. [20] points out that the cuckoo search (CS) is a new heuristic algorithm based on natural element. CS uses Lévy flight to update the solutions so that the convergence rate is improved. However, the random walk mechanism of Lévy flight decreases search efficiency. Ref. [21] proposes a novel algorithm called adaptive-Lévy flower pollination algorithm (ALFPA), which combines Lévy flight mechanism of CS and the flower pollination algorithm. The convergence rate of this algorithm is enhanced due to the introduced additional components. In our previous work, a biogeography-based optimization approach based on local search (BBOLS) [22] is proposed to optimize the beam pattern of the antenna arrays. By introducing the local search operator and the selection operator, the performance of the conventional BBO algorithm is effectively improved.

Several studies have demonstrated that the firefly algorithm (FA) has better performance than other algorithms, such as PSO, in many optimization fields [23]. The accuracy of a FA-based machine learning technique for solar radiation prediction based on some meteorological data is examined [24]. Thus, we will use a FA-based approach to solve the WCN deployment problem.

The main contribution of this paper can be summarized as follows:

(1) A multi-objective optimization problem is formulated in our previous work (accepted by IEEE GLOBALCOM 2017) for improving the charging efficiency of the WRSNs. Different from the charging schemes proposed in [12,25] that only consider one optimization objective, the proposed optimization framework jointly optimizes two objectives.
(2) An improved firefly algorithm (IFA) is proposed to solve the formulated multi-objective optimization problem. IFA introduces two novel improved factors that are the adaptive attractiveness and dynamic location update mechanisms, to further enhance the ability of normal FA, thereby achieving better charging performance in WRSNs.
(3) Simulations are conducted to verify the effectiveness of the proposed IFA and the results show that the performance of IFA is better than other benchmark algorithms for improving the charging efficiency of WRSN.

The rest of this paper is organized as follows. Section 2 introduces the system models. Section 3 formulates the WCN deployment optimization problem and presents the proposed algorithm. Section 4 shows the simulation results and Section 5 concludes the paper.

2. System model

In this section, the network model, the wireless charging model and the structure of the rechargeable sensor node are introduced.

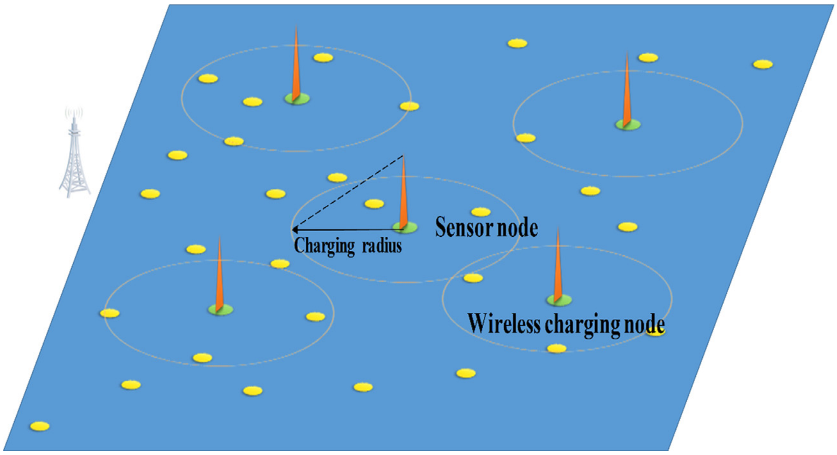

Fig. 1. Sketch map of wireless rechargeable sensor networks based on wireless charging nodes.

2.1. Network model

Fig. 1 shows the sketch map of a WRSN. It can be seen that a WRSN consists of a sensor node set $\boldsymbol{S}=\{S_1, S_2, ..., S_N\}$ and a WCN set $\boldsymbol{C}=\{C_1, C_2, ..., C_K\}$. Each sensor node and WCN can be deployed anywhere in the region and they cannot move after deployment. The locations of the sensor nodes are known. Moreover, WCNs can harvest energy from the environment, so we assume they are unrestricted in energy. In addition, each WCN can charge multiple nodes and each sensor node can be charged by multiple WCNs.

2.2. Wireless charging model

In this work, the Wireless Identification and Sensing Platform (WISP)-reader charging model [12] is used. Compared with other wireless charging models such as that based on the time-period used in Ref. [26], the wireless charging model used in this paper is related to the distance between the charger and the receiver. This is a practical model that has been verified by Ref. [12]. Moreover, WISP-reader charging model can be used in the condition with multiple receivers. Thus, it is suitable for WRSN. According to this model, we define μ as the charging efficiency factor as follows:

$$\mu = \frac{G_s G_r \eta}{L_p}\left(\frac{\lambda}{4\pi(d+\beta)}\right)^2 \tag{1}$$

where d is the distance between the sensor node and the WCN, G_s is the source antenna gain, G_r is the receiver antenna gain, L_p is the polarization loss, λ is the wavelength, η is the rectifier efficiency and β is an adjust parameter of *Friis'* free space equation for short distance transmission. All the parameters in Eq. (1) except d have constant values, and they are determined by the environment and the settings of the nodes. Therefore, Ref. [27] proposes a simplified form of μ, which is described as follows:

$$\mu = \frac{\alpha}{(d+\beta)^2} \tag{2}$$

where α represents the effect of other constant parameters including G_s, G_r, L_p, λ and η in Eq. (1). Thus, the received charging power of a sensor node S_i is:

$$P_i = \sum_{n=1}^{N} \mu_n \cdot P_0 \tag{3}$$

where P_0 is the source power of a WCN, μ_n is the charging efficiency of the nth WCN. We assume $\mu_n=0$ if the received power from the nth WCN is less than a threshold δ. Thus, d can be also regarded as the charging range, which is the effective radius for wireless charging.

2.3. Node structure

Fig. 2 shows the structure of a wireless rechargeable sensor node. As can be seen, a node consists of an energy harvest module, a sensing module, a processing module, a communication module and a rechargeable power source. Different from the conventional sensor node, a rechargeable sensor node has a wireless energy harvesting module with an energy harvesting antenna. During the harvest process, the energy sent by the WCN will be received by the energy harvesting antenna.

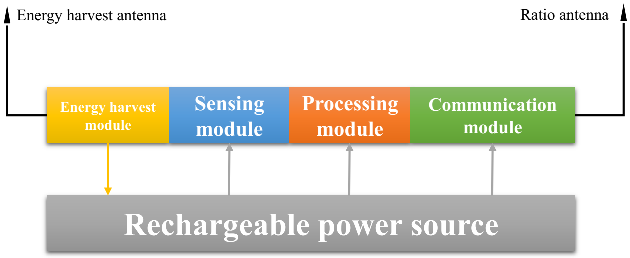

Fig. 2. Structure of a wireless rechargeable sensor node.

The harvested energy is converted to the direct current by the energy harvesting module and then stored in the rechargeable power source. The power source can be a rechargeable battery or a supercapacitor, and it provides energy for other modules.

3. Problem formulation and algorithm

In this section, we formulate the optimization problem and propose the IFA to solve this problem. Note that the proposed WCN deployment approach is a one-time scheme for determining the optimal locations of the WCNs at the network initialization stage. Thus, it does not depend on any particular energy consumption models of the WSN.

3.1. Problem formulation

In this work, each WCN uses an omnidirectional transmitting antenna. Thus, a WCN can charge all the sensor nodes within its charging range. To improve the charging efficiency, more sensor nodes should be included in the charging range of a WCN. Therefore, the first objective of deploying the WCNs is to make each of them to cover more sensor nodes, which can be designed as follows:

$$f_{(1)}^{num} = \max\ num \tag{4}$$

where *num* is the number of sensor nodes covered within the charging range of a WCN.

The second optimization objective is to improve the charging efficiency of each pair of WCN and sensor node. To achieve this goal, the minimum charging efficiency of a charging pair in the network should be maximized. Thus, the second objective function is designed as follows:

$$f_{(2)}^{energy} = \max\left[\min \mu_{ij}\right] \tag{5}$$

where μ_{ij} is the charging efficiency of the charging pair of the ith WCN and the jth sensor node, $i\in[0, K]$ and $j\in[0, N]$. For simplicity and clarity, $f_{(2)}$ can be normalized as:

$$f_{(2)}^{energy} = \min\left[\max(\frac{\mu_{worst}}{\mu_{ij}})\right] \tag{6}$$

where μ_{worst} is the charging efficiency at the upper limit of the charging range and the range of the ratio is normalized to be within [0, 1]. Therefore, in order to jointly optimize the coverage and the charging efficiency for achieving the optimal WCN deployment, the multi-objective optimization function can be defined as follows:

$$f = f_{(1)}^{num} + f_{(2)}^{energy} = \min\left[\max\left(-a\cdot num + b\cdot\left(\frac{\mu_{worst}}{\mu_{ij}}\right)\right)\right] \tag{7}$$

where a and b are the weighting factors and they will be determined based on practical applications.

Ref. [28] shows that the deployment of WCNs is a complex nonlinear programming problem. Thus, an efficient method to solve the hybrid WCN deployment optimization problem is necessary.

3.2. Algorithm

FA is a swarm intelligence optimization algorithm and is an effective method for solving the non-linear problems [23]. To achieve better optimization results for the charging performance of WCNs, we propose an improved FA (IFA) for solving the proposed multi-objective optimization problem shown in Eq. (7). The details of IFA are described in the following subsections.

3.2.1. FA

FA is proposed based on the light emission characteristics and the information exchange behavior of the fireflies in nature. This algorithm uses a firefly to represent a solution, and it has three idealized rules:

(1) All fireflies are unisex so that one firefly will be attracted to others regardless of their sex.
(2) The attraction between the fireflies is proportional to their relative brightness and inversely proportional to the distance between them.
(3) The brightness of a firefly is determined by its fitness or objective function.

It can be seen from the rules above that a firefly in FA has two key factors that are attraction and brightness. These two factors depend on the location of a firefly. Higher brightness represents better position as well as better attraction. Hence, for any two flashing fireflies, the less bright one will move towards the brighter one. If no one is brighter than the other firefly, the firefly will move randomly. Moreover, several definitions in FA are as follows:

Definition 1. The brightness of a firefly varies with the value of an objective function, which can be written as:

$$I(r) = I_0 e^{-\gamma r_{ij}} \tag{8}$$

where I_0 is the maximum light intensity ($r=0$). The value of I_0 is related to the value of the objective function. γ is the light absorption coefficient and it can be set as a constant. Theoretically, $\gamma \in [0, \infty]$. r_{ij} is the Euclidean distance between firefly i and j and can be determined as follows:

$$r_{ij} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k-1}^{d} (x_{i,k} - x_{j,k})}^2 \tag{9}$$

where d is the dimension of the solution, $x_{i,k}$ is the kth component of firefly i in the D-dimensional solution space.

Definition 2. The attractiveness of a firefly is proportional to its light brightness observed by adjacent fireflies and can be calculated using:

$$\beta(r) = \beta_0 e^{-\gamma r^m}, (m \geq 1) \tag{10}$$

where β_0 is the maximum attraction of the fireflies ($r=0$), m is usually set as 2.

Definition 3. The movement of a firefly i attracted to another more attractive (brighter) firefly j is determined by:

$$x_i(t+1) = x_i(t) + \beta(x_j(t) - x_i(t)) + \alpha\varepsilon_i \tag{11}$$

where t is the number of iteration, x_i and x_j are the locations of the firefly i and j, respectively. α is the step factor and it can be chosen between 0 to 1. ε_i is a random factor generated by a function with Gaussian distribution or uniform distribution, $\varepsilon_i \in [0, 1]$.

Based on the definitions above, the steps of FA are shown in Algorithm 1.

3.2.2. IFA

To improve the performance of conventional FA for optimizing WCN deployment in WRSN, a novel IFA is proposed with two additional features: adaptive attractiveness and dynamic location update. The main steps of IFA are presented below and detailed in the following subsections.

Step 1: Parameters initialization: Initialize the values of β, γ, the number of fireflies n, the dimension of the search space d and the maximum number of iterations R_{max}.
Step 2: Generate a position x_i for each firefly randomly and calculate the fitness values of all fireflies.
Step 3: Find the location of firefly x_{best} which has the best global fitness value. If the maximum number of iterations is reached, go to Step 8.
Step 4: Calculate the distance r_{ij} between x_i and x_j according to Eq. (9).
Step 5: Calculate the adaptive attractiveness β_A between firefly i and firefly j according to Eq. (13).
Step 6: Update γ_D and α_D according to Eqs. (15) and (17). Then update the locations of fireflies by using dynamic location update mechanism presented in Eq. (14).
Step 7: Calculate the fitness values of all fireflies and return back to Step 3.
Step 8: Output the global optimal solution.

(a) Adaptive attractiveness

In WCN deployment optimization problems, the locations of WCNs are the solutions. Thus, the search space of each solution is always very huge due to the extensive monitoring area. It can be seen from Eq. (10) that if r_{ij} is large, exp(-γr^m) tends to be zero. In this case, the firefly location update method (Eq. (11)) is as follows:

$$x_i(t+1) = x_i(t) + \beta(x_j(t) - x_i(t)) + \alpha\varepsilon_i \approx x_i(t) + \beta_{\min}(x_j(t) - x_i(t)) + \alpha\varepsilon_i \tag{12}$$

Algorithm 1: FA.

Define the fitness function: $f(x)$, $x=[x_1, x_2, x_3,\ldots, x_n]$.
Set parameters:
  (1) The number of fireflies: n;
  (2) The D-dimensional search space: d;
  (3) The maximum iteration: R_{max};
  (4) The light absorption coefficient: γ;
  (5) The attractiveness coefficient: β_0;
  (6) The randomization parameter: α;
For $i=1$ to n
  $x_i=rand(x_{i1}, x_{i2}, x_{i3},\ldots, x_{id})$;
  $f(x_i)$;
End
Sort the solutions from best to worst (brightest to dimmest);
For $counter=1$ to R_{max}
For $i=1$ to n
    For $j=1$ to n
      Calculate r_{ij} using Eq. (9);
      If Intensity $(i)>$ Intensity (j)
        Update solution using Eq. (11);
      End
    End
  End
End
For $i=1$ to n
$f(x_i)$;
End
Sort the solutions from best to worst (brightest to dimmest);

It can be seen from Eq. (12) that the attractiveness between fireflies i and j becomes a constant when the distance between these two fireflies is too large. This does not conform to the principle of FA. Ref. [18] points out that any monotone decreasing function can be used to implement the attractiveness. Thus, an adaptive attractiveness is proposed as follows:

$$\beta_A = \frac{2}{(\sqrt[p]{r}+2)} \tag{13}$$

with this function, the attractiveness decreases with increasing distance even if the distance between the fireflies is very large.

(b) Dynamic location update mechanism

In the practical applications, the locations of WCN are the solutions of the algorithm. Thus, the value of the attractiveness in the conventional FA is small because of the large distance between different solutions, thereby suppressing the searching ability of the algorithm and reducing the convergence rate, especially at the early iterations. To overcome this shortcoming, we propose a dynamic location update method, which is described as follows:

$$x_i(t+1) = x_i(t) + \beta_A(x_j(t) - x_i(t)) + \alpha_D\varepsilon_i + \gamma_D(xbest_i(t) - x_i(t)) \tag{14}$$

where x_{besti} is the location of the firefly that has the best global objective value in the current iteration, and γ_D is the improved dynamic light absorption coefficient, which is defined as:

$$\gamma_D = \gamma \cdot d_D^t \tag{15}$$

where t is the current iteration index, d_D is designed as follows:

$$d_D = \left(\frac{10^{-4}}{0.9}\right)^{\frac{1}{MaxIter}} \tag{16}$$

with this definition, γ_D monotonically decreases with the increase of the number of iterations.

Moreover, similar to γ, the step factor α in normal FA is also a constant, thereby making it easy for the conventional FA to fall into the local optimum. The improved dynamic step factor α_D is designed as:

$$\alpha_D = \alpha \cdot {d_D}^t \tag{17}$$

In the earlier iterations, the distances between the candidate solutions are much longer than the later iterations. However, the longer distance between the fireflies means the smaller attractiveness value, which significantly reduces the update step length of the solutions in the earlier iterations. By using the dynamic γ_D and α_D, and by introducing the best global solution for guiding, the update step length for location updating in IFA is larger at the earlier stage of iterations, which enhances the global searching ability.

Algorithm 2: WCN deployment optimization based on IFA.

Input: Positions of sensor nodes $\mathbf{C} = \{C_1, C_2, \ldots, C_N\}$
Output: Positions of WCNs $\mathbf{W} = \{W_1, W_2, \ldots, W_K\}$
Initialization parameter;
    The number of sensor node N, the number of WCNs K, the radius of charging scope R, the population size n, the maximum number of iterations $MaxIter$, α_D, γ_D, the upper bound of WCN distribution range U_b and lower bound of WCN distribution range L_b;
Initialize the position of wireless charging node $\mathbf{W} = \{W_i^1, W_i^2, \ldots, W_i^K\}$ randomly for each individuals i of population n;
Set $Iter = 0$;
while $gen < MaxIter$ **do**
Update γ_D and α_D according to Eqs. (15) and (17);
    Calculate the fitness vale of each firefly zn_i for each individual i of population n;
    Sort the fitness values, find out the optimal individual, save the optimal fitness as zn_{best} and save the optimal fitness as $\mathbf{W_{best}} = \{W_{best}^1, W_{best}^2, \ldots, W_{best}^K\}$;
for each WCN $j = 1: K$ **do**
    Move the jth WCN of the ith $(i = 1, 2, \ldots, n)$ individual of the population according to Eq. (14);
end for
$Iter = Iter + 1$;
end while

Table 1
Parameter setups of different cases.

Network scales	Number of sensor nodes	Number of WCNs	Density
10 m × 10 m	30	5	0.3
100 m × 100 m	100	25	0.01
500 m × 500 m	1000	50	0.004
1000 m × 1000 m	3000	100	0.003

Table 2
Parameters settings of IFA.

Parameter	value
Population size	20
α	0.3
γ	0.9
d_D	0.9
P	3

Moreover, since β_A has the opposite monotony as γ_D and α_D, by combining the adaptive β_A with γ_D and α_D, the algorithm can avoid excessive searching, resulting in an accelerated convergence rate. Therefore, the exploration and exploitation can be effectively balanced by the proposed improvements.

The locations of WCNs are the solutions (fireflies) in IFA and the process of WCN deployment optimization based on IFA is shown in Algorithm 2.

4. Simulations

In this section, we conduct simulations using Matlab 2015 to evaluate the performance of the proposed IFA in solving the WCN deployment optimization problem. The CPU of the computer used for the simulation is CORE i3 with 3.70 GHZ and the RAM is 4G. We consider four experimental cases with different scales of WRSNs to verify the performance of the proposed algorithm with different node densities. The parameter setups of different experimental cases are shown in Table 1. Moreover, the sensor nodes are randomly deployed in each case. Thus, the topologies of the networks are different. For the simulation study, first, the parameters of the proposed IFA are tuned for achieving the best performance. Then, the introduced improved factors of IFA are verified. Finally, the optimization results of different cases are presented.

4.1. Parameter tuning

The values of the parameters in IFA will affect the performance of the algorithm. β_A is a core factor in IFA. To determine the optimal value for P, which is the parameter that affects the value of β_A, we vary the values of P from 2 to 4 to determine the optimal value during the tuning process, while using the setting in Ref. [1] for other parameters. Fig. 3 shows the tuning results and it can be seen from the figure that IFA achieves the lowest fitness value when $P = 3$. In addition, while keeping $P = 3$, a joint parameter tuning test for $\alpha$and γin IFA is conducted and the results are shown in Fig. 4. It can be seen from the figure that IFA obtains the best objective function value when $\alpha = 0.3$ and $\gamma = 0.9$. The other parameter settings are listed in Table 2.

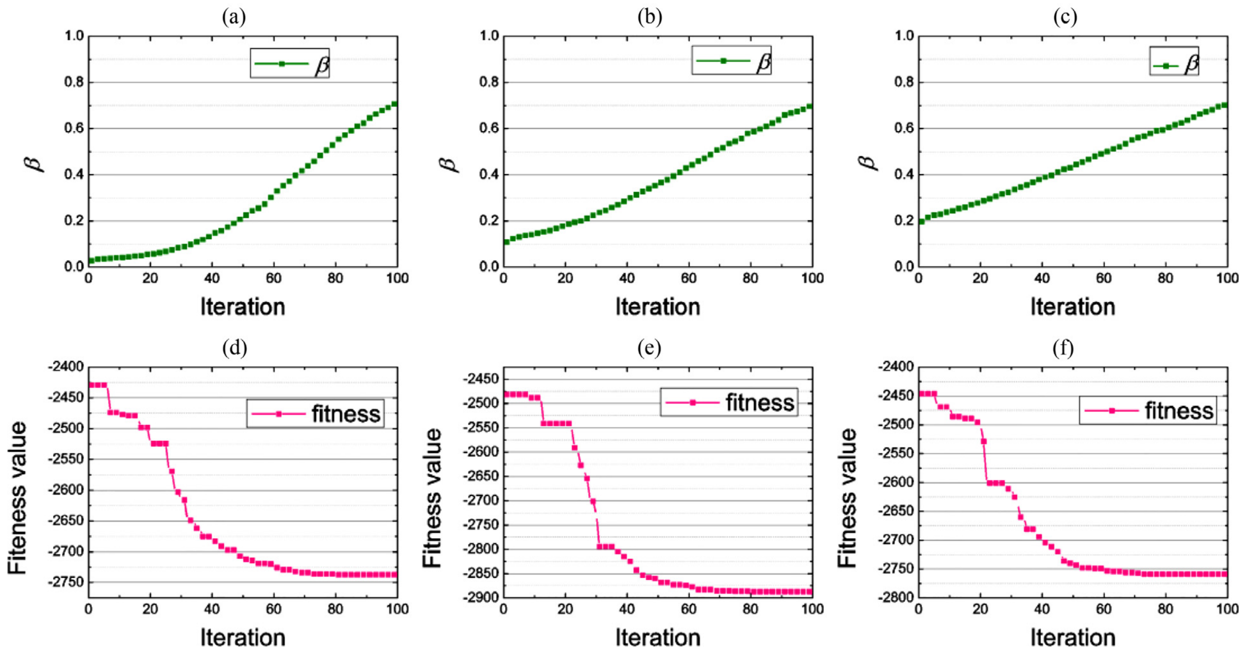

Fig. 3. Parameter tunning for P in β. (a) $P = 2$. (b) $P = 3$. (c) $P = 4$. (d) Fitness values ($P = 2$). (e) Fitness values ($P = 3$). (f) Fitness values ($P = 4$).

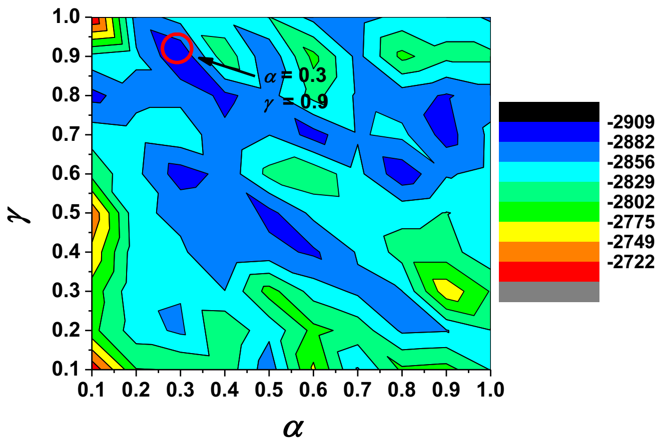

Fig. 4. Joint tuning of α and γ.

4.2. Validation of the improved factors

The efficiency of the introduced factors that are the adaptive attractiveness mechanism and the dynamic location update mechanism are verified by some validation experiments. All the tests are conducted within the large scale WRSN conditions because the solution dimension in this case is higher, thereby improving the validation performance. For the adaptive attractiveness mechanism, Fig. 5(a) shows the relationship between the changing of β and the number of iterations, Fig. 5(b) shows the relationship between the changing of β_A and the iterations, respectively. It can be seen from these figures that by using the adaptive attractiveness mechanism, β_A increases with the increasing of iterations, thereby improving the accuracy of the solution in the later iterations of the algorithm. This phenomenon can be reflected in Fig. 5(c) and (d). As can be seen from the figures that by using the adaptive attractiveness mechanism, FA can achieve a lower value of the fitness function compared with the conventional FA. For the dynamic location update method, Fig. 6(a) and (b) show the convergence rates for solving the multi-objective optimization function obtained by FA with Eq. (11) and by IFA with the location update method in Eq. (14). It can be seen from Fig. 6(a) that the fitness values obtained by conventional FA are not changed in the initial 20 iterations, which indicates a poor convergence performance. Fig. 6(b) shows the curve of the convergence rate obtained by IFA with the dynamic location update mechanism. The fitness value obtained in the 100 th iteration is approximately −2825 which is much lower than −2719 of FA. Thus, IFA achieves a better convergence rate.

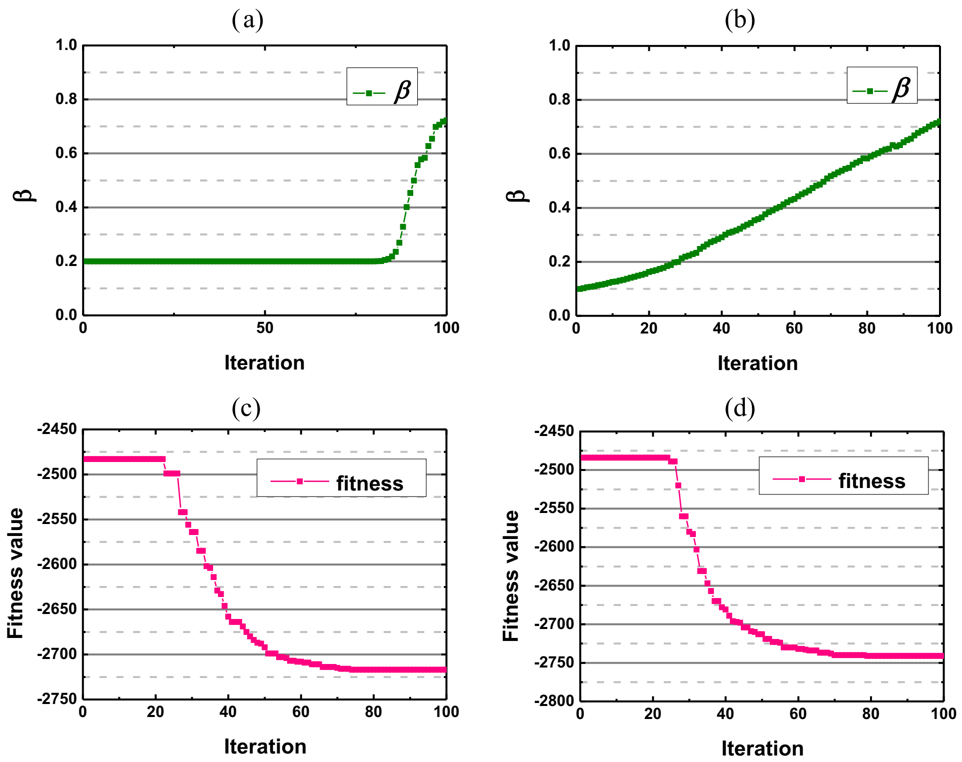

Fig. 5. Validation of the improved factors. (a) Original β. (b) β_A based on adaptive attractiveness. (c) Fitness value with original β. (d) Fitness values with β_A.

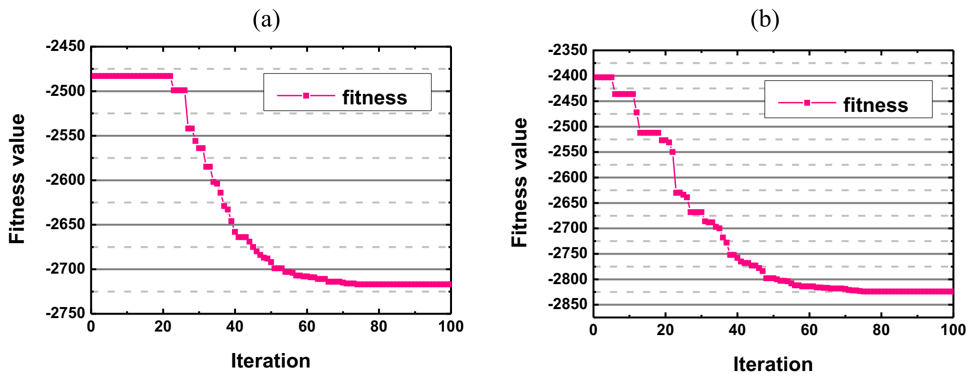

Fig. 6. Convergence rates obtained by different approaches. (a) FA. (b) IFA with dynamic location update mechanism.

4.3. Charging node deployment

In this section, we use the proposed IFA to optimize the WCN deployment, and the results are compared with that of BA [18], IWO [17], CS [20], GWO [19], FA [23], BBOLS [22] and ALFPA [21]. The population sizes of these algorithms are 20. The number of iterations is 20 for these algorithms in the 10 m × 10 m scale WRSNs. The number of the nodes in the small scale WRSN is small, so we can show the results in an intuitive way. Fig. 7 shows the WCN deployment locations obtained by these algorithms. It can be seen that by using IFA, all the sensor nodes are covered by the WCNs and the distance between the WCN and the sensor node is shorter. Thus, IFA has the best performance among all the benchmark algorithms.

For the other scales of WRSN, the number of nodes is too large to intuitively show the deployment results like Fig. 7. Thus, the objective function values and the convergence rates obtained by different algorithms with different network scales are shown in Figs. 8–10, respectively. Different from the 10 m × 10 m scale case, the solution dimension of the larger scale case is much higher. Thus, the maximum iteration for 100 m × 100 m, 500 m × 500 m and 1000 m × 1000 m cases is set to be 100 to get better results. In the 100 m × 100 m scale case, the bound of the objective function is −99 with the parameter settings in the simulation. It can be seen from Fig. 8 that the fitness function values of IFA are better than other algorithms

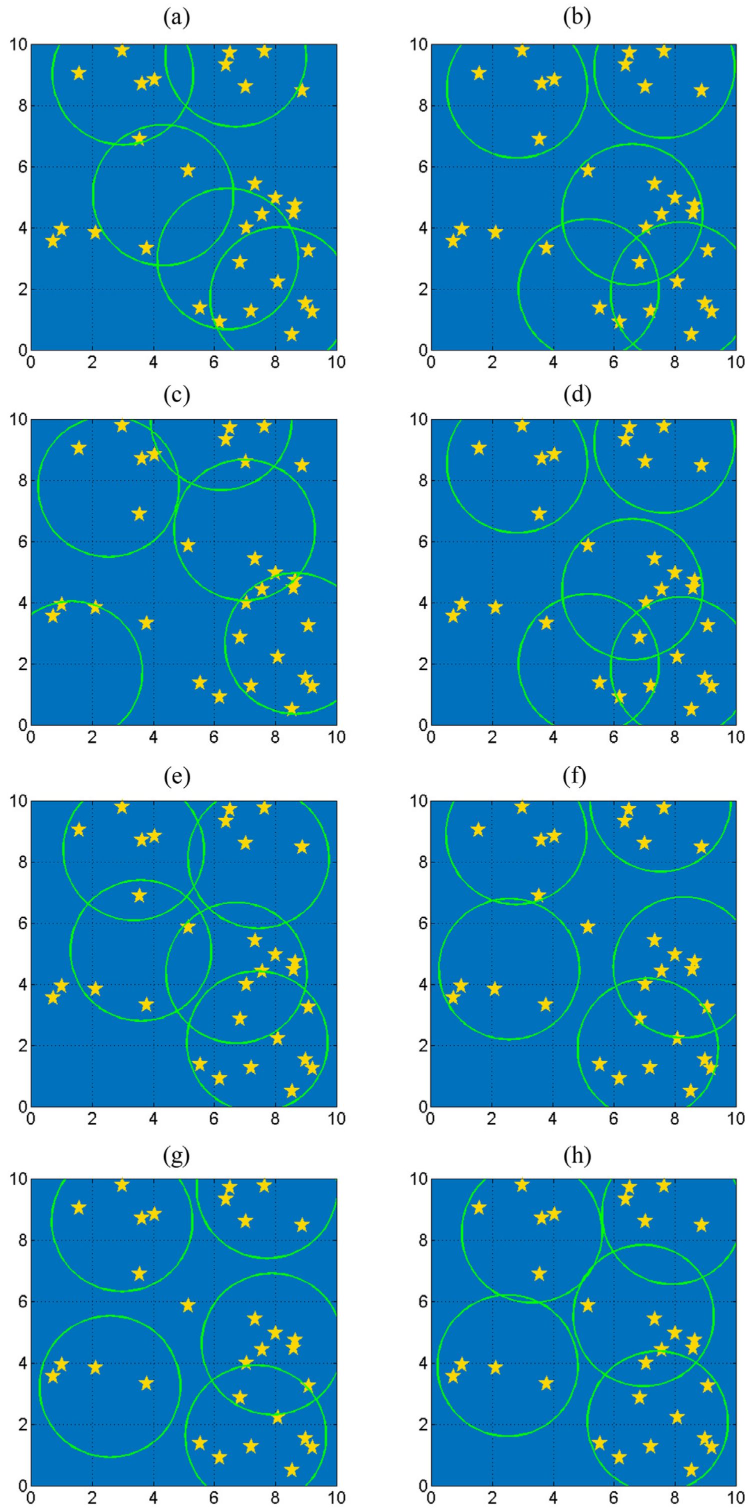

Fig. 7. WCN deployment optimization results obtained by different algorithms. (a) BA. (b) IWO. (c) CS. (d) GWO. (e) FA. (f) BBOLS. (g) ALFPA. (h) IFA.

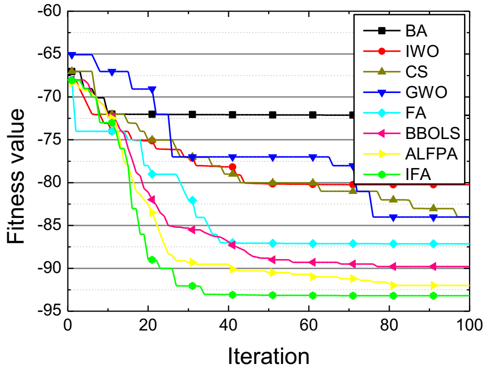

Fig. 8. Convergence rates obtained by different algorithms with the network scale of 100 m × 100 m.

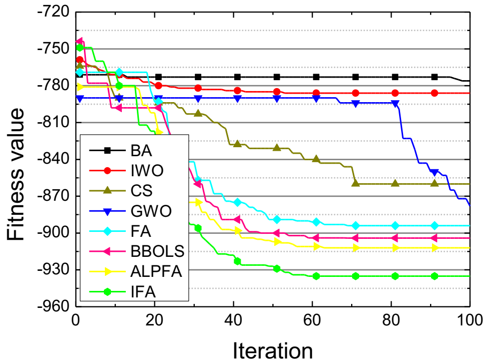

Fig. 9. Convergence rates obtained by different algorithms with the network scale of 500 m × 500 m.

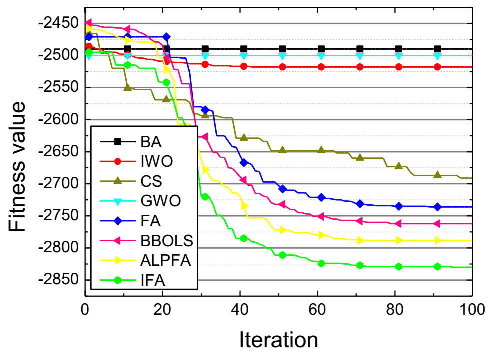

Fig. 10. Convergence rates obtained by different algorithms with the network scale of 1000 m × 1000 m.

within 100 iterations. The fitness value obtained by ALFPA is the best among the benchmark algorithms but it only achieves −92 approximately. However, IFA achieves a value of −94 for the fitness function within 100 iterations, which is very close to the optimal value. In addition, Fig. 8 shows that IFA has obvious advantages in both accuracy and the convergence rate than the other algorithms. This is because the solutions which are the fireflies in the population of FA can effectively exchange their information so that the diversity of the population can be improved. Moreover, by using the attractiveness mechanism, the worse solutions can move to the better ones and hence improve the convergence rate. In addition, due to the introduced adaptive attractiveness mechanism, the attractiveness will increase with the increasing of iterations, thereby improving the accuracy of the solution in the later iterations. Furthermore, the introduced dynamic location update method of IFA is able to adjust its searching step dynamicly according to the condition of the iteration, thereby improving the accucacy of the algorithm.

Moreover, Figs. 9 and 10 show that the proposed IFA also performs better than the other benchmark algorithms in both the 500 m × 500 m and 1000 m × 1000 m scale cases. The objective function values of IFA are also close to the optimal values which are −999 and −2999 of these two cases within the 100 iterations, respectively. Moreover, the convergence rates of IFA are fastest among all the benchmark algorithms.

5. Conclusions

In this paper, The WCN deployment optimization problem in WRSNs is studied and the WCN deployment problem for obtaining better charging performance is investigated. For achieving this goal, a multi-objective optimization framework is proposed for simultaneously maximizing the coverage of each WCN as well as enhancing the charging efficiency. The proposed optimization problem is a complex non-linear optimization problem. Thus, we propose a novel swarm intelligence optimization algorithm called IFA to provide approximate solutions to the optimization problem. Two factors that are the adaptive attractiveness factor and the dynamic location update mechanism are introduced to IFA to improve the performance of FA for solving the proposed optimization problem. Moreover, the key parameters of IFA are tuned so that the algorithm can obtain the best performance for solving the WCN deployment problem. Simulations based on several WRSNs with different network scales are conducted to evaluate the proposed optimization algorithm, and the results show that the proposed IFA performs better than the other benchmark algorithms in both the accuracy and the convergence rate. In our future work, we will use the proposed IFA to optimize the energy efficiency for the full-duplex cognitive radio sensor networks (FD-CRSN) since it is a promising technique for enhancing the efficiency of spectrum utilization.

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