Radio Frequency Identification Networks Planning Using a New Hybrid Evolutionary Algorithm

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Abstract—**The problem of choosing the optimum locations and the associated parameters of readers in RFID communication systems is considered. All these choices must satisfy a set of objectives, such as tag coverage, load balance, economic efficiency, and interference in order to obtain accurate and reliable network planning. In this paper, a novel optimization algorithm, namely the multi-community GA-PSO, is proposed to solve the complicated RFID network planning problem of large-scale system. The main idea of the algorithm is to divide the single population of the canonical PSO into multi-swarm and use the genetic selection and mutation strategy to improve particle swarm dynamic rules. The simulation results show that the proposed algorithm obtains the superior solution for networking planning problem than canonical PSO does.**

Index Terms—**Evolutionary computation, Particle swarm optimization, Radiofrequency identification**

I. INTRODUCTION

Radio Frequency Identification (RFID) as a short-range radio technology for automated data collection is becoming an integral part of our life. The technology is in the ascendant with a concerted effort in recent years to make a further development. Nowadays, an enormous amount of technical and commercial development of RFID has been demonstrated in many industrial applications, such as production automation, anti-theft of merchandises, supply chain management, access control and asset tracking [1]-[2]. The RFID systems consist of two types of devices: unsophisticated, chip, and uniquely-identifiable tags and more powerful electromagnetic readers. RFID interrogators or readers 'senses' the unique identifier and other information stored in RF tags affixed to objects by actively transmitting a signal to communicate with the RF tags [3].

In many applications, the deployment of RFID systems has generated the RFID network planning (RNP) problem that needs to be solved in order to operate the large-scale network of RFID readers in an optimal fashion [4]. However, RNP is one of the most challenging problems that has to meet many requires of the RFID systems. In general, the RNP aims to optimize a set of objectives (coverage, load balance, economic efficiency and interference between readers) simultaneously by adjusting the control variables (the coordinates of the readers, the number of the readers, and the antenna parameters, etc.) of the system [5]. As other wireless communication systems, the network planning is a nonlinear optimization problem and has aroused many researcher' interest. Recently, many studies have been carried out and a large number of approaches have applied in the literature. In [6]-[7], the method for optimal placement of readers is proposed mainly based on the coverage constraint. The work in [8] focuses on the scheduling problem in which the heuristic algorithm is used to solve the interference problem. A load balance problem is rigorously researched in [9] and the minimum multiprocessor scheduling (MMS) algorithm and the maximum network flow (MNF) algorithm is used to solve the load balance problem. In [10], the authors combine the main constraints to propose a combined measure to present an overall optimal solution for the RNP problem.

For the possible combination of RFID reader positions are too numerous, the exhaustive optimization of the nonlinear optimization problem demands an impractically tremendous computational effort which leads to the application of the heuristic algorithm in the filed. The particle swarm optimization and genetic algorithm usually work in a population which search around the solution space by some operators until finding the optimal solution. However, in nature, the common feature of many social networks is community structure, the tendency for individuals to divide into groups, with dense connections within groups and only sparser connections between them [11]. A number of recent results suggest that networks can have properties at the community level that are quite different from their properties at the level of the entire network, so that analyses that focus on whole networks and ignore the community structure may miss many interesting features [12]. Indeed, in biological populations there is a continuous interplay between individuals of the same species, and also encounters and interactions of various kinds of with other species [13]. Inspired by the community structure cluster phenomenon, we extend the single population to the interacting multi-community structure in the heuristic algorithm and combined the genetic strategy and particle swarm dynamic rules to propose a multi-community GA-PSO algorithm. Then the algorithm is applied into the RNP problem compared with canonical PSO to validate the effectively of the proposed method.

Manuscript received June 29, 2012. This work was supported by the "China National Natural Science Foundation Key Program No. 61134009 and by the "China Fundamental Research Funds for the Central Universities".

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An outline of this paper is as follows. In Section II, the formulation model for the network planning in RFID networks is introduced. Section III gives brief reviews of the canonical PSO and the genetic algorithm and then presents the proposed multi-community GA-PSO algorithm in details. In Section IV and Section V, the proposed solution procedures for solving the RNP problem using multi-community GA-PSO algorithm is presented. In Section IV, the propagation pattern of reader is circle and in Section V the propagation pattern of reader is ellipse and corresponding simulation results in two different propagation pattern are illustrated. Finally, in Section VI concluding remarks are stated and ideas are proposed for further research.

II. RFID Network Planning Problem Formulation

In this section, the formulation and some basic elements for RFID network planning are presents. This model simplifies the complexity of spatial transmission of electromagnetic waves. The up-link signal constraint, which ask for the backscatter signals reflected by tags must be received by a reader, is reasonably omitted by increasing the signal threshold size.

A. Propagation Model

In order to calculate the signal strength at each tag, a radio wave propagation model is needed. Such a model is used to compute the propagation loss of an electromagnetic field between a reader and a tag. In many cases, RFID is used in an indoor environment such as production management and anti-theft of merchandises. In this paper, the propagation model on indoor communications [4], [14] is employed:

$$P_{tag} = P_{reader} - L[dB] \tag{1}$$

$$L = 10\log[(4\pi/\lambda)^2 d^n \big/ G_{reader} G_{tag}] + \alpha[dB] \tag{2}$$

Where P_{tag} is the power output by the RFID reader, L is the propagation loss considering multipath fading, n is between 1.5 and 3, α is about 10dB in the worst case and G_{read} and G_{tag} are reader antenna gain and tag antenna gain respectively [4].

B. Readers and Tags

In RFID systems, the RFID readers communicate with the tags by reading/writing the information stored on them. In most cases, the tags are passive and low functionality which means the tags receive power from a reader to operate and then transmit the backscatter signal to the reader. However, the reader has a limit on its interrogation range. If the radio signal received at a tag is higher than a quality threshold, noted R_q hereafter, then the communication between the reader and tag can be established. For the power needed for a tag transmitting the backscatter signal back to the reader is taken from the received power, the threshold in this discussion is reasonably set higher than the rated value which is dependent on the type of RF tags considered and carrier frequency.

As for the reader, we take the power-adjustable antenna to make the optimization problem more flexible. The emitted power is adjusted by the attenuation. In this paper, the problem only concerns the variables of the position and radiated power of the RFID readers serving the working area.

C. Coverage

In the RNP optimization problem, the first objective function represents the level of coverage, which is most important in the RFID systems. For that if any large amount of tags cannot be read by any reader, the RFID systems will be no practical use. Before define the coverage constraint and other constraints, as well as to define the mathematical formulation for optimization, some basic notations are formulated:

- R_q : received power threshold guaranteed reader-to-tag communication
- $P_{r,t}$: the field strength received at a tag t from a reader r
- ST : set of all tags in the working area
- SR: set of the reader serving the area
- $C_v(r)$: the set of tags served by reader r, which is defined [4] as:

$$C_v(r) = \{t \in ST \,\big|\, P_{r,t} \geq R_q, \forall r' \in SR, r' \neq r, \quad P_{r,t} \geq P_{r',t}\} \tag{3}$$

Then the constraint can be formally expressed by the following formula equations:

$$ST = \bigcup_{r \in SR} C_v(r) \tag{4}$$

In order to define a measure to facility the calculation, the function f_1 is defined as follow:

$$\max \quad f_1 = N_{coverag} / |ST| \tag{5}$$

where $N_{coverage}$ is the number of tags covered by all readers, |ST| is the number of total tags which is used to normalize performance indicators.

D. Interference

Reader interference mainly occurs in a dense reader environment, where several readers try to interrogate tags at the same time which will result in an unacceptable level of misreads. The reasonable planning of networks will reduce the interferences and improve the Quality of Service. In order to estimate the interference level, each tag's best service reader should be predicted. Thus, for a tag, the sum of received signals which are less than $Cd_{r,t}$, which represents the best signal received at a given tag t covered by the reader r, and greater than the required sensitivity threshold S_m can stand for interference in a certain sense [4]. Hence, the interference level at tag t is given by:

$$\gamma(t) = \sum (P_{r',t} - S_m), \qquad Cd_{r,t} \geq P_{r',t} \geq S_m \tag{6}$$

The objective of minimizing the total amount of interferences can be expressed as follows:

$$\max \quad f_2 = \sum_{t \in ST} (Cd_{r,t} \big/ (Cd_{r,t} + \gamma(t))) \big/ |ST| \tag{7}$$

It is the optimal condition when f_2 equals to 1, in that case the interference level returns to zero.

E. Load Balance

For various performance measures, it is important to design effective load balancing schemes for distributing tags among readers as evenly as possible [5]. In [9], the author formulated the planning problem into a bipartite graph G=(U ∪ V,E), where U equals to SR and V denotes the set of tags, equivalent to ST defined before, E donates the set of edges between reader and tag if and only if they can communicate with each other. Each edge has a non-negative energy cost $c_{i,j}$ representing the energy cost of reader r_i to read tag t_j once. Then the problem definitions in [9] is to find an assignment $\Phi: V \rightarrow U$ of each tag t_j to a reader $r_i = \Phi(t_j)$ such that the maximum of the total energy cost:

$$C_i = \sum_{r_i=\phi(t_j)} c_{i,j} \tag{8}$$

over all readers is minimized. To simplify our discussion, the energy cost has a fixed unit energy cost, namely $c_{i,j}=1$, then the load balance constraint become:

$$\min \quad C_i = n_i \tag{9}$$

n_i is the number of the tags assigned to reader r_i. The constraint, in other words, is to balance the number of tags assigned to each readers as far as possible. For facilitating the calculation and presenting the fitness function, some measures have been proposed.

The mean square deviation method is to calculate the covariance of the numbers of tags and the lower value indicates the higher equilibrium of the tags assignment. The formula is as below:

$$D(X) = 1/|SR| \times \sum (n_i - E(n))^2 \tag{10}$$

when the label distribution is uniform, this method can achieve minimum value. However, if the n_i not equal to the average number of tag, or all reader are assigned the same number of tags but equal to a small number, for instance 1, the value of D(X) also equal to zero. That is, the measurement only can reflect the balance of tags assigned to reader, but can only be used under the maximum coverage rate premise.

Also the product of n_i is another approach, in that way, the indicator obtains maximum value if and only if in the situation that equal distribution of the label. The formula is as below:

$$\max \quad f = \prod n_i \tag{11}$$

However, this method has the shortcomings of hard to be normalized.

In information theory, entropy is a measure of the uncertainty associated with a random variable. Entropy is a state function of the system; it can be used to describe the state of existence of a certain system, and its changes can also be used to indicate the direction of the evolution of the system. Since 1850 when Clausius put forward the second law of thermodynamics and 1865 when he introduced the state function, entropy and accurately proved the principle of entropy increase in mathematical terms, the concept of entropy has been quickly extensified with swift extension to other disciplines, an extremely strong capability of its development to many fields.

When studying the efficiency of communication system, Shannon introduced the concept of information entropy based on the basic concept of thermodynamics entropy [25], which was defined as:

$$S = -\sum P_i \log P_i \tag{12}$$

P_i is the probability of the *i*th basic event. Here, entropy reflects the degree of a certain "uncertainty" in the state of the system. And the entropy difference of system change provides us with a message like this: RTIE is closely related to matter, energy and information conversion; entropy can be regarded as an important variable for the description of the RTIE. For a complex system such as the RTIE, entropy will not only reflect its state, but also show its uniqueness [24].

Take the form of the information entropy function S, the load balance constraint measurement f_3 is defined using the entropy concept as follows:

$$\max \quad f = -\sum_{i=1}^{|SR|} (n_i/|ST|) \ln(n_i/|ST|) \tag{13}$$

where |SR| is the number of total readers and |ST| is the number of total tags. The form of n_i/|ST| takes the form of P_i , the probability of *i*th basic event. To normalize the measurement, the term ln(|SR|) is used and the performance indicator is as below:

$$\max \quad f_3 = -\sum_{i=1}^{|SR|} (n_i/|ST|) \ln(n_i/|ST|) / \ln(|SR|) \tag{14}$$

then the measurement can achieve maximum value 1 if and only if each reader was assigned the same number of tags.

F. Combined Measures

The overall optimal solution for RNP is represented by a linear combination of the three objective functions:

$$\max \quad f = \sum_{i=1}^{3} \omega_i f_i ; \quad \omega_1 + \omega_2 + \omega_3 = 1 \tag{15}$$

The weight values of each objective function can be flexible varied to account for any specific situation.

III. Multi-Community GA-PSO

A. Basic Concepts of GA and PSO

Genetic algorithm is stochastic search procedures based on the mechanics of natural selection, genetics, and evolution [15]. The individual, or chromosome, is a potential solution which searches in the solution space by three operators - selection, crossover and mutation to find the global best solution. Particle swarm optimization is also a kind of algorithm to search for the best solution by simulating the movement of birds flocking. The particle, akin to the chromosome in GA, updates according to the dynamic rules until the entire particles converge to the optimal solution. However, both canonical PSO and GA both operate in the same population, whereas in the natural world, social community structure is commonly existent in the network [11] and interactions between groups of the same species are easily observed. Inspired by the community structure phenomenon, we extend the single population in the heuristic algorithm to the interacting multi-community structure and propose multi-community GA-PSO.

B. The Hybrid Algorithm of Multi-community GA-PSO

Community organizational structures extensively emerge in many biological, social, man-made engineering systems. In these organizations, all the members are divided into some groups, and it has been demonstrated that the hierarchical structure can be organized more efficiently and thus can address larger scale problem [16].

The multi-colony or multi-swarm PSO algorithm is proposed by many researchers base on the concept of dividing single population into many colonies and the individuals cooperate with each other to achieve the global optimum solution [5],[17]-[22]. The proposed method, however, simulates the mutation and selection phenomenon in nature colony and adds the corresponding operator in the single community to better mimic the natural laws of population.

In the proposed algorithm, the population is divided into some communities. The individuals in the same community can share information with each other and construct a fully connected topology, and all the communities form a ring topology, among which each community can exchange the global best solution found in adjacent group. The topology schematic diagram is shown in Fig. 1.

In this case, each individual of the proposed model evolves based on individual's own cognition, social interaction within each community and information exchanged from other communities. The main parameters and operators of the novel GA-PSO algorithm are described as below.

1) Coding and Initialization: Coding cares about how to represent the practical parameters of the optimization problem into an individual. The novel algorithm adopts the floating point coding scheme. At the beginning of the algorithm, all the individuals in the population should be generated initially and are uniformly distributed random numbers in $[X_{min}, X_{max}]$, where X_{min} is the lower limitation of the particle position and X_{max} is the upper limitation. At the same time, the velocity of the particles should be initialized at first, within the limit of $[V_{min}, V_{max}]$.

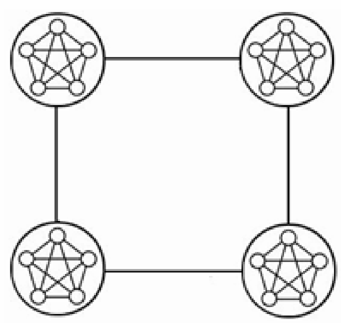


Fig. 1. The topology schematic diagram

2) PSO Updating Rule: In the proposed method, the individual updates the position and velocity according to three guides. The enhanced dynamic rules are formulated as:

$$\vec{v}_i^k(t+1) = \omega\vec{v}_i^k(t) + c_1 r_1[\vec{p}_i^k(t) - \vec{x}_i^k(t)] + c_2 r_2[\vec{p}_g^k(t) - \vec{x}_i^k(t)] + c_3 r_3[\vec{p}_g^m(t) - \vec{x}_i^k(t)] \tag{16}$$

$$\vec{x}_i^k(t+1) = \vec{x}_i^k(t) + \vec{v}_i^k(t+1) \tag{17}$$

where ω is the inertia weight; c_1, c_2 and c_3 are the acceleration constants with positive values; r_1, r_2 and r_3 are uniformly distributed random numbers in [0, 1]; the superscript in each item represents the serial number of community and the subscript indicates the label of individual in corresponding community. The vector p_i^k represents the individual's best position in history in its own community; p_g^k represents the global best position founded in k^{th} community; p_g^m represents the global best position founded in m^{th} community, where k^{th} and m^{th} community are adjacent.

3) Selection Operator: In order to produce well-performing individuals in the novel algorithm, the selection mechanism is adopted in each group. In each generation, after the fitness values of all the individuals in the same community are calculated, the low half worst performing individuals are marked out. Instead of replacing the worst-performing individuals with the top-half well-performing individuals [23] in the same group, the paper only replaces the worst performing one with the previous community's global best position $p_g^k(t-1)$ in order to accelerate the convergence speed.

4) Mutation operator: In Multi-community GA-PSO, mutation occurs after the velocity and position update operator. Mutation is an operator derived from the mimic of biological genetic breeding behaviour and by the operator, the apposition of an individual is altered randomly so that new genetic materials can be introduced into the population. In the proposed method, the mutation operator can be used to overcome the premature convergence. Here, uniform mutation is adopted, that is, the mutated gene is drawn randomly, uniformly from the corresponding search iteration. In the following simulations, a constant mutation P_m probability is used. The mutation operator rests the individual's position by re-initialized the position randomly in the searching space. Compare with traditional methods by which the individual adds a stochastic disturbance to the original position, the method taken in the work is somehow a large scale operation in order to avoid the premature phenomenon.

IV. Circular Propagation Model Simulation

In this section, multi-community GA-PSO is applied to the RFID network planning problem compared with canonical PSO. For RNP problems, the object is to place readers at the best position while optimizing a set of objectives- coverage, load balance and interference between readers simultaneously. To demonstrate the superiority of the proposed algorithm, in simulation, the performance of the proposed algorithm is compared with the canonical PSO.

A. Simulation Scenario

The RFID planning working area is simulated by an ideal square scene (25m×25m) with 80 tags, which are randomly distributed in the working area. Ten radiated-power adjustable RFID readers are considered to cover this working area. Fig. 2 shows the ideal square working area.

B. Parameter and Procedure

For Multi-community GA-PSO, all the individuals forming the whole population should be randomly generated into ten communities, and each community contains ten individuals with random positions and velocities. Each individual in the algorithm takes a floating point coding scheme and has a dimension equal to $3\times|SR|$, in which the first $2\times|SR|$ elements in the individual vector indicate the coordinates of reader positions, and the |SR| elements in vector dimensionalities for radiated powers of each reader. The inertial weight starts at 0.9 and linearly decreases to 0.4 with the increment of the iteration. The acceleration constants c_1, c_2 and c_3 are set to 1.494, the mutation probability constant P_m is set to 0.1 and the maximal epochs is 500.

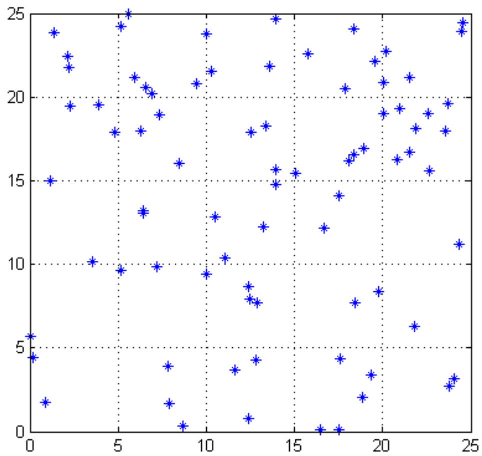


Fig. 2. The square working area

Then the detailed procedures for this algorithm can be summarized as follows:

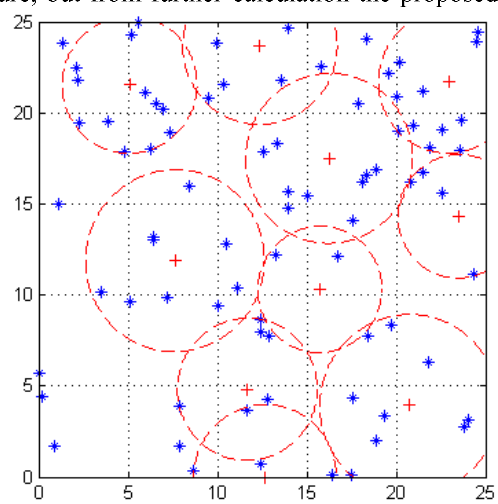
- **Step1**. Initialize the positions and velocities of the whole population of ten communities randomly and set parameter values as described before.
- **Step2**. Evaluate each particle's fitness value using (11) in each group then record each particle's best position P_i^k. Then calculate the global best position P_g^k in each community.
- **Step3**. The position and velocities of all the particles are updated according to (16) and (17). If the new particle's position and velocity are beyond their respective limitation, the value must be set as the nearest boundary.
- **Step4**. Based on the mutation strategy, each particle in each community will mutate according to certain probability P_m, and then produce the new population.
- **Step5.** Evaluate each new particle's fitness value and compare each individual's new fitness value with the previous best record. Then update the particle's best position and the global best position in each group.
- **Step6.** After the fitness values have been calculated, the worst performing individual in each community is marked out. By selection operator, the worst performing individual is replaced by the previous global best position in its community with its current velocity and historical best position unchanged.
- **Step7.** If the maximal iterative generations are achieved, or the global best position's fitness value has achieved the setting precision, it is the ends of the algorithm, else, go to Step 3.

To illustrate the effective of the new algorithm, traditional PSO is used as a comparison. For PSO, the inertia weigh takes the same dynamic value with the proposed algorithm, the acceleration constants c_1 and c_2 are set to 1.494, the population size is 100, and the maximal epoch is 1000.

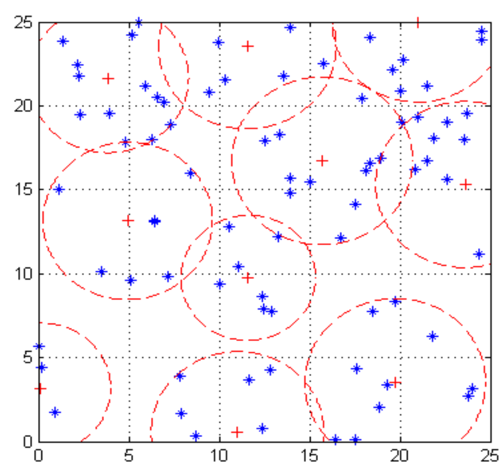
C. Simulation Result

The final network planning results found by two algorithms is presented in Fig. 3 and the fitness of optimization process is shown in Fig. 4.

The red dotted line in Fig. 3 indicates the power threshold R_q, and the plus symbol represents the coordination of each readers. The electromagnetic field strength in the circle descends according to the distance to the reader, however for clarity it is simplified, then the tag in the two circle sphere need to be calculated the received power to determine which reader it belongs to. From the comparison of Fig. 3-(a) and Fig. 3-(b), we can easily observe that the multi-community GA-PSO algorithm can obtain a completely coverage that no tag is neglected by readers. In the dense regions of tags, the tags are distributed to different readers in Fig. 3-(b) to satisfy the load balance constraints while in Fig. 3-(a) all the tags in the dense region belong to one reader. The interference level, however, cannot deduce from the figure, for the power is not depicted in the picture, but from further calculation the proposed method



(a)



(b)

Fig. 3. Experimental results (a) traditional PSO algorithm; (b) Multi-community GA-PSO algorithm

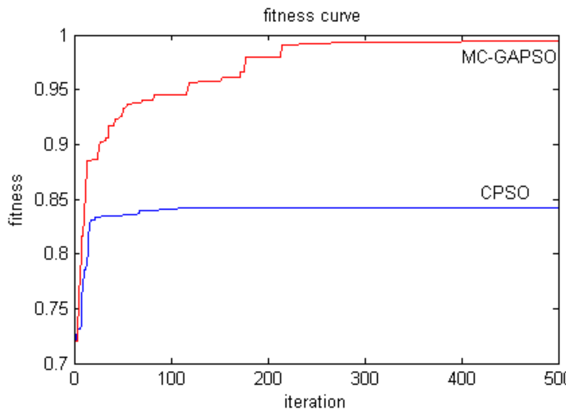


Fig. 4. Fitness curve

also achieves better performance.

Seen from the Fig. 4, the new algorithm is apparently better than the traditional method. The novel algorithm can avoid premature phenomenon while the searching is stagnated in traditional PSO at early iteration. The novel algorithm can keep the diversity of the population and achieve better fitness value, provided verification for the optimized approach.

V. Ellipse Propagation Model Simulation

The reading range is one of the most critical performance indicators of radio-frequency identification (RFID) systems. It depends on many physical and geometrical parameters. Typically, in the ultra-high-frequency band, the maximum size of the reading region is estimated by the free-space propagation model. This is based on the Friis formula, even if much more accurate predictions may be accomplished nowadays by time-consuming electromagnetic simulations, accounting for the antennas and the interaction with the nearby environment [30].

In RFID system, the propagation pattern of RFID reader antenna equal to the space electromagnetic field distribution model of wireless antenna which in some research literature known as identify region [26] .

The RFID reader antenna propagation model is determined by many parameters: the reading and writing of the antenna power, the antenna attenuation value, radio frequency band, tag threshold power, etc. Although communication model calculation is a complicated process, but once these parameters of the RFID system is known, it can through the ray tracing method or the actual way of reading and writing tests to determine the antenna to reading and writing the scope of the label.

The method to classify the pattern of the RFID reader is plenty of, but the most commonly used method is classifying the pattern by its geometric shape and then the pattern is classify into circle pattern and ellipse pattern.

In recently, the type of antenna in used is patch antennas, also known as micro-strip antenna. According to antenna theory, if take the main lobe of antenna signal as the effective coverage areas, then antenna coverage is an approximate the elliptical shape [27-28]. In [29], the author through the antenna electromagnetic field analysis and experimental way, verify the RFID for reading and writing the spread of antenna model roughly into an oval.

In short, the patch antenna of the RFID reader is directional, considering the antenna in the plane of the cover, the coverage area is not a round, so in the deployment of the antenna when RFID can't cover simple with a round instead of, and need to consider the direction of the antenna.

A. Simulation Scenario and the Ellipse Model

In ellipse propagation pattern simulation, the RFID planning working area is as same as the scene of the circle propagation simulation as shown in Fig. 2.

To simplify the calculation process, the reader used in the section is different from the previous ones. The reader has the range of interrogation in an ellipse shape, with fixed length of long axis of 5m and fixed length of short axis of 4m. That means the power of the reader is not adjustable. Considering the direction of the reader, while in the circle propagation the direction make nothing different, then the dip angle of this type is considered as a variable quantity to be optimum.

B. Parameter and Procedure

In the oval propagation pattern, all the individuals forming the whole population should be randomly generated into ten communities, and each community contains ten individuals with random positions and velocities as like in the circle simulation. However, the coding strategy is somehow different from the former simulation.

Each individual in the ellipse simulation takes a floating point coding scheme and has a dimension equal to $3\times|SR|$, in which the first $2\times|SR|$ elements in the individual vector indicate the coordinates of reader positions, and the $|SR|$ elements in vector dimensionalities for the of angle with the horizontal direction of each reader. The angle is illustrated in Fig. 5.

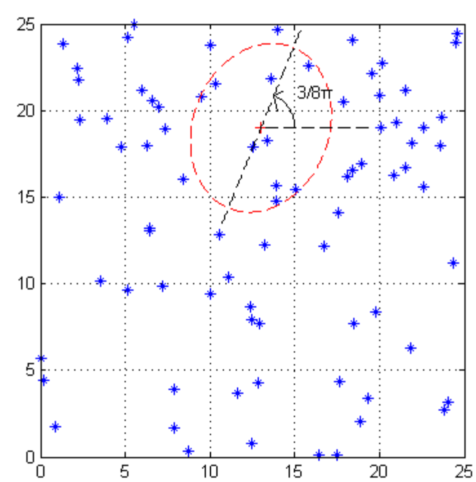


Fig. 5. The ellipse propagation pattern

The inertial weight starts at 0.9 and linearly decreases to 0.4 with the increment of the iteration. The acceleration constants c_1, c_2 and c_3 are set to 1.494, the mutation probability constant P_m is set to 0.1 and the maximal epochs is 500. For the new model only change the propagation of RFID reader, the optimum algorithm apparently will not be modified

C. The fitness value calculation

It is apparently that the fitness calculation is somehow a handicap to solve. In this section, the simplified distribution model of electromagnetic field is shown and the method to calculate the fitness value is illustrated.

Coordinate rotation transformation

The propagation pattern is in ellipse shape that it is not easily solvable in the circle pattern, in which the tags receive power can be calculate by its distance from the reader. Any tag that has the same distance to a reader must have the same receive power. However, in ellipse model, two tags have the same distance to a reader, one in the long axis direction while on in the short axis direction, but the one in the short direction may not be covered by the reader.

Considering the ellipse general equation may take large amount of calculation, while in contrast the calculation of the position of tag is easy to solve, then in this paper, when calculate whether a tag is covered by a reader and the power by simplified calculation, all the tags' position are rotated according to the angle of the ellipse.

Take an example for instance; individual in the algorithm has a dimension equal to 3×|SR|, in which the first 2×|SR| elements in the individual vector indicate the coordinates of reader positions, and the |SR| elements in vector dimensionalities for radiated powers of each reader. That is the individual is in the form of $[x_1,y_1,x_2,y_2,\ldots,x_9,y_9,x_{10},y_{10},\theta_1,\ldots,\theta_{10}]$. Considering the speed and position limit in PSO update rules, the angle of reader variant is separated from its position [x, y] variants such that the individual updating rule is simplified.

Take the *i*th reader's position x_i and y_i and the 20+i element of the particle vector – the angle of the reader θ_i, for instance the i equal to one and the corresponding coordination and angle is [10, 15, 0.25π], then the ellipse is depicted in the area, as shown in Fig. 6.

Then process the coordinate rotation transformation and translation transform, then the area is shown in Fig. 7.

It is easily seen that the relative position of the reader and tags without change, the tags that in the coverage area are still in the domain. But after the coordinate rotation transformation, the coverage area is an ellipse standard equation as below:

$$x^2/a^2 + y^2/b^2 = 1 \tag{18}$$

where the length of the half long axis equal to 5m and the length of the half short axis equal to 4m in this paper.

Coverage rate calculation

After the position transformation, the tags' positions are in a new coordination, but the node indicator does not change. Then put node coordinates into the ellipse standard equation, if the coverage rate, namely the f1, will be calculate by the numbers

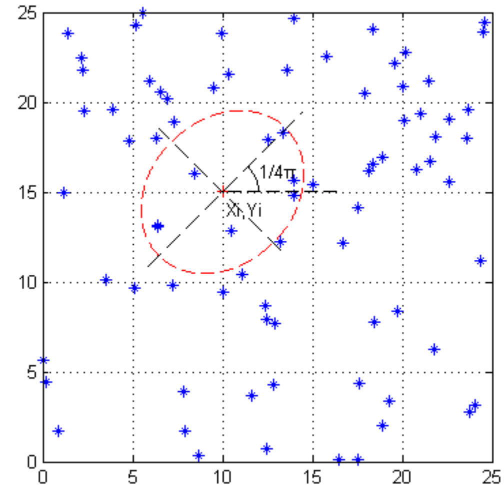


Fig. 6. The reader position and angle

of tags covered by ten readers divided by the total value less than or equal to one, the tag is covered by the reader.

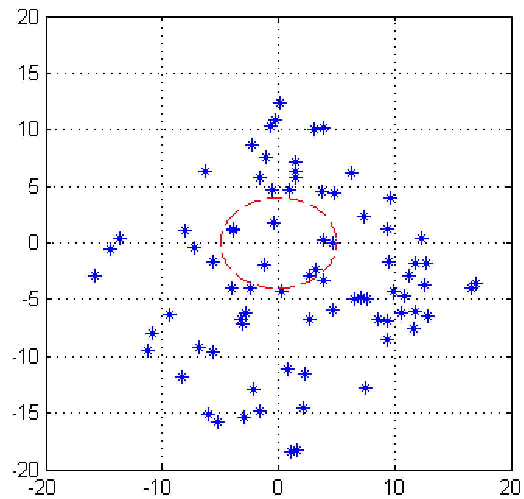


Fig. 7. The coordinate rotation transformation

Do the process again for other nine readers, then the number of tags. The detail description can be seen in Algorithm 1.

Algorithm 1 Coverage rate (CR) calculation

For i=1:1:10
  Transformation (position); //transformation the tag position
  Rotation (position);
  For j=1:1:80
    $value = x^2/25 + y^2/16$;
    status (j,i)=value;
    IF value<=1 **THEN**
      coverage(j)=1;
    END IF
  END FOR
END FOR
f1=sum(coverage)/80;

Load balance rate calculation need to know the number of tags a reader assigned. If a tag is covered by more than one reader, then the tag belongs to the reader which transmits the max power on it.

In the load balance calculation, put node coordinates into the ellipse standard equation and calculate the value. If a tag has the minimum value from a reader, then the tag is assigned to the reader.

The detail description can be seen in Algorithm 2.

Algorithm 2 Load balance rate (LB) calculation

```
For i=1:1:10
   Transformation (position); //transformation the tag position
   Rotation (position);
   For j=1:1:80
      value = x^2/25 + y^2/16;
      status (j,i)=value;
   END FOR
END FOR
FOR i=1:1:80
   [maxpower, indicator]=min( status(i,:) );
   IF maxpower<1 THEN
      assign(pos)=assign(pos)+1;
   END IF
END FOR
SET sum=0
FOR i=1:1:10
   sum=sum-( assign(i)/80 )*log( assign(i)/80 )/log( 10 );
END FOR
f3=sum;
```

However, the calculation of interference level needs to know the interference signal that other readers transmit on it. The reasonable planning of networks will reduce the interferences and improve the Quality of Service. In order to estimate the interference level, each tag's best service reader should be predicted.

Similar to the load balance algorithm, the max power $Cd_{r,t}$, which represents the best signal received at a given tag t covered by the reader r, can be determined by the value of ellipse standard equation. However, the value can reflect the strength of the power of the tag received by a reader, but it can not directly be calculated as the signal. In this paper, the calculation is simplified by considering the power inversely proportional to the value. Under this assumption, the pseudo code of the algorithm is as blew:

Algorithm 3 Interference rate (IR) calculation

```
For i=1:1:10
   Transformation (position); //transformation the tag position
   Rotation (position);
   For j=1:1:80
      value = x^2/25 + y^2/16;
      status (j,i)=value;
   END FOR
END FOR
FOR i=1:1:80
      [maxpower, indicator]=min( status(i,:) );
      temp=status(i,:);
      FOR k=1:1:10
         IF temp(k)==0
            temp(k)=0.01;
         END
         IF temp(k)>1
            temp(k)=0;
         ELSE temp(k)=1/temp(k);
         END
      END
      r_(i)=temp(indicator)/sum(temp);
END
SET sum=0
FOR i=1:1:80
   sum=sum+ r_(i);
END FOR
f3=sum/80;
```

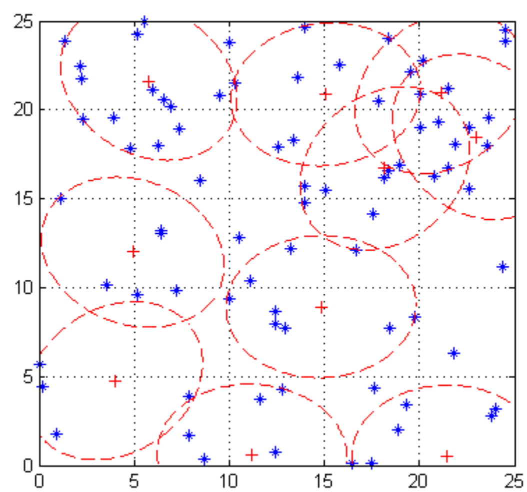
D. Simulation Result

In the ellipse simulation, the weight values of each objective function take the value of [0.7 0.1 0.2], then the fitness function is defined as blew:

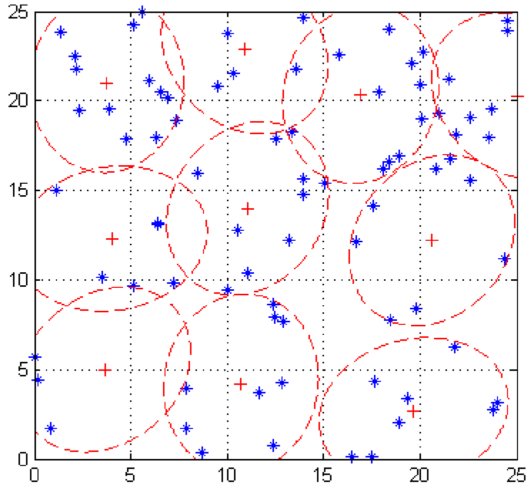
$$f = 0.7f_1 + 0.1f_2 + 0.2f_3 \tag{19}$$

The basic parameter in the ellipse simulation is similar to the circle propagation simulation and the permissible error is set 0.01.

The final network planning results found by traditional PSO and the multi-community GA-PSO is presented in Fig. 8 and the optimization process is shown in Fig. 9.



(a)



(b)

Fig. 8. Ellipse model simulation results (a) traditional PSO algorithm; (b) Multi- community GA-PSO algorithm

The red dotted line in Fig. 8 indicates the power threshold R_q, and the plus symbol represents the coordination of each readers. The electromagnetic field strength in the circle descends according to the ellipse propagation model, however for clarity it is simplified, then the tag in the two circle sphere need to be calculated the received power to determine which reader it belongs to. From the comparison of Fig. 8-(a) and Fig. 8-(b), we can easily observe that the multi-community GAPSO algorithm can obtain a completely coverage that no tag is neglected by readers. In the dense regions of tags, the tags are distributed to different readers in Fig. 8-(b) to satisfy the load balance constraints while in Fig. 8-(a) all the tags in the dense region belong to one reader. The interference level, however, cannot deduce from the figure, for the power is not depicted in the picture, but from further calculation the proposed method also achieves better performance. Also seen from the upper right corner of the region, the reader are clustered, the interference level must be high.

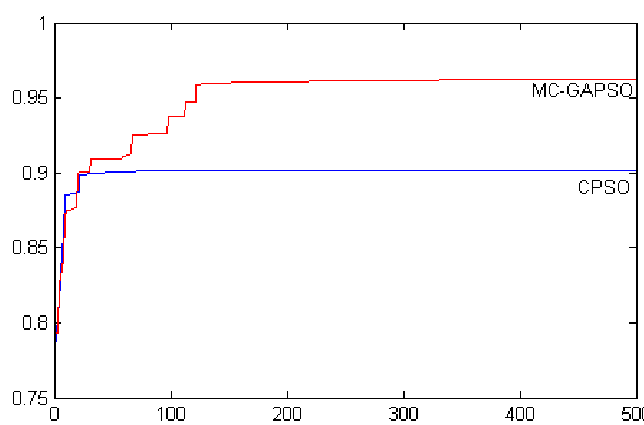


Fig. 9. Fitness curve in ellipse model

Seen from the Fig. 9, the proposed algorithm is apparently better than the traditional method. The novel algorithm can avoid premature phenomenon while the searching is stagnated in traditional PSO at early iteration. The climacteric of the fitness curve indicate the algorithm are stagnated by the mutation operator add new best individual to the population. The novel algorithm can keep the diversity of the population and achieve better fitness value, provided verification for the optimized approach.

For testing the performance of GA-PSO, we use other ten different patterns which are randomly generated in a two-dimensional square scene (25m×25m) with 80 tags. The simulation results are listed in Table I.

TABLE I
SIMULATION RESULTS OF TEN DIFFERENT PATTERNS

No. of patterns	GA-PSO			CANONICAL PSO		
	CR	LB	IR	CR	LB	IR
1	0.94	0.92	0.93	0.85	0.83	0.86
2	0.95	0.92	0.94	0.85	0.83	0.88
3	0.94	0.92	0.94	0.83	0.82	0.87
4	0.93	0.91	0.92	0.82	0.81	0.81
5	0.96	0.95	0.95	0.89	0.88	0.89
6	0.96	0.94	0.95	0.89	0.86	0.88
7	0.94	0.91	0.95	0.82	0.81	0.8
8	0.96	0.92	0.95	0.85	0.83	0.84
9	0.92	0.90	0.92	0.82	0.80	0.81
10	0.93	0.91	0.91	0.83	0.82	0.82

In Table I, the abbreviations CR, LB and IR denote coverage rate, load balance rate and interference rate, respectively. These performance indexes are normalized so that the closer to 1, the better the values are. For each tag distribution pattern, the two algorithms run 10 times respectively, so Table I gives the mean values of the performance indexes averaging over 10 runs. It shows that the GA-PSO algorithm finds better solution for all these ten tags distributing patterns, which has better performance indexes denoted by coverage rate, load balance rate and interference rate than the canonical PSO dose.

VI. CONCLUSIONS

In this paper, an optimization model for planning the position of readers in the RFID network is proposed. The RFID network planning problem is a multi-objective nonlinear optimization problem, and a multi-community GA-PSO algorithm is presented to find the optimum configuration for RFID readers deployment while satisfy coverage, interference and network load balance Constraints.

Finally, although the simulation results show the novel algorithm's effectively, some comments on the future research are given. The algorithm is a static algorithm which can only apply for a certain sense, the propagation model can further be consummated, and the way of setting parameters of the novel algorithm needed to be considered and moreover the novel algorithm remains to be examined for other complicated optimization problem.

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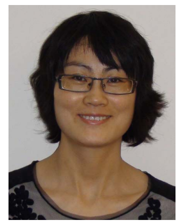

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