Optimizing RFID Network Planning by Using a Particle Swarm Optimization Algorithm with Redundant Reader Elimination

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***Abstract*—The rapid development of Radio Frequency Identification (RFID) technology creates the challenge of optimal deployment of an RFID network. The RFID network planning (RNP) problem involves many constraints and objectives and has been proven to be NP-hard. The use of evolutionary computation (EC) and swarm intelligence (SI) for solving RNP has gained significant attention in the literature, but the algorithms proposed have seen difficulties in adjusting the number of readers deployed in the network. However, the number of deployed readers has an enormous impact on the network complexity and cost. In this paper, we develop a novel particle swarm optimization (PSO) algorithm with a tentative reader elimination (TRE) operator to deal with RNP. The TRE operator tentatively deletes readers during the search process of PSO and is able to recover the deleted readers after a few generations if the deletion lowers tag coverage. By using TRE, the proposed algorithm is capable of adaptively adjusting the number of readers used in order to improve the overall performance of RFID network. Moreover, a mutation operator is embedded into the algorithm to improve the success rate of TRE. In the experiment, six RNP benchmarks and a real-world RFID working scenario are tested and four algorithms are implemented and compared. Experimental results show that the proposed algorithm is capable of achieving higher coverage and using fewer readers than the other algorithms.**

***Index Terms*—Particle swarm optimization (PSO), radio frequency identification (RFID), redundant reader elimination, RFID network planning (RNP)**

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I. Introduction

Radio Frequency Identification (RFID), a developing automatic identification (Auto-ID) technology, has attracted significant attention in recent years [1]-[5]. Identified as one of the top ten contributory technologies in the 21st century, RFID technology is expected to be widely used in various fields such as logistic, supply chain management, asset management, and counterfeit prevention [6]. A typical RFID system consists of three components, namely, (1) an RF tag which is a small electronic data carrying device attached to the item to be identified, (2) a reader to send and receive data to and from the tag via radio frequency signals, and (3) a host computer system to process and distribute data.

Due to the limited interrogation range of the communication between the reader and the tag, many RFID systems involve multiple readers. This gives rise to some questions in the deployment of an RFID network, e.g., how many readers should be deployed, where these readers are to be placed, and what the parameter setting for each reader should be. The RFID network planning (RNP) problem is an important issue in RFID applications and is also a challenging task because it has to meet many requirements such as coverage, Quality of Service (QoS), and cost efficiency. The previous manual trial-and-error approach is time-consuming and a waste of labor. Moreover, as the radio signal propagation is invisible to human eyes, it is difficult to quantitatively and qualitatively evaluate the performance of RFID deployments [6]. With the development of computer and automation technology, the tedious manual approach is going to be replaced by scientific computing. In addition, as a cost-efficient planning of RFID network aims at covering all the items with minimum number of readers, RNP is an NP-hard problem [7][8]. Due to the problem complexity [9], traditional deterministic algorithms are unable to solve practical large-scale RNP instances in acceptable time.

In the past two decades, Evolutionary Computation (EC) and Swarm Intelligence (SI) techniques have gained increasing attention. The corresponding algorithms are shown to have the following advantages: (1) conceptual simplicity (the algorithms have simple iterative processes inspired by nature), (2) high efficiency (they are capable of finding optimal/near-optimal solutions in short computing time), (3) flexibility (with small changes they can be applied to solve various problems), (4) robustness (they are persistent under perturbations or conditions of uncertainty), (5) having potential to use domain knowledge and to hybridize with other techniques, etc. Due to these advantages, EC and SI have been applied in a wide range of industrial applications [10]-[16]. Recently, many EC and SI algorithms have been proposed and developed to solve the RNP problem, such as particle swarm optimization (PSO) algorithms [7][17][18], genetic algorithms (GA) [18]-[20], bacterial foraging algorithms (BFA) [21][22], evolutionary strategy (ES) [18], and differential evolution (DE) [23]. Notice that those works considered static RNP problem in which the positions of tags and readers are fixed and the signal attenuation is constant. This paper also deals with static RNP problem.

For static RNP, coverage problem is the most important sub-problem to tackle. Compared with the area coverage problem, the point coverage problem is more commonly seen [7][17]-[22]. This is because the target of most RFID systems is to identify items (tags) within a geographic area. Among the works dealing with the point coverage problem of RNP, [7], [19], [20], and [21] consider discrete working areas. The area is discretized into a finite number of grids to contain readers and tags. On the contrary, [17], [18], and [22] deal with continuous working areas in which the readers and tags can be placed anywhere.

Due to the fact that the network complexity and the cost of an RFID system highly depend on the number of deployed readers, minimizing the number of readers is a crucial task in planning an RFID network. However, as traditional EC and SI techniques are population-based search algorithms using "fixed" representation (which means the dimensionality of their search space is fixed), they encounter some difficulties in adjusting the number of readers during the search process. In the literature, only a few works consider reducing the number of readers deployed in the network [7][19][20]. These works are all based on discrete working areas and require that a set of candidate reader sites is predefined. Moreover, the algorithms proposed in [7][19][20] are not capable of optimizing the number of readers and the coordinates and radiated power of each reader simultaneously. Due to their inflexibility, they are suitable only to tackle some ad hoc RFID applications.

On the other hand, none of the algorithms based on continuous working areas is capable of adjusting the number of readers during the optimization, because it is hard to define candidate reader sites in continuous working areas. Even though some of the authors confirmed that determining the number of deployed readers is necessary in planning an RFID network [17][18], all the works based on continuous RNP model use predefined and fixed number of readers in their optimization. However, estimating the number of readers needed in the network by human experience is tough and inaccurate.

In this paper, we develop a PSO algorithm to solve the RNP problem on continuous working area. Different from previous works, by designing a novel operator embedded in the optimization process, the number of readers deployed in the network can be adjusted and reduced. The operator is named tentative reader elimination (TRE). On the premise that the current tag coverage is 100%, TRE deletes the reader which covers the fewest tags in the network tentatively. In this way, the number of readers in the network is reduced by one, and at the same time the network coverage may decrease. If the coverage can reach 100% once again in a few generations with the evolution of PSO, the elimination of the reader is considered as permanent. Otherwise, TRE recovers the deleted reader. The algorithm performs TRE several times during its search process in order to minimize the number of readers required to guarantee full coverage. Moreover, along with TRE, a mutation operator is also adopted in the proposed algorithm to repel premature convergence.

Almost all the previous algorithms for RNP apply a weighted-sum method to combine the multiple objectives of RNP into one and then optimize the combined objective. However, as different objectives have different units and dimensions, setting the weight for each objective needs extra works. It is to be noticed that although RNP involves multiple objectives, the priority levels of these objectives are clear in specific applications. Hence, it will be simple and effective to judge which solution is better in a hierarchical manner, i.e., we compare the objectives one by one according to their priorities until one solution wins. Accordingly, the pBest and gBest solutions of PSO algorithms can be easily evaluated. Therefore, in this paper, we adopt the hierarchical approach in the evaluation process of our proposed PSO algorithm to handle the multiple objectives of RNP.

The advantages of our work are summarized as follows: (1) using a novel redundant reader elimination mechanism to intelligently adjust the number of deployed readers; (2) solving the RNP problem in a more comprehensive way (the number of readers, the coordinates and transmitted power of each reader are optimized simultaneously); (3) Considering four objectives in the optimization and using the hierarchical approach to handle the objectives simply and effectively.

In the experiment of this paper, six different RNP instances are tested. Four algorithms, including two traditional PSO algorithms without reader elimination, and the global and the local versions of the proposed PSO with TRE, are compared. Results show that the proposed PSO with a von Neumann topology outperforms the other algorithms, which is very effective and efficient for solving RNP. Furthermore, we apply the proposed algorithm to optimize the RNP in the workshops of Changsha Chushunzhiye (CSZY) Ltd. and obtain promising results. This success shows the significance of the proposed

Fig. 1. Basic components of a typical RFID system.

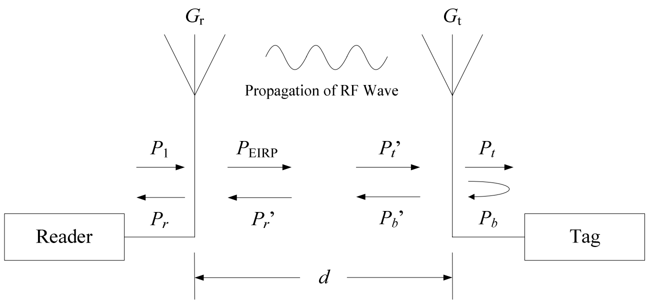


Fig. 2. Transmission process and link budget calculation.

algorithm for the automated industrial system.

The rest of this paper is organized as follows: Section II formulates the RNP problem. Section III introduces particle swarm optimization. Section IV presents the proposed PSO algorithm with full implementation details. Experimental tests are carried out in Section V, with results thoroughly analyzed. In Section VI, a real-world application is conducted, followed by conclusions drawn in Section VII.

II. Model of RFID Network Planning

An illustration of a typical RFID system is shown in Fig. 1, which is composed of a host computer system, one or more RFID readers, and a number of tags. The function of RFID system is mainly based on the wireless communication between the reader and the tag. The tag contains identification and some other information, while the reader reads/writes the information. This communication is carried out by using electromagnetic waves at radio frequencies (RF waves).

A. RFID Tag

The tags in RFID systems are microchips storing identification and other information. According to the power supply principle, RFID tags can be divided into two categories: active tags and passive tags. An active tag has its own power source (e.g., battery) and can broadcast the information to readers by itself, which enables the tag to have a relatively long communication range. However, it has a limited life cycle because the battery could be used out. Moreover, the cost of deploying an active RFID system is very high. These are why active tags have not been used as widely as passive tags in RFID applications.

Passive RFID tags do not need any power source. Instead, they receive power from the signal radiated by readers and build backscatter communication. In this case, the establishment of the communication between a reader and a tag should comply with two constraints: (1) in order to establish reader-to-tag communication the power received by the tag should be larger than a threshold value T_t, and then (2) in tag-to-reader communication the power received by the reader should be larger than another threshold, termed T_r, to guarantee that the reader is sensitive to the signal reflected by the tag. Backscatter communication has a relatively short range. But as passive tags have unlimited life-span and are cost-efficient, they have been widely adopted in various RFID systems nowadays.

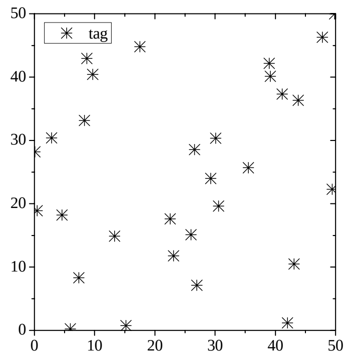


Fig. 3. Example of a 50 m × 50 m working area with 30 RFID tags.

TABLE I
NOTATIONS IN THE FORMULATION OF RNP

Symbols	Descriptions
RS	the set of deployed readers
TS	the set of tags
$PT_{r,t}$	the power received by tag *t* from reader *r*
$PR_{t,r}$	the backscatter power received by reader *r* from tag *t*
T_t	the threshold value of tag to build reader-to-tag communication
T_r	the threshold value of reader to build tag-to-reader communication
N_t	the number of tags distributed in the working area
N_{max}	the total number of readers which could be deployed in the network
N_{red}	the number of redundant readers found by the algorithm
N_r	the number of the readers deployed in the network
PS_r	the amount of power transmitted by reader *r*

B. Link Budget

In backscatter communication, the reader and the tag use their own antennas to send data signal to each other [24][25]. The transmission process and link budget calculation are shown in Fig. 2 and described as follows. Suppose a line-of-sight (LOS) communication is built, the power available to the tag is

$$P_t[\text{dBm}] = P_1[\text{dBm}] + G_r[\text{dBi}] + G_t[\text{dBi}] - L[\text{dB}] \qquad (1)$$

where P_1 is the transmitted power of the reader, G_r is the gain of the reader antenna, G_t is the gain of the tag antenna, and L is the attenuation factor which can be calculated by Friis transmission equation [19][26]-[29].

$$L[\text{dB}] = 10\log\left[(4\pi/\lambda)^2 d^n\right] + \delta[\text{dB}] \qquad (2)$$

As RFID systems are always placed in indoor environments, multipath loss is considered. In Eq. (2), λ is the wavelength; d is the physical distance between the two devices; n varies from 1.5 to 4 due to different environmental conditions; δ stands for other wireless transmission impairments including cable loss, polarization loss, etc.

The backscatter power P_b sent by the tag can be calculated by considering an important coefficient of the tag, the reflection coefficient Γ_{tag}, which indicates the reflected power in proportion to the received power P_t. As shown in Fig. 2, starting with power $P_b = (\Gamma_{tag})^2 P_t$ (in watt), the tag-to-reader communication is built. By using the Friis transmission equation the received power by the reader is calculated as

$$P_r[\text{dBm}] = P_b[\text{dBm}] + G_t[\text{dBi}] + G_r[\text{dBi}] - 20\log(4\pi d/\lambda). \quad (3)$$

C. Problem Formulation

Fig. 3 shows an example of a 50 m × 50 m working area containing 30 RFID tags. The task of RFID network planning is to deploy several RFID readers in the working area in order to achieve the following goals. The notations used in formulating the problem are listed in Table I.

1) Tag coverage

Improving the level of coverage is always the paramount goal in planning an RFID network. In many applications, full coverage, i.e., all tags being covered by at least one reader, is needed. Define ***RS*** as the set of deployed readers and ***TS*** as the set of tags. As the reader-to-tag communication and the tag-to-reader communication are both taken into consideration, for any tag $t \in \boldsymbol{TS}$, it is covered if and only if there is a reader $r_1 \in \boldsymbol{RS}$ satisfying $PT_{r_1,t} \ge T_t$ and a reader $r_2 \in \boldsymbol{RS}$ satisfying $PR_{t,r_2} \ge T_r$. Here $PT_{r_1,t}$ is the power received by tag t from reader r_1 which can be calculated by Eq. (1); PR_{t,r_2} is the backscatter signal received by reader r_2 from tag t according to Eq. (3); and T_t and T_r are the sensitivity threshold values of the tag and the reader respectively.

The coverage rate of the network can be defined as

$$COV = \sum\nolimits_{t\in \boldsymbol{TS}} Cv(t) \big/ N_t \times 100\% \quad (4)$$

$$Cv(t) = \begin{cases} 1, & \text{if } \exists r_1, r_2 \in \boldsymbol{RS},\ PT_{r_1,t} \ge T_t \ \wedge\ PR_{t,r_2} \ge T_r \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

where $N_t = |\boldsymbol{TS}|$ is the number of tags distributed in the working area.

2) The Number of Readers

The network complexity and the cost of an RFID system strongly depend on the number of readers deployed in the system. Therefore, on the premise that the coverage goal is achieved, the minimization of the number of readers is very important in RNP. Suppose that N_{max} is the total number of available readers that could be deployed in the network while N_{red} is the number of redundant readers found by the algorithm. Then the number of the readers deployed in the RFID network (the readers belonging to ***RS***) to achieve service is

$$N_r = |\boldsymbol{RS}| = N_{max} - N_{red}. \quad (6)$$

3) Interference

The overlapped covering area of densely deployed readers has interference when several readers interrogate a tag at the same time. The interference will result in misreading and lower the QoS of the RFID system. Therefore, interference avoidance is also an important task in RNP. The total amount of interference in an RFID network is defined as the sum of the interference value at each tag, which is given by

$$ITF = \sum\nolimits_{t\in \boldsymbol{TS}} \gamma(t) \quad (7)$$

$$\gamma(t) = \sum PT_{r,t} - \max\{PT_{r,t}\},\ r \in \boldsymbol{RS} \wedge PT_{r,t} \ge T_t. \quad (8)$$

It can be observed that only when tag t is covered by exactly one reader, the interference level at t equals to zero.

4) The Sum of Transmitted Power

From the perspective of energy-saving, the sum of transmitted power of all readers should be reduced as much as possible. But according to Eqs. (1) and (3), the interrogation range of a reader strongly depends on its transmitted power, which means that reducing transmitted power may disturb the coverage of the network. Therefore, power-saving is the objective with the lowest priority in planning an RFID network. The total amount of transmitted power of all readers is given by

$$POW = \sum\nolimits_{r\in \boldsymbol{RS}} PS_r \quad (9)$$

where PS_r is the amount of power transmitted by reader r.

III. Particle Swarm Optimization

Particle swarm optimization (PSO), which was first proposed by Kennedy and Eberhart in 1995, is a famous population-based search algorithm. The algorithm emulates the swarm behavior of bird flocking or fish schooling and belongs to the Swarm Intelligence (SI). In PSO, each individual (particle) flies through the problem space with a velocity. The speed and direction of the velocity is adjusted based on the particle's previous best experience (self-cognitive) and the historical best experience in its neighborhood (social-influence). In this way, the particle has a tendency to fly towards a promising area in the search space. PSO algorithm is easy to implement, and has advantages of high efficiency, fast convergence, strong robustness, etc. The algorithm has undergone extensive improvements [30]-[35] and been widely used in various systems [14][15][36][37] in recent years.

A. Global PSO

The particle swarm is composed of M particles, each of which has a velocity vector $V_i = [V_i^1, V_i^2, \cdots, V_i^D]$, a position vector $X_i = [X_i^1, X_i^2, \cdots, X_i^D]$, and a previous best position vector $pBest_i = [pBest_i^1, pBest_i^2, \cdots, pBest_i^D]$ $(i = 1, 2, \cdots, M)$. At the same time, the whole swarm maintains a global best position vector $gBest = [gBest^1, gBest^2, \cdots, gBest^D]$ recording the best position found by all particles. Here D is the dimensionality of the search space.

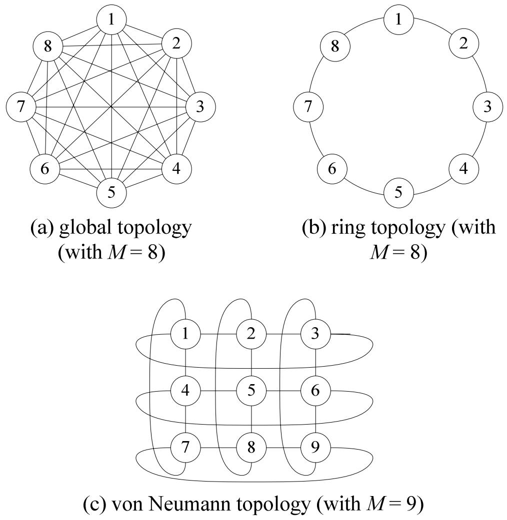


Fig. 4. Neighborhood topologies.

The key issue of PSO is the update of particle's velocity and position, which is defined as

$$V_i^d = \omega \times V_i^d + c_1 \times rand_1^d \times (pBest_i^d - X_i^d) + c_2 \times rand_2^d \times (gBest^d - X_i^d) \tag{10}$$

$$X_i^d = X_i^d + V_i^d \tag{11}$$

where $d = 1, 2, \cdots, D$ represents each dimension of the search space; $i = 1, 2, \cdots, M$ is the index of each particle; ω is called inertia weight; c_1 and c_2 are acceleration coefficients; $rand_1^d$ and $rand_2^d$ are random numbers uniformly distributed in [0, 1].

It can be observed that the update of particle's velocity and position is based on two elements: (1) $\omega \times V_i^d$, the inertia part to avoid particle changing velocity abruptly, and (2) $c_1 \times rand_1^d \times (pBest_i^d - X_i^d) + c_2 \times rand_2^d \times (gBest^d - X_i^d)$,the cognitive part which can be interpreted as external force to pull the particle fly towards better position. Inertia weight ω plays an important role of balancing the exploration and exploitation of PSO algorithm. A good performance is achieved by using a large ω (e.g., 0.9) at beginning to explore the search space, and gradually reducing ω to a lower value (e.g., 0,4) to refine the solution. Among the cognitive part, $c_1 \times rand_1^d \times (pBest_i^d - X_i^d)$ stands for the particle learning from its own flying experience, while $c_2 \times rand_2^d \times (gBest^d - X_i^d)$ determines how the particle is influenced by the swarm's search experience. Acceleration coefficients c_1 and c_2 define the relative weight of the self-cognitive and social-influence, which are commonly set as $c_1 = c_2 = 2.0$ in the literature.

The overall procedure of PSO algorithm is described as follows.

Step 1) In the initialization, the velocities and positions of M particles are randomly generated.

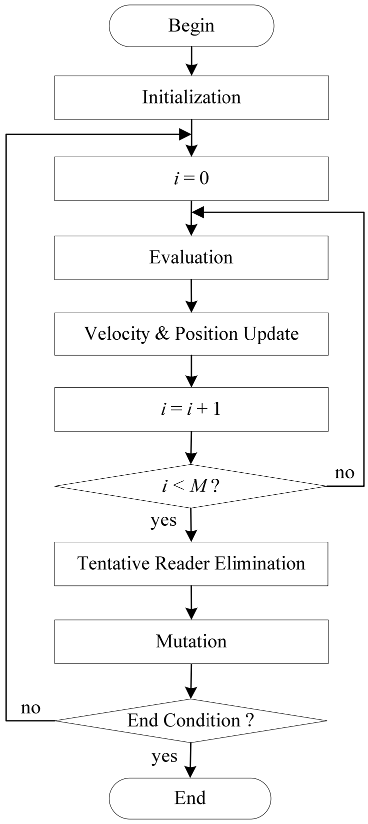


Fig. 5. Flowchart of the proposed PSO algorithm for RFID network planning.

Step 2) For each particle i, evaluate the fitness according to the objective function(s). If the fitness is better than particle i's previous best fitness, update $pBest_i$ and further compare the fitness with the global best fitness found so far. Then, update *gBest* accordingly.

Step 3) Particles update their velocities and positions according to Eqs. (10) and (11).

Step 4) Loop to Step 2) until a stopping criterion such as the maximum number of generations or sufficient solution accuracy is met.

B. Local PSO

In Subsection A, the traditional PSO algorithm with a global topology is introduced. As shown in Fig. 4(a), the global topology can be conceptualized to be a fully connected graph, by which the neighborhood of each particle is the whole swarm. The *gBest* found by the swarm guides the search of all particles.

Different from the global topology, in a local topology, particles have smaller neighborhoods. For example, in the ring topology shown in Fig. 4(b), the neighborhood of each particle consists of itself and another two particles directly connected to the particle. Fig. 4(c) shows the von Neumann topology in which each particle has four neighbors consisting of the particles above, below, to the left, and to the right. When using a local topology, each particle keeps track of a local best position $lBest_i = [lBest_i^1, lBest_i^2, \cdots, lBest_i^D]$ found in its neighborhood. The velocity update is then modified as

$$V_i^d = \omega \times V_i^d + c_1 \times rand_1^d \times (pBest_i^d - X_i^d) + c_2 \times rand_2^d \times (lBest_i^d - X_i^d) \quad (12)$$

As more than one local optimum could be preserved in the search process, local topology preserves the diversity of swarm and helps to repel premature convergence. Meanwhile, the swarm with a local topology converges more slowly than that using the global topology because the search is not so "greedy". The ring topology which has the smallest neighborhood is the slowest. The von Neumann topology, in which each particle has four neighbors, is shown to provide a good balance of diversity and convergence. PSO algorithms with the von Neumann topology have general good performance in various applications.

IV. PSO Algorithm for RFID Network Planning

In this paper, we develop a PSO algorithm for solving RNP, whose flowchart is shown in Fig. 5. It can be observed that, in addition to the general procedure of PSO, the tentative reader elimination (TRE) and the mutation operator are embedded into the algorithm. Detailed implementations of the algorithm are proposed and described in this section. Moreover, it is to be noticed that the proposed PSO algorithm is able to employ either the global topology or a local topology.

A. Particle Representation

The control variables of RNP include the number of deployed readers, the positions of these readers, and the radiated power of each reader. To solve the RNP problem, these variables should be encoded into particle's representation. We employ a representation that each particle is characterized by a $D = 3N_{max}$ dimensional real number vector (as introduced in Section II, N_{max} is the total number of available readers that could be deployed in the network). In the representation, $2N_{max}$ dimensions indicate the coordinates of the N_{max} readers in the 2-dimensional working area, and the other N_{max} dimensions denote the transmitted power of each reader (which determines the interrogation range). Then, the *i*th particle in the swarm is in the form of

$$X_i = [x_i^1, y_i^1, p_i^1, x_i^2, y_i^2, p_i^2, \cdots, x_i^{N_{max}}, y_i^{N_{max}}, p_i^{N_{max}}] \quad (13)$$

where (x_i^k, y_i^k) and p_i^k are the coordinates and radiated power of reader k (k = 1, 2, …, N_{max}).

It can be noticed that N_r, the number of actually deployed readers, is not encoded into each particle. Instead, in the proposed algorithm, the whole swarm maintains an N_{max} dimensional Boolean vector $ON = [on^1, on^2, \cdots, on^{N_{max}}]$ with each $on^k \in \{0,1\}$ ($k = 1, 2, \cdots, N_{max}$) standing for whether the kth reader is deployed in the network. As a result, we have $N_r = \sum_{k=1}^{N_{max}} on^k$. ON is updated according to the TRE operator described in Subsection C. We do not encode this reader-switching vector into each particle because it is improper to do so, as is shown in the following example. Suppose that particle 1 is the global best particle in which the 5th reader is eliminated from the network, and particle 2 still uses the 5th reader. In the update of particle 2, it learns from particle 1, including learning the coordinates and power of the 5th reader. However, the information of the 5th reader in particle 1 is invalid, which gives a wrong guidance for particle 2.

B. Initialization

In the initialization, the positions of all particles are randomly generated, with each (x_i^k, y_i^k) being a random point in the working area and p_i^k being a random value within the transmitted power range of readers (k = 1, 2, …, N_{max}). The velocity of each particle is also randomly generated, while the maximum velocity of each dimension is empirically set to be 20% of the variable range [31][38][39]. Besides, the reader-switching vector is set as ON = [1, 1, …, 1] , which denotes that all the N_{max} readers are initially deployed in the network. The $pBest_i$ of each particle is set the same as its current position, while the *gBest* vector is initialized to be the current best $pBest_i$.

C. Fitness Evaluation

As described in Section II, the objectives of RNP include maximizing tag coverage (defined by Eqs. (4) and (5)), minimizing the number of readers (defined by Eq. (6)), minimizing interference (defined by Eqs. (7) and (8)), and minimizing total transmitted power (defined by Eq. (9)), in an order of decreasing importance. Accordingly, the algorithm handles these four objectives in a hierarchical manner. The evaluation process of each particle is described as follows.

Step 1) Calculate the *COV*, N_r, *ITF*, *POW* values of the particle's current position according to Eqs. (4)-(9).

Step 2) If the current *COV* is larger than the particle's

```
Procedure TRE
  If recoverGen = 0
    If fullCoverage = true
      Delete Reader;
      fullCoverage = false;
      recoverGen = maxRG;
    Else
      Recover Reader;
    End if
  Else
    recoverGen = recoverGen – 1;
  End if
End procedure
```

```
Procedure Delete Reader
  Choose a reader k from set RS – {the reader deleted in the last round}
which covers the fewest tags;
  Update the reader-switching vector ON by setting on^k = 0;
  N_r = N_r – 1;
End procedure
```

```
Procedure Recover Reader
  Update the reader-switching vector ON by setting on^k = 1;
  N_r = N_r + 1;
End procedure
```

Fig. 6. Pseudo code for the proposed TRE operator.

previous best *COV*, go to Step 6); if the two values are equal, go to Step 3); otherwise, end the evaluation process.

Step 3) If the current N_r is smaller than the particle's previous best N_r, go to Step 6); if the two values are equal, go to Step 4); otherwise, end the evaluation process.

Step 4) If the current *ITF* is smaller than the particle's previous best *ITF*, go to Step 6); if the two values are equal, go to Step 5); otherwise, end the evaluation process.

Step 5) If the current *POW* is smaller than the particle's previous best *POW*, go to Step 6); otherwise, end the evaluation process.

Step 6) Set the *pBest* vector of the particle the same as its current position.

Step 7) Update the *gBest* (for global PSO) or *lBest* (for local PSO) in the same way as updating the *pBest*.

D. Tentative Reader Elimination

The TRE operator is used to control the reader-switching vector $ON=[on^1, on^2, \cdots, on^{N_{\max}}]$ held by the swarm. To reduce the number of deployed readers as many as possible without disturbing the tag coverage, TRE tentatively deletes one reader in the current running reader set in each round.

The pseudo code for the TRE operator is shown in Fig. 6, where *fullCoverage* represents whether there is at least one particle that obtains 100% tag coverage, *maxRG* is a control parameter that stands for the maximum number of recovering generations. As shown in Fig. 6, on the premise that a solution with full coverage has been found, the reader k which covers the fewest tags in the network is deleted by TRE. The corresponding on^k in *ON* is set to be 0 and N_r is reduced by one. In this way, the coverage of the RFID network may decrease. In the next *maxRG* generations, if the coverage can reach 100% once again by using fewer readers, the elimination of the reader is considered to be permanent and the TRE operator has successfully reduced one redundant reader in the network. Otherwise, the deleted reader is recovered.

ON, the reader-switching vector, plays a role in the update of each particle i ($i=1,2,\cdots,M$). For each on^k = 0 in *ON* ($k=1,2,\cdots,N_{\max}$), the corresponding dimensions x_i^k, y_i^k, and p_i^k in particle i which represent the coordinates and transmitted power of reader k will not be updated. This prevents particles from learning invalid information and also saves the computational cost. More importantly, it guarantees that the reader elimination in TRE is tentative and could be recovered.

E. Mutation

Mutation is one of the main operators in genetic algorithms. In recent years, many PSO researchers have embedded mutation operator into PSO algorithms in order to repel premature convergence and to improve the performance [40]-[42]. In the proposed PSO algorithm with TRE, mutation is not only a performance enhancement but also an indispensable operator. The reason is illustrated as follows. In the early stage of the algorithm, as a relatively large number of readers are deployed, the required transmitted power of these readers is low. Therefore, in the early evolution, along with the convergence of particles, the swarm may discard some "genes" representing large transmitted power. The deletion of these genes leads to a difficulty of reader elimination, because in order to guarantee the coverage of the network with fewer readers, larger transmitted power of these readers is in need. Therefore, a mutation operator is embedded in the algorithm so as to restore the lost genes.

The procedure of the mutation is very simple. In each generation of the algorithm, a particle i in the swarm is randomly picked ($i=1,2,\cdots,M$), and then a dimension d ($d=1,2,\cdots,D$) of particle i's position X_i is randomly chose to undergo a modification given by

$$X_i^d = X_i^d + random(-\Delta\alpha, \Delta\alpha) \tag{14}$$

where $\Delta\alpha$ is the mutation range. Besides, when X_i^d goes beyond the predefined variable range [$lbound^d$, $ubound^d$] after the mutation, it is set to be the boundary value.

V. Experimental Tests and Discussions

A. Experimental Setup

In the experiment, six RNP instances, namely C30, C50, C100, R30, R50, and R100, are tested. All these instances are based on a 50 m × 50 m working area, among which C30 and R30 contain 30 tags, C50 and R50 contain 50 tags, and C100 and R100 distribute 100 tags in the working area. Instances C30, C50, and C100 have clustered distributed tags, which are relatively easy to solve. In contrast, R30, R50, and R100 are difficult instances in which the tags are distributed uniformly. (For public use, the benchmark instances are presented in web page: http://www.ai.sysu.edu.cn/GYJ/RFID/TII/.)Moreover, it is to be noticed that, the more tags are placed in the working area, the harder the problem is to solve. Twelve readers, whose transmitted power is adjustable from 20 to 33 dBm (0.1 to 2 watt), are available to be deployed in the Network, i.e., $N_{\max}$ = 12. In the backscatter communication, radio frequency is 915 MHz (with wavelength equal to 0.328 m), the sensitivity thresholds of tags and readers are $T_t = -14$ dBm and $T_r = -80$ dBm respectively, the reader antenna gain G_r is 6.7 dBi, and the tag antenna gain G_t is 3.7 dBi.

In this paper, four algorithms are implemented and compared, among which GPSO is the traditional PSO with the global topology, VNPSO is the traditional PSO with the von Neumann topology, and accordingly, GPSO-RNP and VNPSO-RNP are the global and von Neumann versions of the proposed PSO embedded with TRE and mutation. For all the algorithms, the population size is set as M = 20, the maximum number of generations is set to be 20,000, inertia weight ω is initialized to 0.9 and linearly decreased to 0.4, acceleration coefficients are set as $c_1 = c_2 = 2.0$. For GPSO and VNPSO, as they cannot adjust the number of readers during the optimization, the number of readers deployed in the network is fixed to be six. Notice that we do not deploy all the twelve readers in the

TABLE II
COMPARISONS OF THE RESULTS OF THE FOUR ALGORITHMS FOR SOLVING INSTANCE C30

Algorithm	Mean				best				*t*-test
	Coverage	ReaderNum	Interference	Power	Coverage	ReaderNum	Interference	Power	
GPSO	100.00%	6	0.000	35.074	100.00%	6	0	31.865	ReaderNum+
VNPSO	100.00%	6	0.000	34.762	100.00%	6	0	31.951	ReaderNum+
GPSO-RNP	100.00%	3.18	0.000	35.511	100.00%	3	0	33.948	ReaderNum+
VNPSO-RNP	100.00%	3.04	0.000	35.034	100.00%	3	0	33.535	

TABLE III
COMPARISONS OF THE RESULTS OF THE FOUR ALGORITHMS FOR SOLVING INSTANCE C50

Algorithm	Mean				best				*t*-test
	Coverage	ReaderNum	Interference	Power	Coverage	ReaderNum	Interference	Power	
GPSO	95.60%	6	0.000	35.170	100.00%	6	0	31.852	Coverage+
VNPSO	99.20%	6	0.000	35.023	100.00%	6	0	31.742	Coverage+
GPSO-RNP	100.00%	5.04	0.000	36.244	100.00%	5	0	33.418	ns
VNPSO-RNP	100.00%	5.06	0.000	36.565	100.00%	5	0	34.522	

TABLE IV
COMPARISONS OF THE RESULTS OF THE FOUR ALGORITHMS FOR SOLVING INSTANCE C100

Algorithm	Mean				best				*t*-test
	Coverage	ReaderNum	Interference	Power	Coverage	ReaderNum	Interference	Power	
GPSO	98.34%	6	0.002	38.652	100.00%	6	0	37.374	Coverage+
VNPSO	99.72%	6	0.000	38.167	100.00%	6	0	36.803	ReaderNum+
GPSO-RNP	100.00%	5.16	0.000	38.800	100.00%	5	0	37.513	ReaderNum+
VNPSO-RNP	100.00%	5.04	0.000	38.513	100.00%	5	0	37.449	

TABLE V
COMPARISONS OF THE RESULTS OF THE FOUR ALGORITHMS FOR SOLVING INSTANCE R30

Algorithm	Mean				best				*t*-test
	Coverage	Readers	Interference	Power	Coverage	Readers	Interference	Power	
GPSO	92.13%	6	0.000	38.849	100.00%	6	0	38.842	Coverage+
VNPSO	94.53%	6	0.000	38.849	100.00%	6	0	38.656	Coverage+
GPSO-RNP	99.87%	7.46	0.002	39.821	100.00%	6	0	39.265	ReaderNum+
VNPSO-RNP	100.00%	6.86	0.003	40.143	100.00%	6	0	39.574	

TABLE VI
COMPARISONS OF THE RESULTS OF THE FOUR ALGORITHMS FOR SOLVING INSTANCE R50

Algorithm	Mean				best				*t*-test
	Coverage	Readers	Interference	Power	Coverage	Readers	Interference	Power	
GPSO	92.52%	6	0.000	39.692	98.00%	6	0	40.520	Coverage+
VNPSO	93.96%	6	0.000	39.690	98.00%	6	0	39.595	Coverage+
GPSO-RNP	99.84%	8.26	0.012	40.652	100.00%	7	0	40.315	Coverage+
VNPSO-RNP	100.00%	7.66	0.030	40.667	100.00%	7	0	40.080	

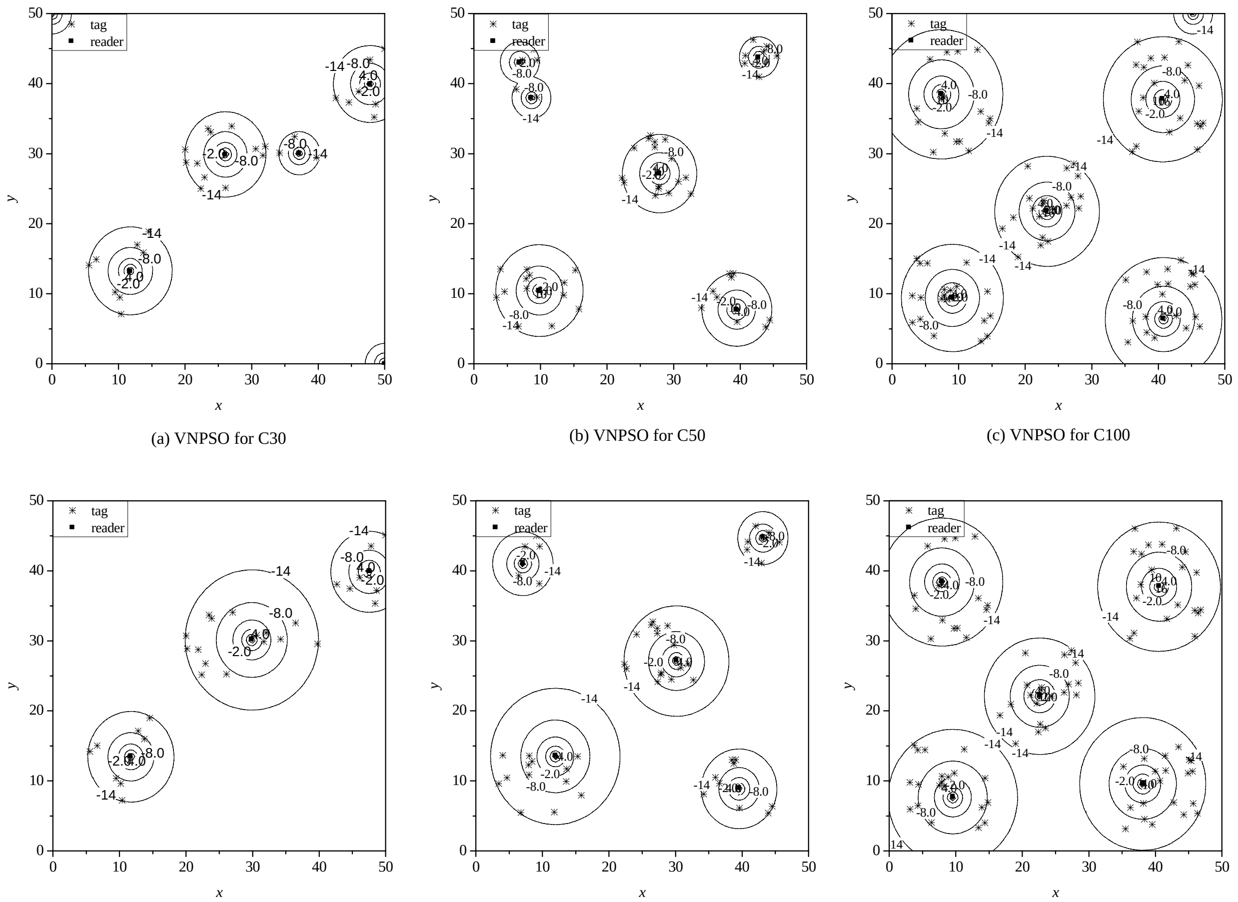
TABLE VII
COMPARISONS OF THE RESULTS OF THE FOUR ALGORITHMS FOR SOLVING INSTANCE R100

Algorithm	Mean				best				*t*-test
	Coverage	Readers	Interference	Power	Coverage	Readers	Interference	Power	
GPSO	91.18%	6	0.014	40.074	95.00%	6	0	40.098	Coverage+
VNPSO	94.14%	6	0.012	40.333	97.00%	6	0.043605	40.657	Coverage+
GPSO-RNP	99.74%	9.24	0.118	41.505	100.00%	8	0	40.925	Coverage+
VNPSO-RNP	100.00%	8.44	0.242	41.462	100.00%	8	0	41.031	

network for the two algorithms, because the excessive use of readers leads to bad experimental results of GPSO and VNPSO. For GPSO-RNP and VNPSO-RNP, the number of deployed readers is set to be 12 in the initialization and reduced by TRE during the optimization. Besides, *maxRG* is set to be 500, and $\Delta\alpha$ is set to be 20% of the variable range. For each instance, all the algorithms perform 50 times independently to obtain statistical results.

B. Experimental Results and Analyses

Table II-Table VII show the experimental results for instances C30, C50, C100, R30, R50, and R100 respectively, where the mean and best results obtained by the four algorithms are reported. In the optimization of instances C30 and C50, all the four algorithms can guarantee full coverage of the network in all runs. Moreover, by embedding TRE and mutation, GPSO-RNP and VNPSO-RNP use much fewer RFID readers than GPSO and VNPSO do. When solving instances C100 and R30, GPSO and VNPSO cannot provide full coverage in each run, whereas the mean coverage obtained by the proposed VNPSO-RNP is 100%. GPSO-RNP performs worse than VNPSO-RNP, but still outperforms GPSO and VNPSO. In



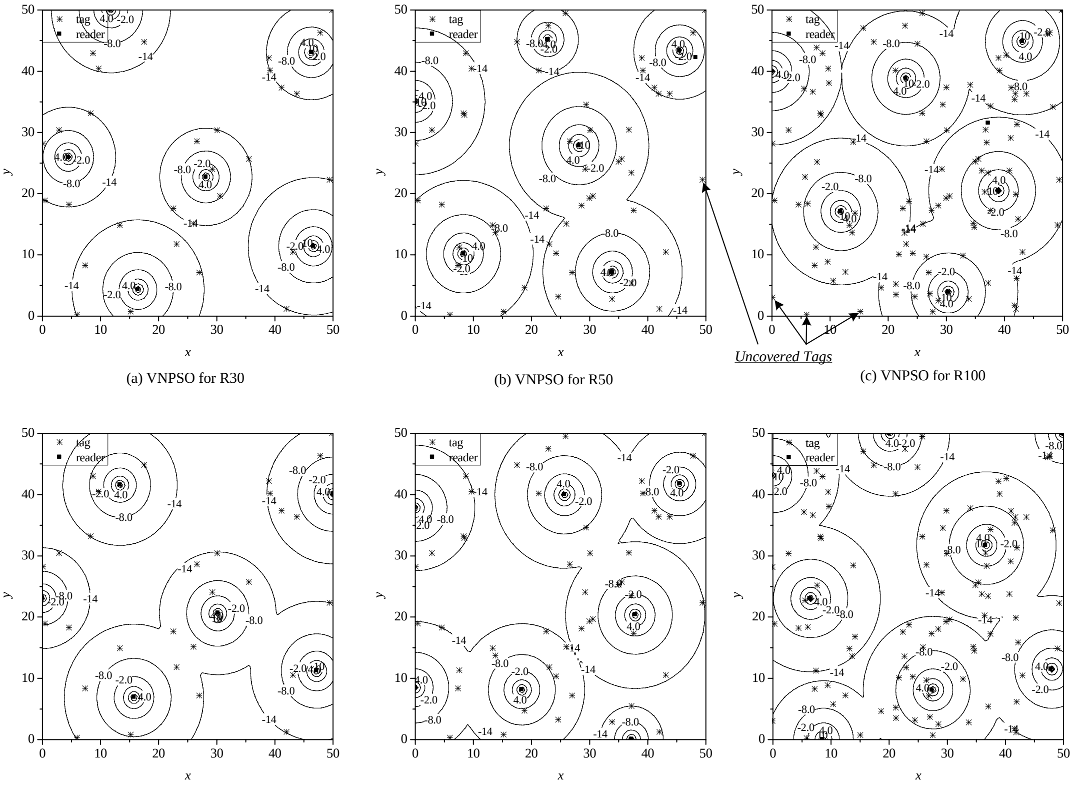
(a) VNPSO for C30
(b) VNPSO for C50
(c) VNPSO for C100
(d) VNPSO-RNP for C30
(e) VNPSO-RNP for C50
(f) VNPSO-RNP for C100

Fig. 7. Reader distribution and radiated power contour for C30, C50, and C100 obtained by VNPSO and VNPSO-RNP.

addition, it can be observed from Table VI and Table VII that GPSO and VNPSO with fixed number of readers cannot reach 100% coverage even in their best runs. On the contrary, GPSO-RNP and VNPSO-RNP can obtain much better results than GPSO and VNPSO for optimizing instances R50 and R100. VNPSO-RNP is the only algorithm that guarantees 100% network coverage for all the instances in all runs. Moreover, the best result of VNPSO-RNP shows that it is able to provide solution with interference equals to 0. That means, each tag in the network is covered by one and only one reader, which greatly improves the QoS of the system.

We also compare the results of VNPSO-RNP with those of GPSO, VNPSO, and GPSO-RNP by hypothesis testing method in order to check the significance of the improvement brought by VNPSO-RNP. Two-sample *t*-test with 98 degrees of freedom at level $\alpha = 0.05$ is performed for each instance. The last columns of Table II-Table VII show the *t*-test results, where "Coverage+" means that the coverage obtained by VNPSO-RNP is significantly higher than that obtained by the other algorithm. Then, if the difference of coverage is not significant, the differences of other objectives are compared. In this way, "ReaderNum+" in Table II-Table VII stands for that the number of readers used by VNPSO-RNP is significantly fewer than that used by the other algorithm. Besides, if the differences of the results yielded by the two algorithms are not significant considering all the four objectives, we place an "ns" in the cell. The *t*-test results show that for all the instances, the proposed VNPSO-RNP algorithm can obtain much higher coverage or fewer readers than GPSO and VNPSO. Moreover, for optimizing five out of the six instances, VNPSO-RNP significantly outperforms GPSO-RNP. This is because, by using the von Neumann topology, the particle swarm is capable of maintaining diversified information in the search process and has stronger global search ability. VNPSO-RNP is not easy to get trapped into local optimum and therefore obtain better mean results.

Fig. 7 and Fig. 8 show the reader locations and radiated power contours for the six instances, in which the best results obtained by VNPSO and VNPSO-RNP are compared in a visible way. A contour in the figures represents the points with the same radiated power (which equals to the value assigned to that contour). It can be seen in Fig. 7 and Fig. 8 that the power peaks in the working area are the points where the readers are placed. Then, the signal strength decreases with respect to the distance to the readers. For the area having no superposition of



(a) VNPSO for R30 (b) VNPSO for R50 (c) VNPSO for R100

(d) VNPSO-RNP for R30 (e) VNPSO-RNP for R50 (f) VNPSO-RNP for R100

Fig. 8. Reader distribution and radiated power contour for R30, R50, and R100 obtained by VNPSO and VNPSO-RNP.

signals, the radiated power contours are circles. As the tag sensitivity threshold is -14 dBm, the tags located within the contour marked -14 are covered by readers. The figures clearly show that VNPSO have redundant readers when solving C30, C50 and C100, and on the other hand it cannot provide full coverage for R50 and R100. The proposed VNPSO-RNP outperforms VNPSO for five out of the six instances. Only when optimizing R30, the results obtained by the two algorithms are similar. But from Table V we can see that, for solving R30, VNPSO cannot guarantee a full coverage in every run and its average result is worse than that of VNPSO-RNP.

These results illustrate the drawbacks of previous works using fixed number of readers in the optimization. Because the required number of readers is hard to estimate, on the one hand deploying too many readers in the network is not cost-efficient, and on the other hand a shortage of readers cannot guarantee the coverage of the network. In contrast, the TRE operator allows the algorithm to begin with a relatively large number of readers, then adaptively delete redundant readers during the optimization, and finally obtain a high coverage by using a proper number of readers. This is the reason why the proposed GPSO-RNP and VNPSO-RNP outperform GPSO and VNPSO.

VI. Application in an Industrial Company

A. Application Background

Changsha Chushunzhiye (CSZY) Ltd. is one of the largest machine-tool manufacturing bases in south central China, which has over 30 years manufacturing history. Equipped with 115 sets of equipments, CSZY produces 7,000 tons of castings, steel structure parts, and other spare parts per year.

In the past, CSZY's job shops adopted a manual pen-and-paper mode to record its processed parts, which has two shortcomings. First, for each job shop, an officer should be employed to supervise the manufacturing work. The officers spent lots of time checking and recoding the processed parts one by one, and were extremely busy when several jobs were finished at the same time. Second, as human errors cannot be

TABLE VIII
The Result of VNPSO-RNP for the Real-World Case

Coverage	ReaderNum	Interference	Power
100%	3	0	35.783

TABLE IX
Detailed Planning for the Real-World Case

Reader ID	Coordinates	Radiated Power	Number of Covered Points
1	(26.81, 0.31)	24.341	3
2	(11.51, 10.32)	31.819	9
3	(44.23, 8.07)	33.000	6

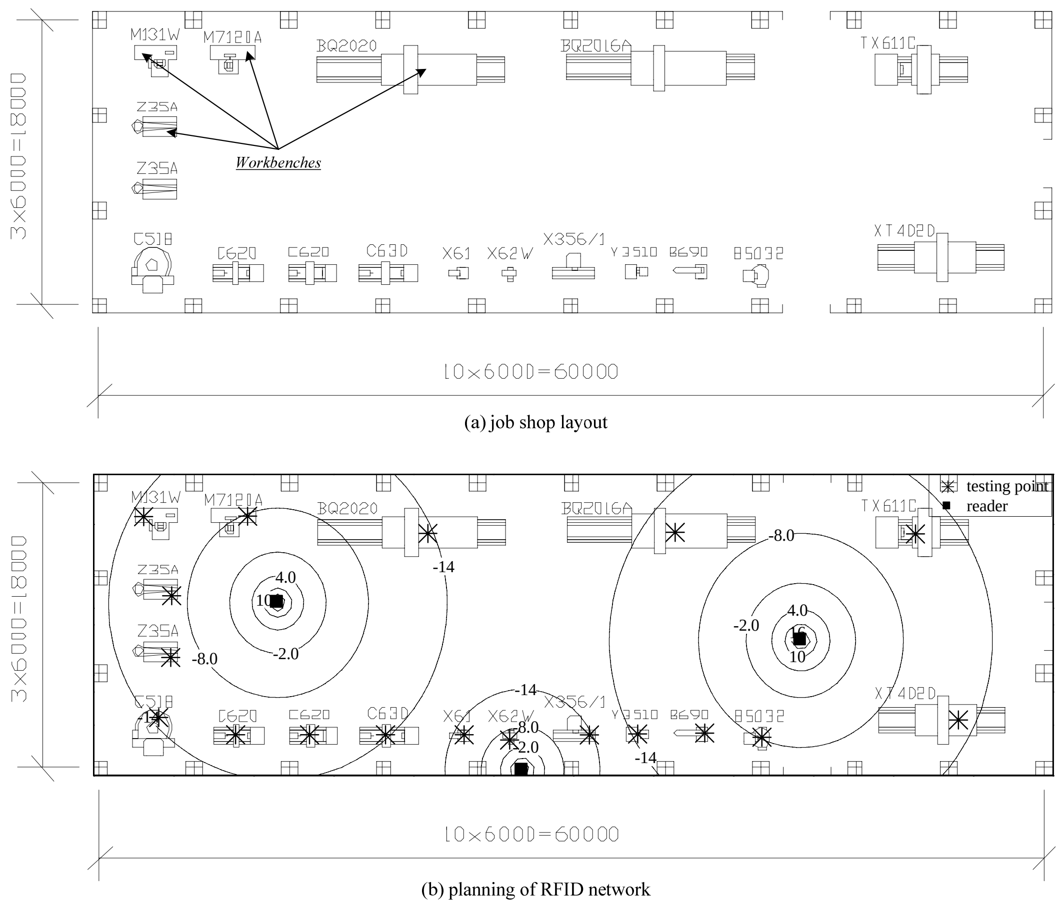


Fig. 9. Illustration of the job shop layout and the corresponding RFID network planning produced by VNPSO-RNP.

avoided, the company has found that the recordings were sometimes incomplete and inaccurate.

To improve efficiency and reduce human mistakes, CSZY seeks to find an RFID-enabled automated solution including:

(1) Install RFID tags on all parts being processed;

(2) Deploy RFID readers to read/write the tags attached to the parts being processed on the workbenches;

(3) Minimize the number of deployed readers;

(4) Replace existing paper forms with electronic spreadsheets;

(5) Develop job shop surveillance software.

It can be observed that CSZY needs an integrated solution to realize automatic information recording, in which the RFID network planning is a crucial issue. As the experimental results in Section V have shown that VNPSO-RNP is very promising for RNP, we apply the proposed algorithm to solve the RNP in each job shop of CSZY. In the following Subsection B, the optimization of the RNP in a specified job shop of CSZY is presented.

B. Experiments and Results

The job shop layout is shown in Fig. 9(a), with a 60 m × 18 m working area containing 18 machines. Tags are attached to the items being processed on the workbenches of those machines. It is required that the signals radiated by the RFID readers cover the testing points on the workbenches in the job shop.

The proposed VNPSO-RNP algorithm is applied to optimize the number of readers used and the coordinates and radiated power of each reader, with parameters the same as those in Section V. Table VIII shows the optimization results, while Table IX presents the corresponding deployment information. Then, a schematic diagram of the RFID network is shown in Fig. 9(b). It can be seen that, by deploying three RFID readers, each testing point is covered by exactly one reader, and the surveillance task in the job shop is accomplished. To summarize, the benefits of the solution produced by the proposed algorithm are three-fold: 1) achieving full coverage; 2) being cost-efficient; 3) excluding signal interference.

VII. Conclusion

In this paper, a PSO algorithm is developed for optimizing RFID network planning. The algorithm does not need to artificially estimate the number of readers deployed in the network, which is always difficult and inaccurate. Instead, by embedding the tentative reader elimination (TRE) operator, the algorithm is capable of intelligently adjusting the number of deployed readers during the optimization process. Therefore, it can begin with a relatively large number of readers in order to guarantee that full coverage of the network can be reached and then eliminate the redundant readers to improve cost-efficiency. Besides, a mutation operator is adopted in the algorithm in order to add diversity to the algorithm as well as to improve the success rate of TRE. Four objectives, namely maximizing tag coverage, minimizing the number of deployed readers, interference, and total transmitted power, are considered in the algorithm and handled in a hierarchical fashion.

In the experiment, the global version and the local version (with the von Neumann topology) of the proposed PSO are implemented, with performance compared with traditional global and local PSO algorithms for solving RNP. Experimental results and comparisons verify the effectiveness and efficiency of proposed algorithm. In addition, the algorithm has been successfully used for automatic information recording in practice. It is a powerful technique for RFID network planning.

Future work is to develop dynamic PSO algorithm or some other online techniques for solving dynamic RNP problems with tags and readers in motion.

REFERENCES

[1] G. M. Gaukler, "Item-level RFID in a retail supply chain with stock-out-based substitution," *IEEE Transactions on Industrial Informatics*, vol. 7, no. 2, pp. 362-370, 2011.

[2] T.-M. Choi, "Coordination and risk analysis of VMI supply chains with RFID technology," *IEEE Transactions on Industrial Informatics*, vol. 7, no. 3, pp. 497-504, 2011.

[3] J. Vales-Alonso, V. Bueno-Delgado, E. Egea-Lopez, F. J. Gonzalez-Castano, and J. Alcaraz, "Multiframe maximum-likelihood tag estimation for RFID anticollision protocols," *IEEE Transactions on Industrial Informatics*, vol. 7, no. 3, pp. 487-496, 2011.

[4] Y.-H. Chen, S.-J. Horng, R.-S. Run, J.-L. Lai, R.-J. Chen, W.-C. Chen, Y. Pan, and T. Takao, "A novel anti-collision algorithm in RFID systems for identifying passive tags," *IEEE Transactions on Industrial Informatics*, vol. 6, no. 1, pp.105-121, 2010.

[5] S. Chalasani and R. Boppana, "Data architectures for RFID transactions," *IEEE Transactions on Industrial Informatics*, vol.3, no.3, pp.246-257, 2007

[6] S. K. Kwok, A. Tsang, and B. Cheung, *Realizing the Potential of RFID in Counterfeit Prevention, Physical Asset Management, and Business Applications: Case Studies of Early Adopters, Department of Industrial and Systems Engineering*, The Hong Kong Polytechnic University, 2007.

[7] I. Bhattacharya and U. K. Roy, "Optimal placement of readers in an RFID network using particle swarm optimization," *International Journal of Computer Networks & Communications*, vol. 2, no. 6, pp. 225-234, 2010.

[8] W.-C. Ke, B.-H. Liu, and M.-J. Tsai, "Constructing a wireless sensor network to fully cover critical grids by deploying minimum sensors on grid points is NP-complete," *IEEE Transactions on Computers*, vol. 56, no. 5, pp.710-715, 2007.

[9] O. Goldreich, *Computational Complexity: A Conceptual Perspective*, Cambridge: Cambridge University Press, 2008.

[10] S. H. Yeung, W. S. Chan, K. T. Ng, and K. F. Man, "Computational optimization algorithms for antennas and RF/Microwave circuit designs: an overview," *IEEE Transactions on Industrial Informatics*, vol. 8, no. 2, pp.216-227, 2012.

[11] N. Pham, A. Malinowski, and T. Bartczak, "Comparative study of derivative free optimization algorithms," *IEEE Transactions on Industrial Informatics*, vol.7, no.4, pp.592-600, 2011.

[12] C. H. Lo, E. H. K. Fung, and Y. K. Wong, "Intelligent automatic fault detection for actuator failures in aircraft," *IEEE Transactions on Industrial Informatics*, vol. 5, no. 1, pp. 50-55, 2009.

[13] S.-H. Hur, R. Katebi, and A. Taylor, "Modeling and control of a plastic film manufacturing web process," *IEEE Transactions on Industrial Informatics*, vol. 7, no. 2, pp. 171-178, 2011.

[14] F. Tao, D.-M. Zhao, Y.-F. Hu, and Z.-D. Zhou, "Resource service composition and its optimal-selection based on particle swarm optimization in manufacturing grid system," *IEEE Transactions on Industrial Informatics*, vol. 4, no. 4, pp. 315-327, 2008.

[15] K. Y. Chan, T. S. Dillon, and C. K. Kwong, "Modeling of a liquid epoxy molding process using a particle swarm optimization-based fuzzy regression approach," *IEEE Transactions on Industrial Informatics*, vol. 7, no. 1, pp. 148-158, 2011.

[16] J. Zhang, H. S.-H. Chung, W.-L. Lo, "Clustering-based adaptive crossover and mutation probabilities for genetic algorithms," *IEEE Transactions on Evolutionary Computation*, vol.11, no.3, pp.326-335, 2007.

[17] H.-N. Chen, Y.-L. Zhua, K.-Y. Hua, and T. Kua, "RFID network planning using a multi-swarm optimizer," *Journal of Network and Computer Applications*, vol. 34, no. 3, pp. 888-901, 2011.

[18] H.-N. Chen and Y.-L. Zhu, "RFID networks planning using evolutionary algorithms and swarm intelligence," *4th International Conference on Wireless Communications, Networking and Mobile Computing (WiCOM'08)*, pp.1-4, 2008.

[19] Q. Guan, Y. Liu, Y.-P. Yang, and W.-S. Yu, "Genetic approach for network planning in the RFID systems," *Sixth International Conference on Intelligent Systems Design and Applications (ISDA'06)*, vol. 2, pp. 567-572, 2006.

[20] Y.-H. Yang, Y.-J. Wu, M. Xia, and Z.-J. Qin, "A RFID network planning method based on genetic algorithm," *2009 International Conference on Networks Security, Wireless Communications and Trusted Computing (NSWCTC 2009)*, vol. 1, pp.534-537, 2009.

[21] H.-N. Chen, Y.-L. Zhua, and K.-Y. Hua, "Multi-colony bacteria foraging optimization with cell-to-cell communication for RFID network planning," *Applied Soft Computing*, vol. 10, no. 2, pp. 539-547, 2010.

[22] W. Liu, H.-X. Chen, H.-N. Chen, and M.-S. Chen, "RFID network scheduling using an adaptive bacterial foraging algorithm," *Journal of Computational Information Systems*, vol. 7, no. 4, pp. 1238-1245, 2011.

[23] J.-H. Seok, J.-Y. Lee, C. Oh, J.-J. Lee, and H. J. Lee, "RFID sensor deployment using differential evolution for indoor mobile robot localization," *The 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 3719-3724, 2010.

[24] A. M. A. Salama, "Antennas of RFID tags," in *Radio Frequency Identification Fundamentals and Applications Design Methods and Solutions*, ch. 6, pp. 93-110, InTech Education and Publishing, 2010.

[25] P. Sanghera, "The physics of RFID," in *CompTIA RFID+ Study Guide and Practice Exam (RF0-001)*, ch. 2, pp. 21-47, Syngress, 2007.

[26] K. V. S. Rao, P. V. Nikitin, and S. F. Lam, "Antenna design for UHF RFID tags: a review and a practical application," *IEEE Transactions on Antennas and Propagation*, vol. 53, no. 12, pp. 3870- 3876, 2005.

[27] P. V. Nikitin, K. V. S. Rao, S. F. Lam, V. Pillai, R. Martinez, and H. Heinrich, "Power reflection coefficient analysis for complex impedances in RFID tag design," *IEEE Transactions on Microwave Theory and Techniques*, vol. 53, no. 9, pp. 2721- 2725, 2005.

[28] P. Pursula, M. Hirvonen, K. Jaakkola, and T. Varpula, "Antenna effective aperture measurement with backscattering modulation," *IEEE Transactions on Antennas and Propagation*, vol. 55, no. 10, pp. 2836-2843, 2007.

[29] C. Floerkemeier and S. Sarma, "RFIDSim—a physical and logical layer simulation engine for passive RFID," *IEEE Transactions on Automation Science and Engineering*, vol. 6, no. 1, 2009.

[30] J. Kennedy and R. Mendes, "Neighborhood topologies in fully informed and best-of-neighborhood particle swarms," *IEEE Transactions on Systems, Man, and Cybernetics - Part C: Applications and Reviews*, vol. 36, no. 4, pp. 515-519, 2006.

[31] Z.-H. Zhan, J. Zhang, Y. Li, and H. S.-H. Chung, "Adaptive particle swarm optimization," *IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics*, vol. 39, no. 6, pp. 1362-1381, 2009.

[32] Z.-H. Zhan, J. Zhang, Y. Li, and Y.-H. Shi, "Orthogonal learning particle swarm optimization," *IEEE Transactions on Evolutionary Computation*, vol. 15, no. 6, pp. 832-847, 2011.

[33] W. N. Chen, J. Zhang, H. Chung, W. L. Zhong, and Y. H. Shi, "A novel set-based particle swarm optimization method for discrete optimization problems," *IEEE Transactions on Evolutionary Computation*, vol. 14, no. 2, pp. 278-300, 2010.

[34] W.-N. Chen, J. Zhang, Y. Lin, N. Chen, Z.-H. Zhan, H. S.-H. Chung, Y. Li, and Y.-H. Shi, “Particle Swarm Optimization with an Aging Leader and Challengers,” *IEEE Transactions on Evolutionary Computation*, in press.

[35] J. J. Liang, A. K. Qin, P. N. Suganthan, and S. Baskar, “Comprehensive learning particle swarm optimizer for global optimization of multimodal functions,” *IEEE Transactions on Evolutionary Computation*, vol. 10, no. 3, pp. 281-295, 2006.

[36] M. R. AlRashidi and M. E. El-Hawary, “A survey of particle swarm optimization applications in electric power systems,” *IEEE Transactions on Evolutionary Computation*, vol. 13, no. 4, pp. 913-918, 2009.

[37] R. V. Kulkarni and G. K. Venayagamoorthy, “Particle swarm optimization in wireless-sensor networks: a brief survey,” *IEEE Transactions on Systems, Man, and Cybernetics - Part C: Applications and Reviews*, vol. 41, no. 2, pp. 262-267, 2011.

[38] S. L. Sabat and L. Ali, “The hyperspherical acceleration effect particle swarm optimizer,” *Applied Soft Computing*, vol. 9, no. 3, pp. 906-917, 2009.

[39] T. Zhang and J.-d. Cai, “A novel hybrid particle swarm optimization method applied to economic dispatch,” *International Journal of Bio-Inspired Computation*, vol. 2, no. 1, 2010.

[40] J. Liu, J. Sun, and W.-B. Xu, “Quantum-behaved particle swarm optimization with adaptive mutation operator,” *Advances in Natural Computation, Lecture Notes in Computer Science 2006*, vol. 4221, pp. 959-967, 2006.

[41] C.-H. Li, Y. Liu, A.-M. Zhou, L.-S. Kang, and H. Wang, “A fast particle swarm optimization algorithm with Cauchy mutation and natural selection strategy,” *Advances in Computation and Intelligence, Lecture Notes in Computer Science 2007*, vol. 4683, pp. 334-343, 2007.

[42] S. H. Ling, H. H. C. Iu, K. Y. Chan, H. K. Lam, B. C. W. Yeung, and F. H. Leung, “Hybrid particle swarm optimization with wavelet mutation and its industrial applications,” *IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics*, vol. 38, no. 3, pp. 743-763, 2008.

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