A Decomposition-based Multi-objective Self-adaptive Differential Evolution Algorithm for RFID Network Planning

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***Abstract*—In radio frequency identification (RFID) networks, designing the positions and the transmitter power parameters of readers to achieve optimal coverage, interference, load balance, power consumption, and total cost is the task of RFID network planning (RNP) problems, which is the core challenge and an NP-hard optimization problem, where nature-inspired optimization methods have been proved extremely useful. In this paper, on account of the well-known multi-objective evolutionary algorithm based on decomposition (MOEA/D), we propose a Decomposition-based Multi-objective Self-adaptive Differential Evolution algorithm (MOSDE/D), in which all these objective functions are optimized simultaneously in a single run by decomposition, and the improved cyclic crowding distance sorting strategy is introduced to ensure the diversity of solutions. Our approach is tested on standard static RFID networks and compared with other algorithms. Our approach is better than other compared methods in terms of the coverage, interference, load balance, number of readers, and power consumption.**

***Index Terms*—RFID network planning, Multi-objective differential evolution algorithm, Decomposition, EA.**

I. Introduction

The Radio Frequency IDentification (RFID) technology is widely used in automatic identification systems. It automatically identifies items and transfers data between readers and tags by wireless communication. The RFID technology has the advantages of working in harsh environment, low cost and fast response. According to the movement state of tags, readers and the variability of readers' power, RFID networks are divided into static RFID networks and dynamic RFID networks. Static RFID networks have been proved useful in many industrial applications, such as supply chain management [1], innovative application [2], and asset tracking [3]. The research of static RFID network planning is very important for industrial applications. It is also the subject of this paper. A standard RFID system usually consists of tags, readers for tags detection, and a central host system, which is used to process the information received by readers. Generally, a RFID network consists of many tags. Due to the scant coverage of a single reader, it is necessary to deploy enough readers in appropriate locations to cover all tags. This problem is called the problem of RFID network planning (RNP), which aims to optimize four objectives: coverage, total cost, interference, and load balance [4]–[6]. The RNP problem has been proved to be NP-hard [4]–[10].

The RNP problem is a typical multi-objective problem. Generally, transforming the multiple objectives into a single objective by the weighting methods is a strategy. However, it is hard to set the appropriate weight to obtain optimal solutions. Recent years, nature-inspired optimization methods have been widely used. The most successful of them are genetic algorithm (GA) [10]–[12] and Swarm Intelligence (SI). In [4], Gong et al. proposed a particle swarm optimization (PSO) combined with a reader elimination strategy to solve the RNP problem. In [14], Tao et al. transformed three objectives, namely coverage, signal interference and load balance, to a single objective by a linear weighted method. They combined a PSO algorithm and a simulated annealing algorithm to deploy RFID readers. In [13], differential evolution is used to solve multi-objective optimization. J. H. Seok et al. [13] were also solve the multi-objective problem by forming an objective through a linear weighted method. However, it is hard to set the appropriate weights.

In this paper, we propose a multi-objective evolutionary algorithm based on decomposition, named as Decomposition-based Multi-objective-Self-adaptive Differential Evolution algorithm (MOSDE/D), to solve the static RNP problem. We use the decomposition strategy to solve the RNP problem as a multi-objective problem. In other words, each objective is considered and optimized at the same time, which improves the performance. In addition, because the performance of differential evolution algorithm is susceptible to parameters, we design a parameters self-adaptive differential evolution algorithm whose parameters are constantly modified in the process of evolution, which makes the solution more accurate.

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The major contributions of our work include:

1. In MOSDE/D, five objectives, namely, coverage, interference, power cost, the number of readers and load balance, are considered simultaneously. These five objectives conflict with each other, and the previous algorithms for the RNP have not considered them simultaneously.

2. A self-adaptive differential evolution algorithm based on decomposition approach is proposed to solve the RNP problem which is a multi-objective problem. Our proposed algorithm optimizes every objective function simultaneously in a single run by decomposition.

3. The parameter adaptive method we propose enables differential evolution algorithms to get better solutions for RNP problems. Due to adopting the improved cyclic crowding distance sorting strategy to ensure the diversity of solutions, the performance of the algorithm is improved.

In the experiments, we test the performance of MOSDE/D in six RNP instances, and compare with curling algorithm (CA-RNP) for RNP problems and PSO with TRE operator. The results show that MOSDE/D obtains better results.

The rest of the paper is organized as follows. A multi-objective RNP problem modelling is formulated in Section II. The self-adaptive differential evolution algorithm (MOSDE/D) is introduced in detail in Section III. In Section IV, the experimental results are presented. Finally, conclusions are given in Section V.

II. Multi-objective RFID network planning problem modelling

A. RFID system

A standard RFID system usually consists of tags, readers, and a central host system, as shown in Fig.1.

Fig. 1. RFID system.

Readers and tags transmit data wirelessly. Tags record data, while readers collect tags' data and transmit them to the central host system.

The RFID tags have two types: active tags and passive tags. Passive tags receive electromagnetic wave from readers and transfer the data back. Because of the characteristics and advantages of passive tags, they are often used in reality. We also use passive tags in this paper.

The reader provides energy to the tag through electromagnetic waves. According to the Frist equation, the power received by a tag from a reader P_t and the power received by a reader from a tag P_r are defined as follows [7]–[9],

$$P_t = P_1 + G_t + G_r - 20log\left(4\pi d/\lambda\right) \tag{1}$$

$$P_r = P_b + G_t + G_r - 20log\left(4\pi d/\lambda\right) \tag{2}$$

where P_1 is the operating power of the reader, G_t and G_r are the antenna gain of tag and reader, d is the distance between the reader and the tag, and λ is the wavelength. P_b is the transmitted power of the tag. According to the Frist equation, $P_b = \delta^2\ P_t$; If P_t and P_r are simultaneously larger than the threshold value T_t and T_r, it is considered that the tag is covered by the reader. From the above equation, we find that the reader can be simplified to an effective range model when the parameters are set. The simplified reader model is presented in Fig.2.

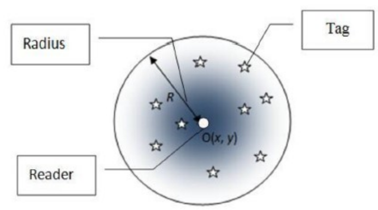

Fig. 2. Simplified reader model.

If the tag is within the power radius of the reader, the tag will be covered; otherwise, the tag is uncovered.

B. Multi-objective RFID network planning

In the RFID network, there are many objectives, such as coverage,total cost, interference, and load balance. A good planning of the RFID network needs to achieve these requirements as much as possible. The evaluation indexs for evaluating RFID systems are given as follows:

1) Coverage: The most important objective in the RFID network planning is coverage. We should try to make the coverage as close as possible or even equal to 1. The coverage is defined as follows:

$$COV = \sum_{t\in \mathbf{TS}} \frac{Cv(t)}{N_t} \times 100\% \tag{3}$$

$$Cv(t) = \begin{cases} 1, & if \exists r \in \mathbf{RS}, d_{r,t} < Radius_r \\ 0, & else \end{cases} \tag{4}$$

where **TS** is the set of tags, **RS** is the set of readers, N_t is the total number of tags, $d_{r,t}$ is the distance between reader r with tag t and $Radius_r$ is the power radius of reader r . Any tag $t \in$ **TS** will be considered to be covered by the reader if there exists a reader $r \in$ **RS** and $d_{r,t} \leq r$. $Cv(t)$ is 1 if tag t is covered; otherwise, $Cv(t)$ is 0.

2) Interference: If a tag is covered by multiple readers at the same time, communication will be unstable and unreliable. This interference should be minimized. For each tag, the more readers that cover it, the larger the amount of interference.The total interference of RFID network is defined as follows:

$$ITF = \sum_{t\in TS} \frac{In(t)}{N_t} \tag{5}$$

$$In(t) = \begin{cases} C(t) - 1, & if \quad C(t) > 1 \\ 0, & else \end{cases} \tag{6}$$

3) Power: In the simplified reader model, power is converted into power radius. Therefore, we can convert the total power of all readers in the RFID system into the total power radius, which is more convenient to use in calculation. The total power radius is defined as follows:

$$POW = \sum_{r\in\mathbf{RS}} Radius_r \tag{7}$$

where $Radius_r$ is the power radius of reader r.

4) The number of readers: Assume that the maximum number of readers could be deployed is N_{max}. The final number of readers N_R should be as small as possible. Obviously, N_R should not be larger than N_{max}.

5) Load balance: Load balance means a more reliable RFID network. It is an important objective of RFID system and defined as follows:

$$LB = \prod_{r=1}^{m} \frac{1}{N_r} \tag{8}$$

where N_r is the total number of tags covered by reader r. A reasonable reader N_r should be greater than 0. If N_r is zero, it means that the reader does not cover any tag. It is redundant and should be moved.

Summarize the above analysis, the multi-objective RFID network planning problem can be formulated as follows:

$$MAXCOV = MinF_1(X,P,S) = 1 - \sum_{t\in\mathbf{TS}} \frac{Cv(t)}{N_t} \tag{9}$$

$$MinF_2(X,P,S) = ITF = \sum_{t\in TS} \frac{In(t)}{N_t} \tag{10}$$

$$MinF_3(X,P,S) = POW = \sum_{r\in\mathbf{RS}} Radius_r \tag{11}$$

$$MinF_4(X,P,S) = N_R \tag{12}$$

$$MinF_5(X,P,S) = LB = \prod_{r=1}^{m} \frac{1}{N_r} \tag{13}$$

$$s.t. X \in D^R \tag{14}$$

$$P_{\min} \le P \le P_{\max} \tag{15}$$

where $F_1(X,P,S)$ is the tag uncoverage, $F_2(X,P,S)$ represents the interference of the system, $F_3(X,P,S)$ is the power cost of the system, F_3 is the number of readers and F_5 is the load balance of the system. The vector X represents coordinates of existing readers, the vector P is the power radius of readers and the vector S is switch of readers which means whether the reader is used. In order to use the Tchebycheff decomposition, we transform the coverage into uncoverage. Thus, all five objective functions need to be minimized.

III. Methodology

In this section, a multi-objectives evolution algorithm based on decomposition is proposed.

First, the basic differential evolution algorithm is briefly introduced and a multi-objective self-adaptive DE for the RNP problem is shown, including solution representation and updating. Then, the improved cyclic congestion distance sorting strategy is introduced. Finally, based on the decomposition method, the framework of MOSDE/D is proposed.

A. Differential Evolution

Differential Evolution algorithm (DE) is a population-based optimization algorithm, which is a type of evolutionary algorithms. Compared with other EAs, DE has lots of advantages, such as simple structure, easier to implement, faster convergence, and stronger robustness. DE uses a greedy approach to solve problems. DE continuously optimizes the quality of the whole population by fusing differential operations into crossover and mutation operations to generate new individuals.

B. Multi-objective Self-adaptive DE for RNP

1) Definition of individual: To solve the RNP problem, we design each individual as follows:

$$\begin{aligned} F_i = \quad & \{x_{i,1}, x_{i,2}, ..., x_{i,N_{\max}}, y_{i,1}, y_{i,2}, ..., y_{i,N_{\max}}, p_{i,1}, p_{i,2}, \\ & ..., p_{i,N_{\max}}, s_{i,1}, s_{i,2}, ..., s_{i,N_{\max}}\}, \quad i = 1, 2, ...pop \end{aligned} \tag{16}$$

where pop is the population size, N_{max} is the maximum number of readers. $(x_{i,d}, y_{i,d})$ is the coordinate of reader d of individual i. $p_{i,d}$ is the power of reader d and $s_{i,d}$ is the switch flag of reader d. If reader d of individual i is used, $s_{i,d}$ is 1;otherwise, $s_{i,d}$ is 0.

2) Initialization of individual: To make the population have better diversity, a good initialization strategy is proposed. In this paper, each reader should not only meet the requirements (14) and (15) in the initialization, but also be screened by coordinates. A reader will be reinitialized when it is too close to previous readers in the initialization, which prevents the generation of redundant readers in advance.

3) Evolutionary operation of individual: The basic differential evolution algorithm mainly includes mutation, crossover and selection, which are given as follows:

- Mutation:
$$v_i = x_{r1} + F(x_{r2} - x_{r3}) \tag{17}$$
where v_i is variation of x_i, and $i, r1, r2, r3 \in \{1, 2, ..., pop\}$ are different indexes. $F \ge 0$ is the scaling factor. What should be noted is that in one mutation operation, only one s_{id} is randomly selected for updating. Others remain the same as x_i. The purpose is to avoid frequent variation of s_{id}.
- Crossover:
In order to ensure that u_i and x_i are different, at least one dimension of u_i and the same v_i are randomly

selected. Other dimensions are generated in the following way:

$$u_{ij} = \begin{cases} v_{ij}, & if(r < R_c) \\ x_{ij}, & if(r \geq R_c) \end{cases} \tag{18}$$

where j=1, 2, ..., N_{max}, r is a uniform random number between 0 and 1. R_c is cross probability factor. Like mutation operations, cross operations allow only one s_{id} to be updated in once cross operation.

- Selection:

  For multi-objective optimization problems, we use the following standard to select the offspring:

  - If u_i Pareto dominates x_i, u_i is chosen as the offspring; If x_i Pareto dominates u_i, x_i is chosen as the offspring;
  - If they do not dominate each other, u_i is chosen as the offspring to maintain diversity of external population (**EP**).

- Self adaptive:

  At the early stage of evolution, the values of F and R_c should be larger in order to control the number of non-dominant individuals and ensure the diversity of the population. At the later stage of evolution, in order to retain good information, the values of F and R_c should be reduced. So the adaptive operator F and R_c is designed as follows:

$$F(t) = F_{\min} + (F_{\max} - F_{\min}) \times e^{-\frac{2t}{Gen}} \tag{19}$$

$$R_c(t) = R_{c\min} + (R_{c\max} - R_{c\min}) \times e^{-\frac{2t}{Gen}} \tag{20}$$

  where t is the number of generations and Gen is the maximum number of generations.

4) Improved cyclic crowding distance sorting strategy: In MOEA/D, **EP**'s diversity is maintained indirectly through uniform weight vectors instead of directly using diversity preservation strategy. The crowding distance ranking strategy does not consider the effect on adjacent solutions after a solution is deleted [16]. In this paper, only one solution with the smallest crowding distance is deleted at a time, and then the crowding distance of its adjacent solutions is updated. This process is repeated until the number of individuals in **EP** decreases to the specified number of non-dominated solutions–K.

5) The framework of MOSDE/D: MOEA/D decomposes multi-objective optimization problems into N scalar single objectives optimization sub-problems, and then optimizes these sub-problems while evolving. In this paper, we used the Tchebycheff approach for the multi-objective decomposition, which is defined as follows [17]:

$$g^{te}(x|w, z^*) = \max_{1 \leq i \leq n} w_i \left| f_i(x) - z^* \right| \qquad st.x \in \Omega \tag{21}$$

where z^*=(z_1^* , z_2^*, ..., z_n^*) is the reference point. The weight vector $w_1, ..., w_M$ are all the weight vectors in which each individual weight takes a value from $\{\frac{1}{H}, \frac{2}{H}, ..., \frac{H}{H}\}$. Here, $M = C_{H+m-1}^{m-1}$, where M denotes the number of weight vectors and m is the number of objective functions. The parameters for dealing with different problems are also different. Details about parameters setting are shown in Section IV.

The framework of MOSDE/D for MORNP is shown in Fig.3.

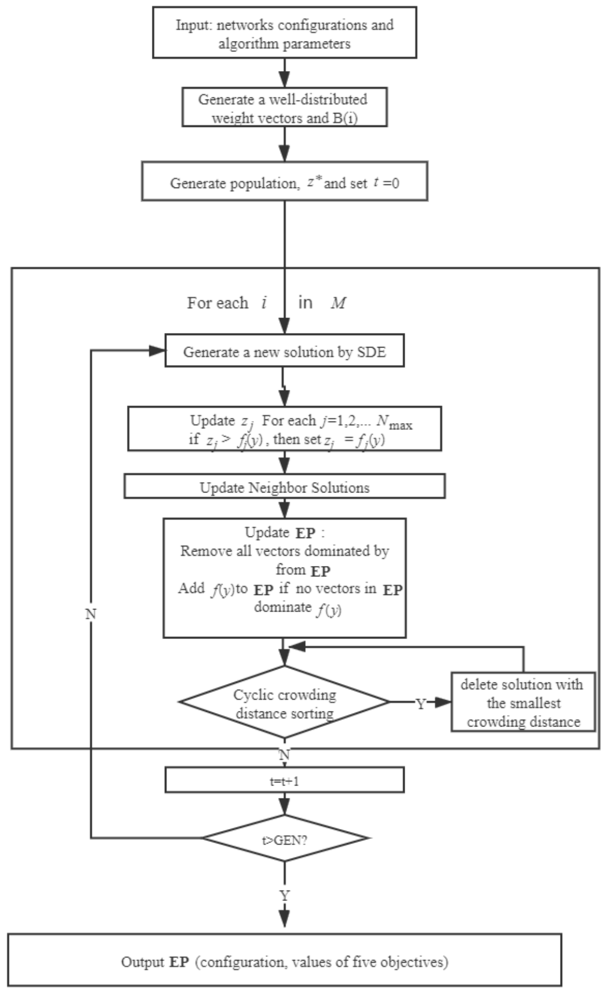

Fig. 3. The framework of MOSDE/D

The specific process is given as follows:

- Step 1: Initialization
  1) Input: $GEN, H, T, m, F_{max}, F_{min}, R_{cmin}, R_{cmax}$ and network configuration;
  2) Setting **EP**=∅;
  3) Generate M weight vectors and compute the T closest weight vectors to the ith weight vector and record their indexes as a set denoted as $B(i)$={i^1,..., i^T}, where w^{i1},...,w^{iT} is the neighbor weight vector of w_i;
  4) Set t=0, initial the population by the initialization method mentioned above;
  5) Take the minimum of each objective as the reference point z^*=(z_1^*,z_2^*,...,z_n^*);
- Step 2: Update

For i=1,...,M, do

1) Reproduction: Randomly select three indexes, k, l, q from $B(i)$, and then generate a new solution y from x^k, x^l, x^q by using self-adaptive differential evolution;
2) Update z: For each j=1, ... , N_{max}, if $z_j > f_j(y)$, then set $z_j = f_j(y)$;
3) Update neighboring solutions: For each index $k \in B(i)$, if $g^{te}(y|w^k, z^*) \leq g^{te}(x^k|w^k, z^*)$, then set $x^k = y$, $f(x^k) = f(y)$;
4) Update **EP**:
Remove all the vectors dominated by $f(y)$ from **EP**;
Add $f(y)$ to **EP** if no vectors in **EP** dominate $f(y)$;
If the number of non-dominant solutions in **EP** exceeds the limit, we use the improved cyclic crowding distance sorting strategy to maintain diversity of **EP**;

- Step 3: If stopping criteria are satisfied, then stop; otherwise, go to Step 2.

IV. Experiments

In the experiments, we test the performance of MOSDE/D on six RNP instances. All instances are taken from [15], which are divided into two types: Samples with clustered distributed tags and samples with randomly distributed tags. Static RFID networks can be divided into random distribution type and clustering distribution type according to the different distribution types of tags. The first letter of the instances' name represents the type of the instance, and the number represents the number of tags in the instance.

The parameters of these RNP instances are given as follows: a 50 m 50 m working space, and the range of radius of power is [8m, 15m]. The parameters of MOSDE/D are given as follows: M=pop=715 (H=9, m=5), Gen=2000, T=10, F_{max} =0.95, F_{min} =0.5, R_{cmin} =0.8, and R_{cmax} =0.95.

The result of MOSDE/D on these six instances are shown in Figs.4-9. MOSDE/D has a good performance on these six instances. The coverage is 100% in all instances. The interference is almost zero on the RFID network with clustering distribution instances. In larger-scale random distribution networks, the amount of interference increases slightly. In each instance, the number and power of readers are small, which means the total cost is low. It shows that MOSDE/D realizes multi-objective optimization and obtains good solutions. No matter the clustered distribution or the random distribution, MOSDE/D can well solve RNP problem.

Next, CA-RNP and PSO_TRE are selected for comparison. They have been optimized especially for the static RFID network planning, and have achieved excellent performance. In Tables I-VI, we compare MOSDE/D, CA-RNP and PSO_TRE on every instance. We record the best, average, and the worst results for each algorithm over 30 independent runs. The performance of MOSDE/D is similar to others in small scale networks. With the increasing number of tags, MOSDE/D shows better performance. In larger scale RFID networks, MOSDE/D always has the best performance in the best case. However, in the worst case, MOSDE/D has the worst performance. Due to the randomness of evolutionary algorithm, MOSDE/D is not stable enough. But MOSDE/D has the best optimization ability, which has the best performance in terms of every objective in the best cases. When the minimum number of readers are the same, MOSDE/D can find the solutions with the lowest power, which means the lowest cost.

In Table VII, the average value of each system index is shown. Each experiment runs 30 times independently and MOSDE/D has a good performance for every instance. At the same time, we find that the coverage decreases with the increase of the number of tags. This appearance is more obvious in the random distribution. After analysis, we consider that two of the five objectives are emphasizing low-cost (power and number). When there are more outlier tags in random distribution, the coverage will be sacrificed to ensure the low cost.

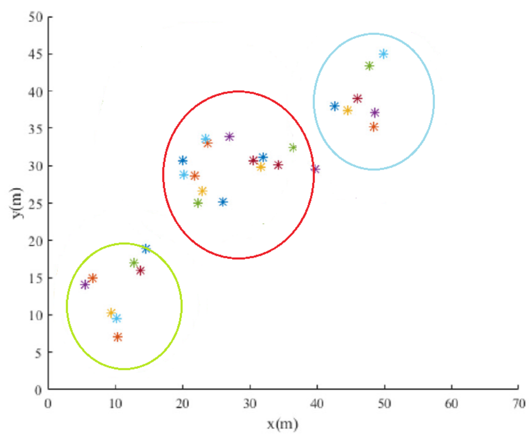

Fig. 4. C_30

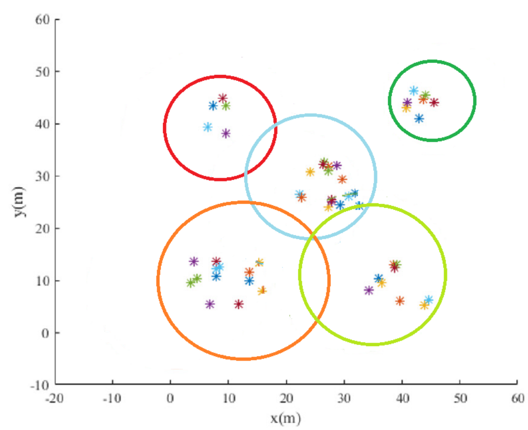

Fig. 5. C_50

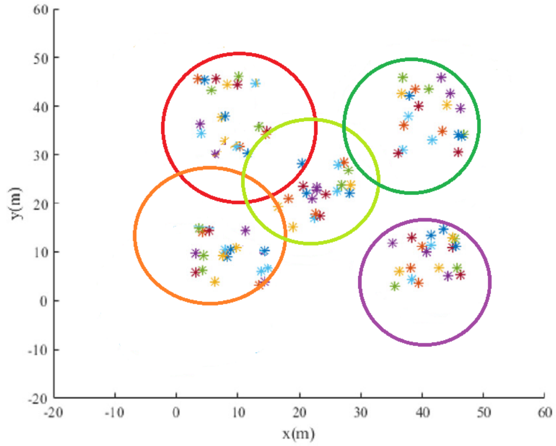

Fig. 6. C_100

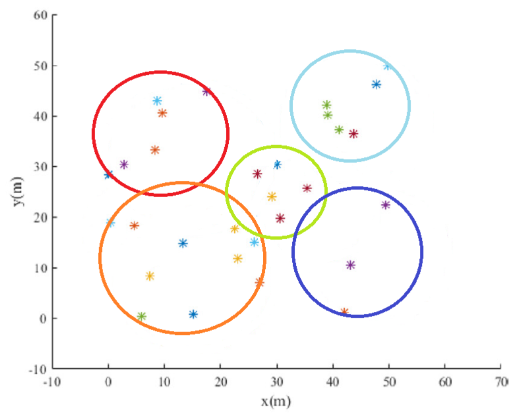

Fig. 7. R_30

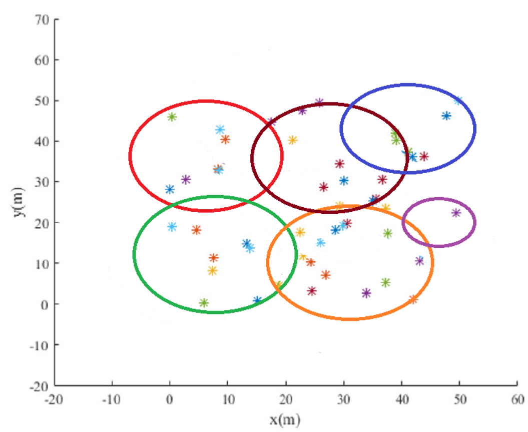

Fig. 8. R_50

TABLE I
COMPARISON AMONG DIFFERENT ALGORITHMS ON C_30

	MOSDE \D			CA			POS_TRE		
	Worst	Mean	Best	Worst	Mean	Best	Worst	Mean	Best
Coverage	0.97	0.98	1.00	0.98	**0.99**	1.00	0.96	0.98	1.00
Interference	0.05	0.02	0	0.05	0.02	0	0.06	0.04	0
LB(10^{-6})	22.3	20.17	19.88	20.46	**19.74**	**16.55**	26.54	23.14	21.08
Power	49	42	**38**	44	**40**	39	46	45	41
Reader number	3	3	3	3	3	3	3	3	3

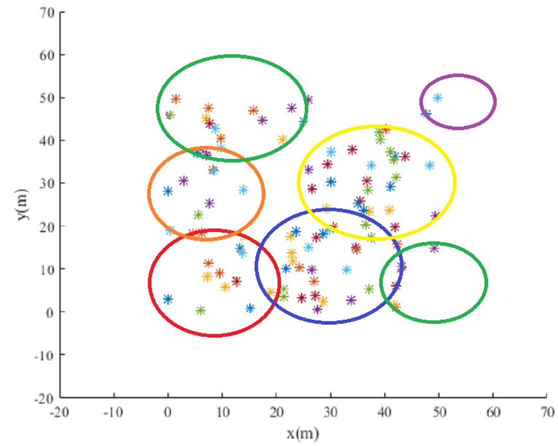

Fig. 9. R_100

TABLE II
COMPARISON AMONG DIFFERENT ALGORITHMS ON C_50

	MOSDE \D			CA			POS_TRE		
	Worst	Mean	Best	Worst	Mean	Best	Worst	Mean	Best
Coverage	0.91	0.99	**1.00**	0.95	0.99	1.00	0.93	0.97	1.00
Interference	0.09	0.04	**0**	0.04	**0.02**	**0**	0.06	0.03	0.01
LB(10^{-6})	18.7	11.5	**9.88**	19.7	12.3	11.9	20.3	14.5	13.4
Power	65	54	**44**	58	51	46	61	58	51
Reader number	5	5	5	5	5	5	5	5	5

TABLE III
COMPARISON AMONG DIFFERENT ALGORITHMS ON C_100

	MOSDE \D			CA			POS_TRE		
	Worst	Mean	Best	Worst	Mean	Best	Worst	Mean	Best
Coverage	0.91	0.98	**1.00**	0.88	0.95	1.00	0.91	0.96	0.99
Interference	0.29	0.11	**0.01**	0.31	0.17	0.02	0.15	0.06	0.04
LB(10^{-6})	3.2	2.14	**0.88**	4.00	2.67	1.01	2.55	1.27	1.01
Power	75	64	**52**	80	68	54	75	69	64
Reader number	**5**	**5**	**5**	6	5.3	5	6	5.5	5

TABLE IV
COMPARISON AMONG DIFFERENT ALGORITHMS ON R_30

	MOSDE \D			CA			POS_TRE		
	Worst	Mean	Best	Worst	Mean	Best	Worst	Mean	Best
Coverage	0.93	0.98	**1.00**	0.94	**0.97**	1.00	0.93	0.96	0.99
Interference	0.06	0.03	**0**	0.05	0.03	0	0.08	0.04	0
LB(10^{-6})	19.7	15.5	13.5	18.9	15.2	**12.8**	20.4	17.7	14.4
Power	57	49	**43**	54	48	46	59	53	49
Reader number	5	5	5	5	5	5	5	5	5

TABLE V
COMPARISON AMONG DIFFERENT ALGORITHMS ON R_50

	MOSDE \D			CA			POS_TRE		
	Worst	Mean	Best	Worst	Mean	Best	Worst	Mean	Best
Coverage	0.88	0.95	**0.97**	0.90	0.94	0.96	0.88	0.93	0.95
Interference	0.17	0.11	**0.07**	0.14	0.11	0.09	0.15	0.13	0.10
LB(10^{-6})	12.41	7.79	**4.43**	10.54	8.86	5.69	13.61	9.88	8.12
Power	69	60	**54**	68	64	59	71	64	60
Reader number	7	**6.2**	**5**	7	6.4	5	7	6.5	6

TABLE VI
COMPARISON AMONG DIFFERENT ALGORITHMS ON R_100

	MOSDE \D			CA			POS_TRE		
	Worst	Mean	Best	Worst	Mean	Best	Worst	Mean	Best
Coverage	0.87	0.93	**0.95**	0.88	0.91	0.93	0.85	0.88	0.91
Interference	0.29	0.17	**0.11**	0.26	0.19	0.16	0.28	0.21	0.19
LB(10^-6)	1.85	1.43	**1.05**	1.91	1.53	1.31	2.02	1.77	1.31
Power	70	62	**59**	69	64	61	73	69	66
Reader number	8	7.7	7	8	7.6	7	8	8	8

TABLE VII
THE COMPARISON IN TERMS OF INDEXES AMONG DIFFERENT INSTANCES

	C_30	C_50	C_100	R_30	R_50	R_100
Reader number	3	5	5	5	6	7
Coverage	1.00	0.99	0.98	0.98	0.95	0.93
Interference	0.02	0.04	0.11	0.03	0.11	0.17
LB(10^-6)	20.17	11.5	2.14	15.53	7.79	1.13
Power	42.55	54.52	63.82	49.53	59.93	62.21

V. CONCLUSIONS

In this paper, we propose a Decomposition-based Multi-objective-Self-adaptive Differential Evolution algorithm for the static RFID network planning. We use the decomposition method to treat the RNP problem as a multi-objective optimization problem and optimize all sub-objectives simultaneously to ensure that the optimal solution can be obtained. We use a simple, efficient and robust differential evolution algorithm as the basic evolutionary algorithm of MOEA/D. We design a set of strategies for multi-objective evolutionary algorithm to solve RNP problems, including coding, mutation, crossover, selection, and so on. At the same time, we improve its static parameters to self-adaptive parameters, which can make algorithm run more efficiently. Moreover, we also improve the diversity protection strategy of **EP** in MOEA/D to make final solutions more accurate.

The experimental results show that MOSDE/D has a good performance in different instances. MOSDE/D can also obtain better solutions than PSO_TRE and CA-RNP. MOSDE/D is more accurate than two other methods in those more complex instances. Based on more detailed objective decomposition, each objective can be considered and optimized. MOSDE/D can usually obtain better and more accurate solutions. However, for the same reason, the calculation cost of MOSDE/D is larger and the time to obtain the optimal solution is longer than that of CA-RNP. When the number of tags is huge, we have to put lots of readers into working space at the beginning to ensure full coverage. Although we use tricks in the population initialization and evolutionary algorithms to speed up as much as possible, we still spend more time than CA-RNP. Thus, we plan to combine MOSDE/D with some parallelize methods in the future to reduce the running time while guaranteeing the performance.

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