An Integrated Model of Placement Optimization and Redundancy Elimination in RFID Network Planning

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Abstract. Radio frequency identification network planning (RNP) is the issue of placing readers in a work area so that the readers cover most of the tags, while satisfying some constraints such as the minimum number of readers used, the minimum interference, the minimum energy consumption, etc. RNP is assessed as an NP-hard problem and natural evolution-based approaches are often used to AQ1 solve them. The paper proposes an integrated model of placement optimization and redundancy elimination, in which the optimal position of readers is found by a genetic-based method and the elimination of redundant readers is accomplished AQ2 by a filtering policy. Gridding the work area is also analyzed, in which the finer the cell size is, the more efficient the reader placement is. The simulation results show that the cell whose size equal to the radius of the reader's interrogation area gives the best efficiency in terms of coverage, amount of used readers and fast AQ3 convergence, but it also suffers a little extra interference.

Keywords: RFID network planning · gridding · cell size · GA-based placement optimization · redundany elimination

1 Introduction

Radio frequency identification (RFID) technology has demonstrated many outstanding advantages such as no physical contact, fast transmission, high security and high storage capacity. Unlike traditional barcode recognition technology, RFID is more widely used to tag of physical objects for monitoring in many different fields such as healthcare, supply chain management, logistics, transportation and agriculture. RFID technology is seen as the foundation for the Internet of Things (IoT), where RFID systems provide the information infrastructure for large-scale IoT applications [1, 2].

An RFID network consists of a collection of RFID tags, one or more RFID readers connected, and a central server to store and process collected data. An RFID tag can be

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active, when it has its power supply, or it can be passive, when it has no power source. In order to respond to an interrogation or transmit its data, a passive RFID tag must draw power from readers. Passive tags are quite cheap, so they are widely used in reality, such as public security, traffic control, warehouse monitoring, etc. [3, 4].

Each RFID reader has a limited coverage range, so it is necessary to place them properly so that the network of RFID readers can cover almost all tags. In addition, the minimum number of used readers, the minimum interference, the minimum energy consumption, etc. are other requirements of an RFID system. Finding an appropriate placement of RFID readers in a work area is known as RFID network planning (RNP) [5] and solving the issue is often hard work because it is rated as NP-Hard [6]. Therefore, the methods inspired by natural evolution, such as genetic algorithms, particle swarm optimization, cuckoo search, etc. are often exploited to solve this problem [7].

The paper proposes an integrated model of placement optimization and redundancy elimination. A genetic algorithm (GA) is used to find the optimal position of readers in terms of maximum tag coverage, minimum number of readers used and minimum interference. For the redundant reader elimination, a policy is proposed to eliminate the redundant readers without or with little impact on the tag interrogation efficiency. To reduce the computational complexity, the number of candidate readers to place is to be limited. The workspace is thus gridded, where each cell is a candidate position to place a reader. The finer the gridding, the smoother the placement of readers will be, but the higher the number of candidate positions and the more complicated the calculation. The paper investigates and analyses some cases of cell size to determine the best gridding.

The main contributions of the article include the following:

(1) proposing an integrated model of GA-based placement optimization and policy-based redundancy elimination; and
(2) investigating and analyzing the impact of the cell size on the reader placement efficiency.

The centents of the next sections are as follows. Section 2 presents works related to the use of GA in solving RNP. Section 3 introduces the proposed model, which describes in detail finding the optimal reader placement based on GA and removing redundant readers based on the proposed policies. The implementation and analysis of simulation results are shown in Sect. 4 and the conclusion is in Sect. 5.

2 Related Works

Since RNP is rated as NP-hard [6], the commonly used methods to solve RNP are based on natural evolution, in which the genetic algorithm (GA) has attracted much attention in literature because of its robust and global search. The following are the reviews of using genetic algorithms in solving RNP.

The first application of GA in solving RNP was proposed by Guan et al. [8], where the goals are to minimize the number of placed readers, maximize the coverage, minimize the interference, and guarantee uplink/downlink signals. These goals are formulated into component objective functions and a fitness function is built as the weighted sum of the component objective functions. To implement GA, Guan et al. proposed a multilevel encoding model for chromosomes, where level 1 identifies the readers' position, level 2 identifies the antenna type, and level 3 contains other parameters (such as signal attenuation). Experimental results on a rectangular area of 120 m^2 show only six readers are needed to cover 92% of a work area, while that proposed by Vasquez et al. [9] requires up to 7 readers, but covers only 90%.

Similarly, Yang et al. [10] proposed a GA-based solution to the multi-objective RNP optimization by mapping the planning into the structure of genes, the chromosome and the operations such as selection, crossover and mutation. This proposal not only eliminates the search errors of the traditional multi-objective optimization method, but also provides an effective solution to RNP.

With Botero & Chaouchi [11], RNP is considered with six objectives, including the minimum overlap area, the minimum number of used readers, the maximum number of covered tags, the minimum number of readers placed out of the work area, the minimum number of redundant readers and the minimum number of tags located in the overlap range. These objectives are formulated as component objective functions and weighted sum to form the fitness function. The chromosome is encoded as a 21-bit sequence that carries information about the energy level and readers' position. Experiments performed on two propagation models of Friis and ITU in a square area of 20×20 m^2 show that ITU model has a smaller coverage, fewer number processing loops and faster processing time than the Friis model.

Xiong et al. [12] use a genetic algorithm to determine the minimum number of readers and their optimal reader placement in a work area of 30×30 m^2 with 99 randomly distributed tags. In the case of using only ten readers, the interrogation area of readers only covered 76 tags, however, it also outperformed those of the previous studies that covered only 72 tags. To cover all 99 tags, Xiong's proposal required 21 readers, but these was still much less than the previous studies that required 30 readers.

Different from the above studies, Tang et al. [13] consider the case of the heterogeneous coverage range. Component objectives including the minimum overlap, reader collision, and interference are formulated into a multi-objective function. The proposed algorithm is an improvement of GA by integrating with a divide-and-conquer greedy heuristic algorithm. The results show that the multi-objective GA achieves better results than some other recently developed evolution-based methods.

Although the genetic algorithm was successfully applied to RNP, the fixed-length encoding scheme limits the adjustment of the number of encoded readers in each chromosome. Therefore, Zhang et al. [14] developed a flexible genetic algorithm in which chromosomes are variable-length, crossover is performed by sub-region swapping and mutation is based on Gaussian-distribution. The experimental results show that the flexible genetic algorithm achieves higher efficiency, in terms of coverage, interference and convergence, compared to traditional genetic approaches.

The proposals for applying GA to solve RNP mainly use fixed-length encoding for chromosomes, but this approach is inefficient in terms of resource usage. The variable-length encoding approach depending on the number of readers in each candidate solution presents more advantages, but the sub-region swapping-based crossover approach does not prove its efficiency in terms of convergence speed. This paper proposes a 2-phase model, in which Phase 1 uses a GA to find the optimal position of readers according to different cell sizes and Phase 2 uses a set of policies of redundancy elimination to minimize the number of used readers.

3 Integrated Model of Placement Optimization and Redundancy Elimination

3.1 Description of RFID Network Planning

We consider a work area of size X × Y m^2 (e.g. 50 × 50), in which the tags are distributed evenly and randomly. To limit the number of candidate positions to place readers, the work area is gridded into cells. Coarse gridding will make the algorithm converge quickly, but it won't find the best placement for readers; while finer gridding increases the chances of finding the optimal placement position, it also increases the computational volume. The problem is how to determine the best cell size without increasing computational complexity.

Assuming that the readers are isomorphic with their transmission frequency of 915 MHz, their transmission power of 2 watts (W), their receive power threshold of 0.1 milliwatts (mW), and their equipped scalar antenna with circular coverage, the antenna coverage radius (r) is determined by $r = \frac{\lambda}{4\pi}\sqrt{\frac{P_t G_t G_r}{P_r}}$, where P_t is the power transmitted by a reader (2 W), P_r is the power transmitted by a tag (0.1 mW or −10 dBm), Gt and Gr, are the gain of the reader and the tag (assumed to be 1), and λ is the signal wavelength (0.3278 m).

By using the above values, the coverage radius (r) of each reader is determined to be 3.69 m. The hexagonal packing-based approach in [15] is an example of the reader placement that covers the entire work area with minimal interference. With a radius of 3.69 m, the distance of two consecutive readers is 2 × 3.69 × cos(30°) ≈ 6.4 m, as shown in Fig. 1. So to cover the entire work area of 50 × 50 m^2 we need (50/6.4)^2 ≈ 64 readers. This is also the maximum number of readers to use (n_{max}). However, depending on the distribution of tags, the number of used readers (n) may be less.

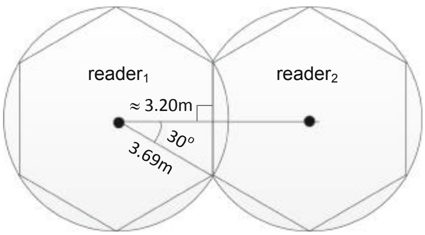

Fig. 1. The circular coverage area is "organised" into a hexagonal cell.

We can choose a smaller cell size to increase the smoothness and flexibility of placement. However, this increases the number of candidate positions. As shown in Fig. 2, by reducing the cell size by half (3.2 m), the number of candidate locations increases to 16 × 16 = 256. This also increases the number of candidate solutions when n readers are placed on these 256 locations and increases computational complexity.

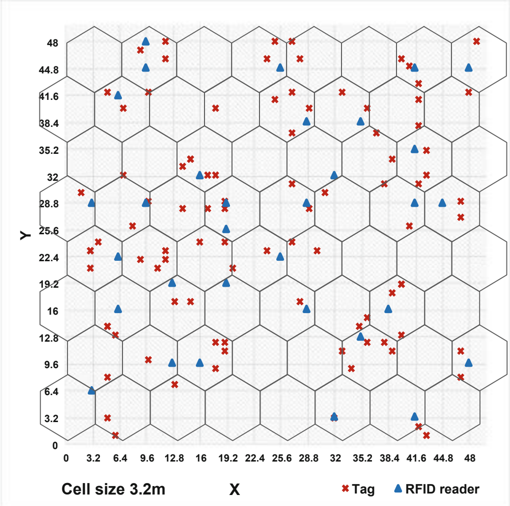

Fig. 2. Example of a gridded work area.

The objective of RNP is to find the position of readers so that the minimum number of used readers and the maximum number of covered tags. Let x_i be indexed to determine the state of reader i, $x_i = 1$ if reader i is used and $x_i = 0$ if reader i is free. The objective of RNP is to minimize the number of used readers:

$$f_1 = \sum_{i=1}^{n_{\max}} x_i \tag{1}$$

subject to cover up to the tags in the work area:

$$f_2 = \sum_{i=1}^{n_{\max}} T_i x_i \tag{2}$$

where T_i is the number of tags covered by reader i and T is the total number of tags in the work area.

In addition, the signal-to-interference ratio (SIR) should also be kept to a minimum. There are two types of interference:

(1) the downlink interference (from reader to tag), which is calculated as the sum of the peak signals received at tag j from reader i divided by the sum of the above signals and interference from other readers:

$$f_3 = \frac{\sum_{j=1}^{n} \sum_{i \in R_j} \max(D_{i,j} x_i)}{\sum_{j=1}^{n} \sum_{i \in R_j} \max(D_{i,j} x_i) + \sum_{j=1}^{n} \sum_{i \in R_j} \sum_{k \in S_j} \max(D_{i,j} x_i)} \tag{3}$$

and the uplink interference (from tag to reader) which is calculated similarly to downlink interference but in the opposite direction:

$$f_4 = \frac{\sum_{j=1}^{n} \sum_{i \in N_j} \max(U_{i,j} x_i)}{\sum_{j=1}^{n} \sum_{i \in N_j} \max(U_{i,j} x_i) + \sum_{j=1}^{n} \sum_{i \in N_j} \sum_{k \in S_j} \max(U_{i,j} x_i)} \tag{4}$$

where R_j is the set of readers i covering tag j (whose distance to tag j is less than the reader coverage radius) and S_j is the set of readers i generating interference at tag j (assumed to be readers have the same distance to tag j). $D_{i,j}$ and $U_{i,j}$ are downlink and uplink signals received/sent at tag j from reader i. For simplicity, $D_{i,j}$ and $U_{i,j}$ are considered as Euclidean distances in coordinates between tag j and reader i.

3.2 Formulation

To solve RNP, an 2-phase model (Fig. 3) is proposed, in which, Phase 1 (the placement optimization) exploits a genetic algorithm to find the optimal position of n readers and, Phase 2 (the redundancy elimination) uses some proposed policies to eliminate redundant readers without or with little effect on tag coverage. Detailed descriptions of Phase 1 and Phase 2 are presented in the next subsections. In fact, eliminating redundant readers can reduce tag coverage, so Phase 1 can be repeated several times to fine-tune the position of used readers. However, before implementing the 2-phase model, the determination of the best gridding should be made to limit the number of candidate positions when readers are trying to be placed.

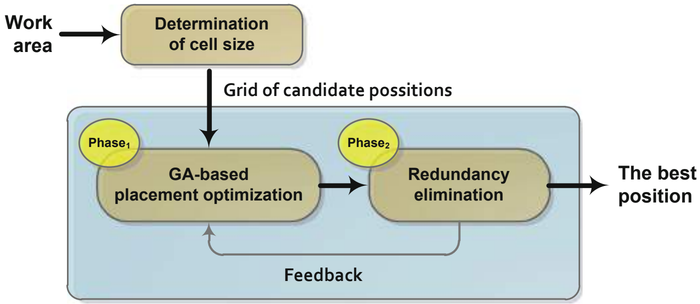

Fig. 3. The 2-phase model of placement optimization and redundant reader elimination

Phase 1: GA-Based Placement Optimization

A genetic algorithm is a search method inspired by natural evolution, in which good parental features are passed to offspring. To be able to apply a GA to solve a real problem, the candidate solutions need to be encoded into chromosomes. Then, evolutionary operations such as selection, crossover (recombination), and mutation are performed to produce offspring. The individuals, including parents and offspring, are then selected to form a new population. The evolution process is repeated until the best individual is found or the convergence condition is satisfied [16]. The operations are described in detail as follows.

To formulate RNP into GA, candidate solutions in the phenotype space need to be mapped to chromosomes in the genotype space. With the goal of determining the optimal position of readers in a work area, the coordinates of readers on the grid are of primary interest. In our formulation, each candidate solution is encoded as a sequence of genes, where 2 consecutive genes represent the coordinate of a reader. As a result, the chromosome is represented as a sequence of $2 \times n$ genes, where n is the number of used readers.

The population needs to be well initiated before performing the algorithm. Initiating the population involves determining the population size and the initial position of individuals. This is important because they affect the speed of convergence and the found optimal solution. For RNP, the initial population is randomly initialized and the number of individuals per population is 5% of the total of candidate solutions. The initial position of individuals has a Gaussian distribution.

At each iteration, the selection of parents for crossover, as well as the selection of individuals for the next generation population, is done based on their fitness. The goal of RNP is to minimize the number of used readers and is subject to the constraints of maximum coverage and minimum interference. Therefore, the fitness function is the weighted sum of the component functions from Eq. (1) to Eq. (4):

$$fitness = f_1 w_1 + f_2 w_2 + (f_3 + f_4) w_3 \tag{5}$$

where w_k is the weight of the k-th objective function and $\sum_{k=1}^{3} w_k = 1$. The best individual has the greatest fitness.

There are different ways to select parents to crossover, such as: randomly, roulette wheel-based, tournament-based, etc., among which the roulette wheel-based selection is the fairest because all individuals have a chance to be selected. Specifically, the selection probability of each individual is converted to the size of a wheel pie corresponding to its fitness value. With this approach, the individual with large fitness has a high probability to be selected (thanks to its large pie), while the individual with small fitness has the low probability of selection.

Crossover can be single-point, multiple-point or uniform. Multiple-point or uniform crossover helps “disturb” the position of the readers at each generation, thus the chances of finding a good position for readers are increased. However, this slows down the algorithm convergence. Therefore, for RNP, the two-point crossover is chosen for the first few generations and a single-point crossover for next generations to increase the chance of global optimization and speed up the convergence.

The mutation is an operation that creates diversity for a population and escapes local optimal positions. However, to ensure that the mutant is not too different from its parent, the mutation probability is often chosen to be very small. With RNP, the mutation is in only one gene with a probability of 0.05. The mutation value must belong to the gridded work area.

The selection of individuals for a new population is made based on the fitness values of offspring and their parents, where 30% of elite parents (with the best fitness) are transferred directly to the new population; the remaining 70% are individuals from the offspring with the best fitness.

The algorithm stops when the fitness does not change anymore over a few generations (e.g. 5 generations), or a given threshold for the maximum number of generations is reached (e.g. 50). The individual with the best fitness in the current population is selected as the encoding of the best-found candidate solution.

Phase 2: Redundant Reader Elimination

The output of Phase 1 is the best position for readers. However, there may be some redundant readers whose elimination does not or significantly affects tag coverage. Therefore, in Phase 2, a set of policies is proposed to eliminate redundant readers and thus reduce the number of used readers. A reader that is considered to be eliminated or disabled must meet the following three criteria:

– Eliminating does not or only reduces less than 1% tag coverage but the total coverage does not reduce below 90%;
– Eliminating can reduce more than 10% of interference; and
– Eliminating does not or only reduce less than 1% of the fitness value.

With the set of redundancy elimination policies, the overall system efficiency is not significantly affected.

4 Simulation and Analysis

The simulation is performed in a work area of 50 × 50 m^2, in which 99 tags were randomly distributed (Fig. 2). The number of readers used is n = 0.5 × n_{max} = 32. The algorithm stops after 50 generations or the fitness does not change after 5 generations. The fitness function is chosen in Eq. (5). Table 1 describes other simulation parameters.

Table 1. Simulation parameters

Parameters	Value
Experimental grid sizes	3.2, 1.6 and 0.8
Individuals/population	8
Selection method	Roulette wheel
Crossover	Single-point and two-point
Mutation (with probability)	Only one gen (0.05)
New population	30% elite parents, 70% best offspring
Weights of the component objective functions	$w_1 = 0.2$; $w_2 = 0.6$ and $w_3 = 0.2$

Simulation objectives include:

– Determining the optimal cell size of the work area at which the optimal position of readers is achieved; and
– Reducing the number of used readers by eliminating redundant readers.

4.1 Determining the Optimal Cell Size

Three surveyed cell sizes include 3.2, 1.6 and 0.8 m respectively, representing 1, 1/2 and 1/4 of the reader coverage radius. The placement efficiency, in terms of fitness, convergence and coverage ratio, is shown in Table 2.

Table 2. Comparison of placement efficiency with different cell sizes

No.	Grid size (m)	Candidate solutions	Best fitness	Convergence (loops)	Coverage ratio
1	3.2	$16^2 = 256$	0.904147	16	94%
2	1.6	$32^2 = 1024$	0.932430	22	98%
3	0.8	$64^2 = 4096$	0.936176	30	98%

From Table 2, we see that the smaller the cell size is, the higher the number of candidate solutions is. That increases the computational complexity and the convergence time. Specifically, with the grid size of 3.2 m, the number of candidate solutions is only 16^2, so only 16 iterations are needed to converge. However, when the grid decreases to 0.8 m, the number of candidate solutions increases to 64^2, so it takes 30 iterations to converge.

Large cell gridding does not help achieve the best fitness because there are few candidate solutions that can choose from. But as the cell size gets smaller, the reader placement becomes smooth and thus an optimal solution can be found where the fitness gets the best value. However, too small cell gridding explodes the computational complexity and prolongs the convergence time, however it improves little fitness and tag coverage. As described in Table 2, the cell size 1.6 m gives good results in terms of fitness, coverage ratio and convergence as that of the cell size 0.8 m. Figure 4 shows that after 30 generations, the fitness value corresponding to the cell size 1.6 m is 3% better than that of the cell size 3.2 m and its fitness value is approximately equal to that of the cell size 0.8 m.

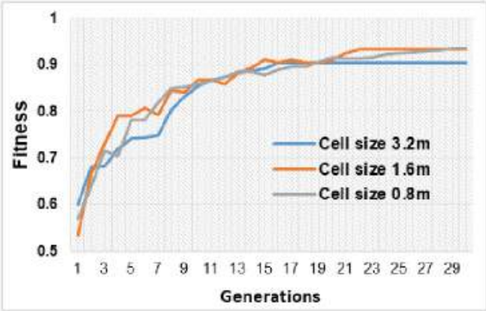

Fig. 4. Comparison of the fitness corresponding to different cell sizes

4.2 Reducing the Number of Used Readers

After finding the optimal position of readers, reducing the number of used readers by the policies of redundancy elimination is considered. As shown in Fig. 5, 4 readers (dotted circles) are eliminated for all 3 cell sizes of 3.2 m, 1.6 m and 0.8 m. However, the reduction of these readers also has an impact on the tag coverage as shown in Table 3, where the fitness corresponding to 2 cell sizes of 1.6 m and 0.8 m is slightly reduced, but the fitness corresponding to the cell size of 3.2 m is slightly increased. It is clear that eliminating some readers has increased the number of uncovered tags. The coverage corresponding to the cell size of 3.2 m is reduced by 2%, but the interference is also reduced by about 7%. In the case of cell sizes of 1.6 m and 0.8 m, the coverage is reduced by 4% and the interference is also reduced by about 7%.

Table 3. Comparison of the coverage and the interference before and after eliminating redundant readers

No.	Grid size (m)	Fitness value		Readers		Coverage (%)		Interference (%)	
		Before	After	Before	After	Before	After	Before	After
1	3.2	0.904147	0.909925	32	28	94	92	17.8	11.4
2	1.6	0.932430	0.924471	32	28	98	94	17.8	11.0
3	0.8	0.936176	0.925513	32	28	98	94	16.6	10.7

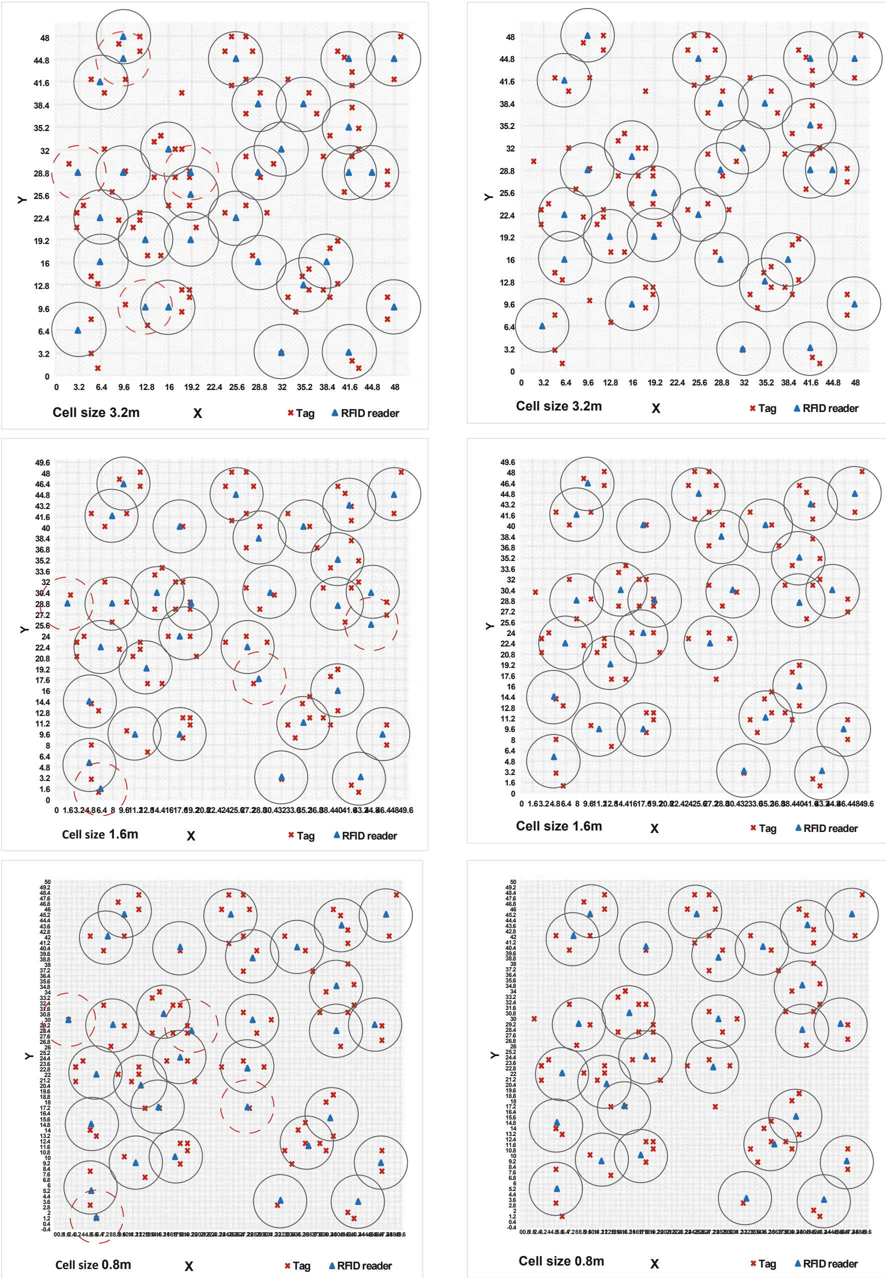

Fig. 5. The optimal position of readers before (left column) and after (right column) eliminating redundant readers with 3 cell sizes of 3.2, 1.6 and 0.8 m.

5 Conclusion

The article has successfully applied the genetic algorithm to find the optimal position of readers with the constraints of maximum coverage and minimum interference. In addition, the article also proposes a set of policies to eliminate redundant readers, so that the redundancy elimination does not or significantly affect tag coverage, interference and fitness. A 2-phase model is proposed, in which Phase 1 optimizes the position of readers based on a genetic algorithm and Phase 2 reduces the number of used readers by eliminating redundant readers. The article investigated and analyzed the impact of different cell sizes on the efficiency of RFID network planning. Simulation results show that our proposal has determined the best cell size (1.6 m) where the minimum number of readers is needed but it still ensures the overall tag reading efficiency for the whole system.

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