An Optimal Model for Allocation Readers with Grid Cell Size and Arbitrary Workspace Shapes in RFID Network Planning

Van Hoa Le[1*]

[1*]Faculty of Event Management and Communication Technology, School of Hospitality and Tourism, Hue University, Hue City, Vietnam. levanhoa@hueuni.edu.vn, https://orcid.org/0000-0001-6621-8617

Received: October 23, 2023; Accepted: December 28, 2023; Published: February 29, 2024

Abstract

RFID Network Planning (RNP) is the problem of deploying RFID readers within a workspace so that each tag can be covered by at least one reader. The objective of RNP is to determine the optimal positions of readers while satisfying certain constraints, such as maximum coverage, minimal interference, load balance among readers, etc. However, most previous studies considered the workspace rectangular or square and assumed a fixed number of readers. They then employed some heuristic methods to find the optimal reader positions. This approach is not practical because the workspace can have any shape, and an approach adaptable to the actual shape of the workspace is needed. This paper proposed an improved adaptive model considering the workspace shape, called RNP-3P. The objectives of RNP-3P are to minimize the number of readers, maximize coverage area, minimize interference, and achieve load balance. RNP-3P optimizes the problem in three phases: Phase 1 involves modeling the workspace with grid cell size, Phase 2 determines the objective function, and Phase 3 proposes the iGAPO algorithm to optimize the number and positions of readers within the workspace. Simulation results demonstrate that the proposed model is more effective compared to other heuristic methods.

Keywords: RFID Networks, RFID Network Planning, Genetic Algorithms, Optimization Number and Positions of Readers.

1 Introduction

Internet of Things (IoT) is an inevitable trend in technology in the near future, the device's communication ability is the most important point of IoT, in Radio Frequency Identification (RFID) technology is contributing to promoting the development of this trend. RFID has been widely applied in the retail business when it is expected to completely replace barcodes or in medical applications with monitoring capabilities to take care of the elderly or infants. In addition, this technology is widely used in security systems, the transportation industry, etc (Costa et al., 2021).

An RFID network consists of a set of RFID tags, one or more RFID readers interconnected, and a central base station for data storage and processing (Figure 1). An RFID tag can be active or passive. Active RFID tags are powered by their energy source, such as a battery, while passive RFID tags do not have their power source. They derive power from the interrogation signal of the reader to respond with a small amount of data (typically the tag ID). Passive tags are relatively small and inexpensive, which

---

Journal of Internet Services and Information Security (JISIS), volume: 14, number: 1 (February), pp. 180-194
DOI: *10.58346/JISIS.2024.I1.012*

*Corresponding author: Faculty of Event Management and Communication Technology, School of Hospitality and Tourism, Hue University, Hue City, Vietnam.

makes them widely applicable in real-world scenarios, such as public security, traffic control, warehouse monitoring, and more.

Each RFID reader has a limited coverage area, so there is a need for an RFID network that allocates RFID readers in a way that they can cover/read all the tags. Additionally, some other constraints such as minimizing the number of readers, minimizing interference, achieving load balance among readers, etc, are additional requirements that can be present in RFID systems. The problem of deploying a network of RFID readers with multiple objectives is known as RFID Network Planning (RNP). Optimizing RNP is a challenging task and is considered NP-hard (Khamayseh et al., 2020). Various proposals have been made to address this problem, primarily using heuristic algorithms such as Genetic Algorithms (GA) (Suriya & Porter, 2014), Particle Swarm Optimization (PSO) (Bhattacharya & Roy, 2010), Cuckoo Search (CS) (Jaballah & Meddeb, 2017), etc. However, these solutions often consider the workspace as rectangular or square. Furthermore, the number of readers in the workspace is usually assumed to be fixed initially, and a heuristic algorithm is used to optimize the positions of these readers. This approach is not realistic since the workspace can have any shape, and the distribution of tags can vary.

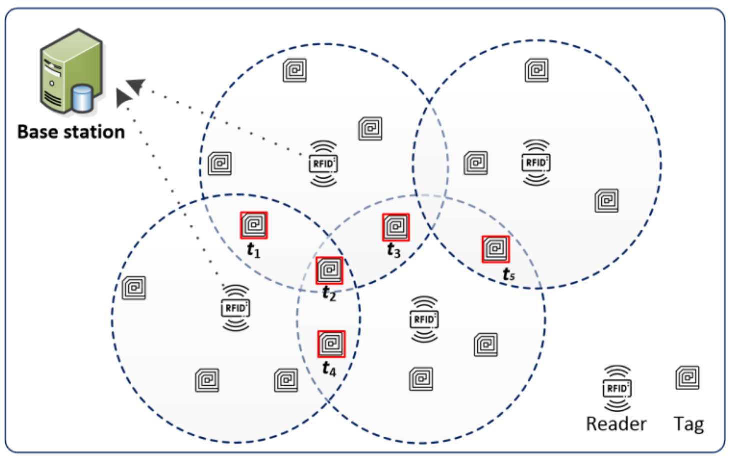


Figure 1: An Example of an RFID System

In this paper, we proposed a method for arranging RFID readers within a workspace of arbitrary shape and subsequently presented a method for optimizing the number and positions of readers using a grid cell size-based approach. The proposed model is named RNP-3P and performs optimization in three phases: Phase 1 involves modeling the workspace based on grid cell size; Phase 2 defines the fitness function; and Phase 3 introduces the iGAPO algorithm to optimize the number and positions of the readers within the workspace.

The subsequent sections of this paper include: Section 2 presents related studies in the field of RNP, Section 3 introduces the proposed RNP-3P model, Section 4 covers implementation results and analysis, and Section 5 concludes the paper.

2 Related Works

Since the RNP problem belongs to the category of NP-hard problems (Guan et al., 2006), the commonly used approach is to use mainly heuristic methods, especially evolution-based methods. chemistry. Among them, the most popular and effective solution is GA and its variations. Guan et al. (2006) is one of the first works to apply GA to the RNP problem. Their goals include minimizing the number of readers needed, minimizing interference, maximizing reader coverage, and ensuring an uplink signal from the tag to the reader. These objectives are formulated into component objective functions and the fitness function is defined as the weighted sum of these component objectives. Experimental results on a rectangular workspace of $120m^2$ show that the genetic algorithm only needs 6 readers to cover 92% of the monitored area, while Vasquez et al. (2001) required 7 readers to achieve 90% coverage.

Applying GA to the RNP problem was also explored by Botero and Chaouchi (2011), considering 6 objectives: minimizing the overlap between readers' coverage areas, minimizing the required number of readers, maximizing the covered number of tags, minimizing the number of readers positioned outside the workspace, minimizing excess readers, and minimizing the number of overlapping tags within reading ranges. Experiments were conducted on two propagation models, Friis and ITU, within a $20 \times 20m^2$ workspace. The results showed that the ITU model exhibited less coverage range, required fewer iterations, and had faster processing times compared to the Friis model.

The study by Xiong et al. (2013) proposed using GA to minimize the number and position of readers in a $30 \times 30m^2$ workspace, using 99 randomly distributed tags. Where only 10 readers are used, the coverage area of these readers can cover 76 tags, which is an improvement over previous studies that only covered 72 tags. To include all 99 tags, the proposal of Xiong et al. (2013) required 21 readers, which is still significantly less than previous studies requiring 30 readers.

In contrast to the above-mentioned studies, the proposal of Tang et al. (2016) proceeds to consider heterogeneous coverage areas. The goal proposed by Tang et al. (2006) is to minimize the cost and interference of readers. The method is to use a divide-and-conquer policy. Simulation results show that the proposed multi-objective genetic algorithm performs better than several evolution-based methods.

One of the limitations of the evolutionary algorithm in the RNP problem is that the coding scheme (chromosome) has a fixed length; This limits the adjustment of the number of readers. Therefore, Zhang et al. (2017) developed a flexible genetic algorithm in which chromosome length can vary. Techniques such as crossover are achieved through region swapping and Gaussian mutation. Simulation results show that the flexible genetic algorithm brings higher efficiency in terms of coverage, interference, and convergence compared to the traditional genetic method.

A combination of GA and PSO has also been proposed by Feng and Qi (2013), where Feng and Qi (2013) introduced the GA-PSO solution for optimizing the allocation of RFID reader positions. The main idea of this hybrid algorithm is to divide the PSO population into multiple swarms and use genetic selection and mutation techniques to improve swarm performance. In another study, Zhu and Li (2018) used a combination of GA and PSO to directly deploy RFID readers for monitoring predictable moving objects.

The combination of using GA with different grid sizes has also been proposed by Le et al. (2023), where three grid sizes of 3.2m, 1.6m, and 0.8m were investigated. The results showed that smaller grid sizes led to higher deployment efficiency. However, this benefit was counterbalanced by increased computational complexity. A recommendation for a grid size of 1.6m was suggested as a compromise between network planning effectiveness and computational complexity. Additionally, the proposal by Le et al. (2023) utilized an ON/OFF policy for readers to eliminate non-compliant readers based on predefined conditions.

However, in all of the aforementioned studies, the assumption of a square or rectangular workspace is unrealistic, as workspaces can have arbitrary shapes. Moreover, the initial number of readers is also assumed to be fixed. Then an effort is made to reduce the actual number of readers needed by deactivating or removing some readers. This lack of flexibility arises when there are changes in the number of tags and the distribution density of tags within the workspace. This paper addresses these issues by proposing a 3-phase model named RNP-3P, in which the first phase involves modeling the workspace using grid cell sizes. The second phase determines the fitness function values, and the third phase employs the improved GA-based Placement Optimization (iGAPO), an enhancement of GA, to optimize the quantity and positions of readers within the workspace. The detailed model is described in the following sections.

3 The RNP-3P Model

Formulation

To optimize the RNP, we proposed an RNP-3P model with 3 phases: In Phase 1, the workspace is transformed into a list of candidate installation positions based on the given grid cell sizes; Phase 2 involves constructing a fitness function that represents the objectives and constraints of the RNP problem; and in Phase 3, an optimal installation position search is performed using an improved version of the Genetic Algorithm (improved GA-based Placement Optimization - iGAPO). The detailed operation of the model is described in Figure 2.

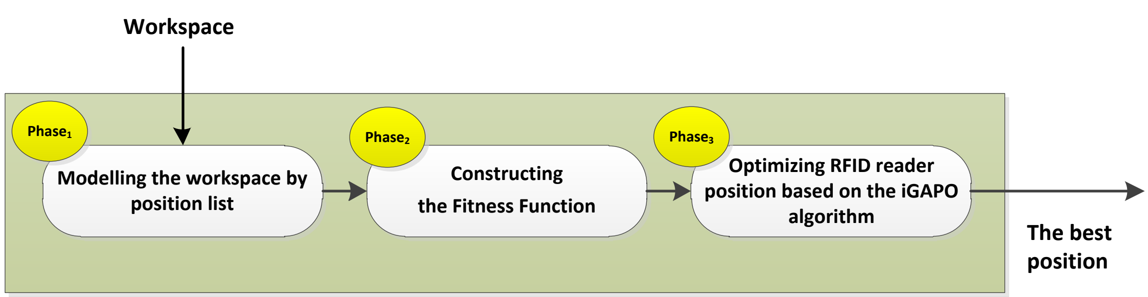


Figure 2: The RNP-3P model

Phase 1: Modelling the Workspace by Position List

Determining the Grid Cell Sizes

Assuming the readers are configured at a frequency of 915 MHz, transmit power of 2 watts (W), receiver power threshold of 0.1 milliwatts (mW), and equipped with an isotropic antenna having circular coverage with a radius determined by Equation (1) (Huang & Chang, 2011; Le et al., 2023).

$$r = \frac{\lambda}{4\pi}\sqrt{\frac{P_t G_t G_r}{P_r}} \tag{1}$$

where:

P_t : The power transmitted by the reader (2 W)

P_r : The power transmitted by the tag (0.1 mW or –10 dBm)

G_t, G_r, : The gain of the reader and tag (assumed to be 1)

λ : The wavelength of the signal (0.3278 m)

r : The radius of the antenna coverage area

By using the aforementioned values, the reading radius of each reader is determined to be r = 3.69m. The access approach based on the concept of hexagonal tiling (Huang & Chang, 2011; Le et al., 2023) serves as an example of arranging readers to cover the entire workspace with the minimum interference region size. With the wave coverage radius of each reader being 3.69m, the distance between the placements of two consecutive readers will be $r = 2\times3.69\times\cos(30^o) \approx 6.4$m, as indicated in Figure 3.

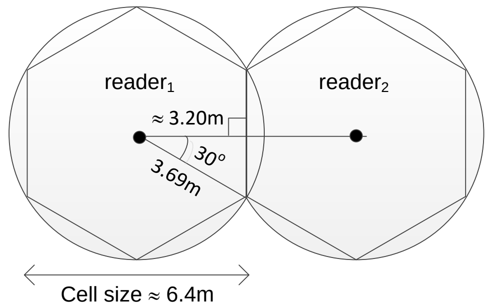


Figure 3: Circular coverage area organized into Hexagons

Thus, with the organization of the circular coverage area into hexagons, the ideal distance between two readers is 6.4m. The RNP problem can therefore be transformed into a reader placement problem with various objectives (maximum coverage area, minimum Interference, maximum load balance, etc.), with an additional constraint that the minimum distance between two neighboring readers is 6.4m. Note that the value of 6.4m might change depending on the RFID hardware technology and the available power of the readers. Newer RFID reader technologies might have broader coverage areas, but as the reader's power decreases, its coverage area might shrink. Nevertheless, the solution we propose remains adaptable to these assumptions.

Determining the List of Installation Positions

As mentioned above, the proposed solutions for the RNP problem often consider a rectangular or squared workspace, which is not suitable for real-world deployments. In this paper, we examine a workspace of arbitrary shape, and without loss of generality, we assume an elliptical working area with a major axis of 50m and a minor axis of 30m, as shown in Figure 4. The tags are randomly and uniformly distributed within the working area. To limit the number of candidate installation positions, the working area is divided into a hexagonal grid (Figure 3). The grid cell diameter is 6.4m as analyzed in the above section.

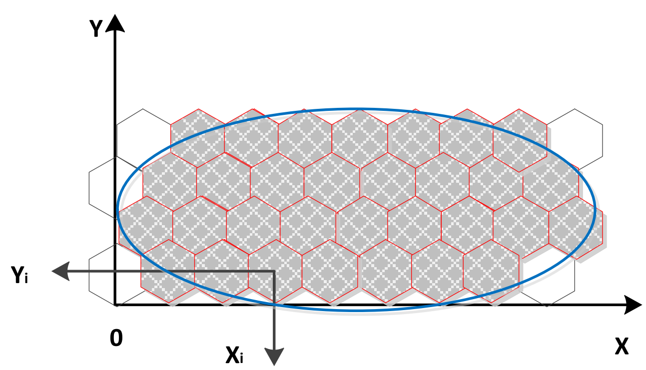


Figure 4: An example of a working area divided into a cell size

As depicted in Figure 4, only grid cells size with an area larger than 50% of the working area (grey cells) are considered for reader placement, while the remaining cells with an area less than 50% of the working area are excluded from reader placement consideration (white cells). Based on this criterion, we create K positions (assuming there are K positions) of candidate installation positions. The RNP problem is then transformed into a search problem to find the optimal positions of n readers from K positions of candidate cells. There will be C_K^n possible solutions.

Phase 2: Constructing the Fitness Function

Deploying readers within a working area needs to satisfy various criteria, which are formulated as objective functions. Common criteria such as coverage, interference, and load balance are often considered in RNP problems by many studies. This paper also considers these criteria to evaluate the effectiveness of the RNP-3P model.

Coverage

Improving coverage is always a crucial goal in RFID network design. In many applications, full coverage is required, meaning that each tag is covered by at least one reader. Let N_r be the set of initially deployed readers, and TS be the set of tags. Since both communications from the reader to the tag and communication from the tag to the reader are considered, for any $tag \in TS$, it is considered to be covered if and only if there exists a $tag \in TS$, that satisfies the condition $Distance(reader, tag) < r$ (the Euclidean distance from the reader to the tag is less than the reading range).

The coverage ratio of the network can be defined as in Equation (2), where f_1 is the coverage objective function.

$$f_1 = COV = \sum_{tag \in TS} \frac{cv(tag)}{|TS|} \tag{2}$$

where

$$cv(tag) = \begin{Bmatrix} 1 & if\ \exists\ reader\ \in\ RS, Distance\ (reader, tag) < r \\ 0 & otherwise \end{Bmatrix}$$

and $|TS|$ is the number of tags distributed within the working area.

According to Equation (1), the value of f_1 belongs to the range (0, 1): a larger f_1 indicates greater efficiency as it implies a higher number of tags being covered.

Interference

Achieving complete tag coverage can lead to overlapping interrogation areas for the readers. This coverage can cause interference when multiple readers attempt to query a tag simultaneously, resulting in read errors and consuming more energy (Figure 1, tags are named from t_1 to t_5). Therefore, one of the important next tasks of RNP is to reduce interference. To address this, the paper proposed a function to reduce the number of tags read in interference areas, as described in Equation (3):

$$f_2 = \frac{|TS|}{|TS| + I_t} \tag{3}$$

Where I_t represents the number of tags within the interference area. The value of $f_2 = 1$ when $I_t = 0$, indicates that in this case, the installation of readers does not cause interference.

Load Balance

In an RFID system, load balance for the readers is essential because it affects the balance of their energy consumption. In practice, the energy of the readers is not unlimited. If a reader is responsible for too many tags, it will quickly deplete its energy, and communication quality will deteriorate. However, if a reader operates below its average capacity because it only handles a few tags, this will result in resource waste and increase network planning costs. Therefore, building an RFID system needs to consider load balance. The formula for determining the load balance objective function (Cao et al., 2021) is as follows:

$$f_3 = \prod_{i=1}^{|N_r|} {}^{1}\!/_{T_i} \tag{4}$$

In which T_i represents the number of tags handled by reader i.

Combining the Objective Functions: Fitness Function

While the primary objective of the RNP problem is to minimize the number of required readers, it's important to ensure other constraints such as coverage, interference, and load balance are met. Therefore, the fitness function for each candidate solution is calculated as the weighted sum of the objective functions (2), (3), and (4) using the following Equation (5):

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

Where w_k represents the weight of objective function k, and $\sum_{k=1}^{3} w_k = 1$. The best solution has the highest fitness value.

Phase 3: Optimizing RFID Reader Position based on the iGAPO Algorithm

iGAPO Algorithm

Currently, there are numerous research studies applying heuristic algorithms such as GA, PSO, CS, etc., to optimize the placement of RFID readers. Each solution comes with its advantages and disadvantages. However, most of these studies fix the initial number of readers (N_r), which limits adaptability. If N_r is set to a small value, achieving complete tag coverage becomes challenging. Conversely, if N_r is set too high, it leads to inefficiencies, increased interference, and load balance.

Therefore, we propose an algorithm named iGAPO (improved Genetic Algorithm Placement Optimization) to search for the optimal placement positions of *n* RFID readers with the smallest possible value N_r. The details of the iGAPO algorithm are described in Figure 5.

The goal of our proposed iGAPO algorithm is to optimize the number and position of readers allocated in a workspace of arbitrary shape, which is consistent with real-world workspaces. Optimizing the number and position plays a crucial role in the RNP problem. On one hand, it helps minimize equipment investment costs by finding the optimal number of readers. On the other hand, determining the optimal locations aids in the installation and control of evaluation criteria related to coverage, interference, and achieving a better load balance. This forms the basis for the algorithm's ability to deploy and install RFID reader devices in real-world workspaces.

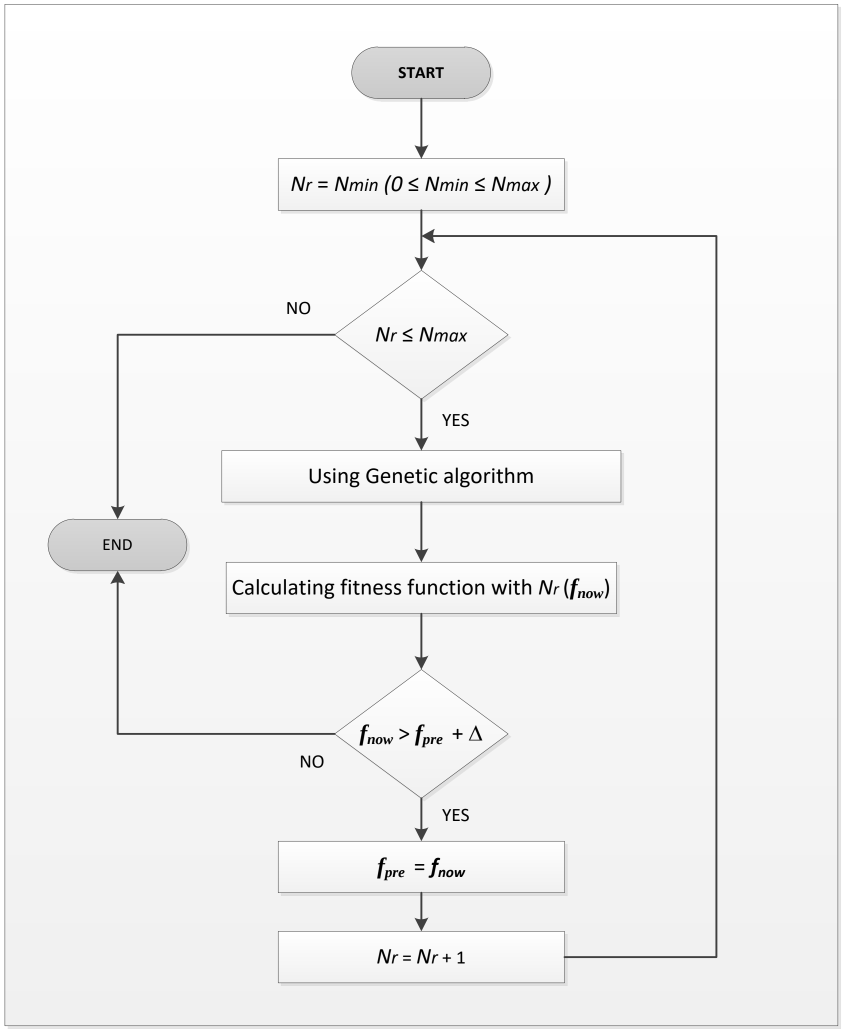


Figure 5: Flowchart of proposal iGAPO algorithm

The algorithm is executed as follows:

First, we determine N_r (the number of readers allocated within the workspace) using the formula $N_r = N_{min}$, where N_{min} represents the minimum number of readers that can be allocated in the system and và $0 \leq N_{min} \leq N_{max}$. N_{max} is the maximum number of readers that can be allocated. As shown in Figure 4, N_{max} is calculated as $N_{max} = K = 34$.

The iGAPO first checks the condition $N_r \leq N_{max}$. If $N_r = N_{max}$, the algorithm terminates because at this point, the number of readers is nearly covering the entire workspace, and there is no need to search for optimal installation positions anymore. If $N_r \leq N_{max}$, the improved GA is invoked (see Section **Using Genetic Algorithm**) to determine the optimal positions for N_r readers. The fitness function value f_{now} is determined based on the current N_r readers.

Next, the condition $f_{now} > f_{pre} + \Delta$ is checked, where f_{pre} is the previous fitness value when the number of readers was N_r -1, and Δ is the fitness change value (determining the extent of fitness value change beyond a certain threshold to adjust the number of readers). If this condition is satisfied (**YES**), f_{pre} is updated to f_{now}, and the value of N_r is increased. If this condition is not met (**NO**), the algorithm terminates because increasing the number of readers at this point does not improve the objective fitness function value. In this case, the current number of readers N_r is considered optimal for the working area. The algorithm will terminate in two scenarios: (1) when N_r reaches N_{max} or (2) when it finds the best N_r value according to the fitness function provided.

Using Genetic Algorithm

The objective of the RNP problem in this paper is to determine the optimal positions of readers within the workspace, so the position of each reader on the grid is of primary concern. Therefore, candidate solutions are encoded as pairs of genes representing the positions of readers in each candidate solution. The result is a chromosome structure consisting of a sequence of $2N_r$ genes, where N_r represents the number of readers. Figure 6 illustrates the structure of a chromosome.

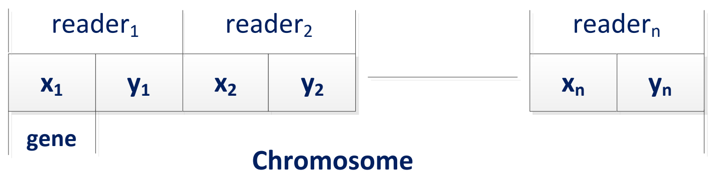


Figure 6: Chromosome Structure

The genetic algorithm is executed as depicted in the diagram in Figure 7.

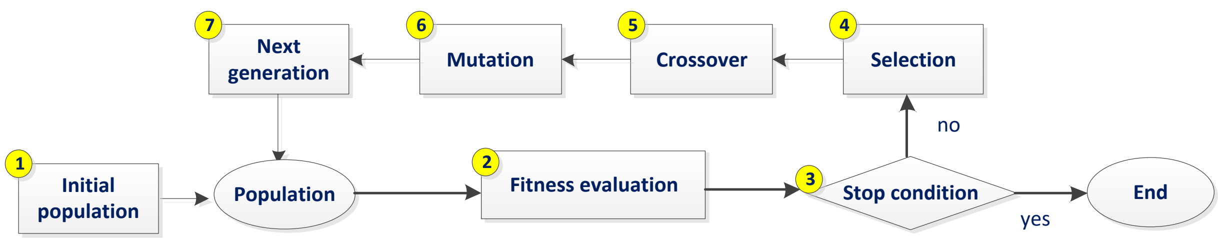


Figure 7: Genetic Algorithm Flowchart

1. The initial population is randomly initialized with several individuals in the population equal to 5% of the total number of individuals in the population. To ensure that individuals are evenly distributed in the solution space, we initialize them according to a Gaussian distribution.
2. To select the best individuals for the next generations, we use the fitness value described in Equation (4).
3. For Genetic Algorithms, the stopping criterion is often a specific number of generations (e.g., 50 or 100). Additionally, we recommend adding a condition where the fitness value remains unchanged for a certain number of generations (e.g., 3 or 5 generations) to reduce the number of generations further.
4. The method for selecting parents for crossover is based on the roulette wheel, where the size of each slice (pie) of the wheel corresponds to the fitness of each individual in the population. With this selection method, any individual has a chance to be chosen. Individuals with higher fitness have a higher probability of selection, while individuals with lower fitness have a lower probability of selection (as shown in Figure 5). An example of the probability of selecting parents for mating among 5 individuals based on their fitness values in Figure 8.

Individual	Fitness
1	0.865
2	0.569
3	0.9856
4	0.1258
5	0.6895

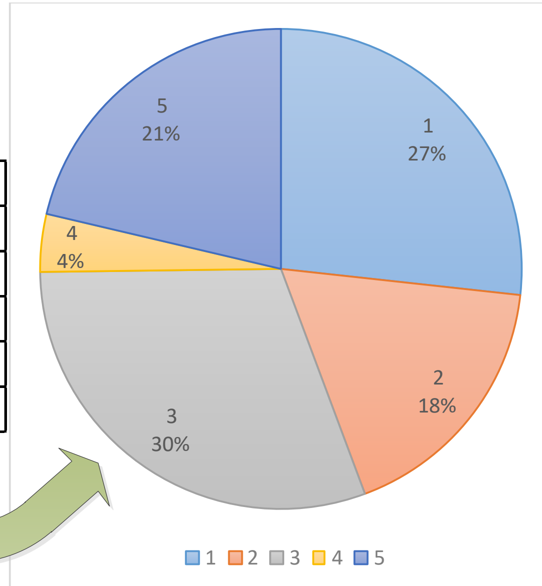


Figure 8: An example of the probability of selecting parents for mating among 5 individuals based on their fitness values

1. In Genetic Algorithms, crossover can occur at a single point, multiple points, or uniformly. In this RNP problem, the crossover is performed at a single point, where the crossover point is randomly chosen.
2. The mutation is typically performed only at one gene and with a relatively low probability (around 0.01), aiming to introduce diversity in the offspring while ensuring that the mutated individual is not too different from its parents. The mutation value range must be within the coordinate domain of the working region.
3. The new population is selected based on the fitness values of the offspring and their parents, of which 20%-30% of elite individuals are transmitted directly to the next generation and 70%-80% The remaining individuals (including the remaining parents and newborn offspring) have the best fitness.

The algorithm stops when the fitness value does not change for a certain number of generations, for example, 5 generations. The individual with the best fitness in the population will finally be chosen as the encoding for the best candidate solution found.

4 Simulation Results and Analysis

The simulation is implemented using the Python programming language. To maintain generality, we assume an elliptical working area with a major axis of 50m and a minor axis of 30m, as shown in Figure 4, where 90 RFID tags are randomly distributed within the test area. The weights of the objective functions f_1, f_2 and $f3$ are determined as follows: $w_1 = 0.6$, $w_2 = 0.2$, and $w_3 = 0.2$. The coverage criterion is still considered the most important, so it has a higher weight. By dividing the area into cells with a size of 6.4m, the maximum number of readers that can be deployed in the working area is $N_{max} = 34$. The simulation parameters are as shown in Table 1.

Table 1: Simulation Parameters

Parameters	Value
Fitness weight	w_1 =0.6; w_2 =0.2; w_3=0.2
Fitness function	Equation (5)
N_{max}	34 RFID reader
N_{min}	15 RFID reader
Δ value	0.01
stopping condition	Over 100 generations or 5 generations, fitness remains unchanged
The number of individuals/population	8
The selection method	Roulette wheel
Crossover method	A crossover point
Mutation method (probability)	A gene (0.05)
Selecting the next generation	30% from the best of parents and 70% from the best of offspring

The Simulation Objectives Include

- Comparing the efficiency of RFID network planning based on GA and iGAPO;
- Comparing the efficiency of the iGAPO as the number of tags varies.

Comparing the Efficiency of RFID Network Planning based on GA and iGAPO

We conducted a comparison between iGAPO and GA in a workspace with 90 tags, and the number of readers varied between 15, 20, and 25 for GA. The results are illustrated in Figure 9. The findings indicate that iGAPO has a better fitness value than GA in all three cases when GA is used with a fixed number of readers at 15, 20, and 25. Additionally, the generation count to achieve convergence for iGAPO is also better than GA. Specifically, GA with a fixed number of readers at 15 converges in 50 generations, with 20 readers converging in 60 generations, and 25 readers converging in 70 generations. In contrast, iGAPO achieves convergence in 50 generations.

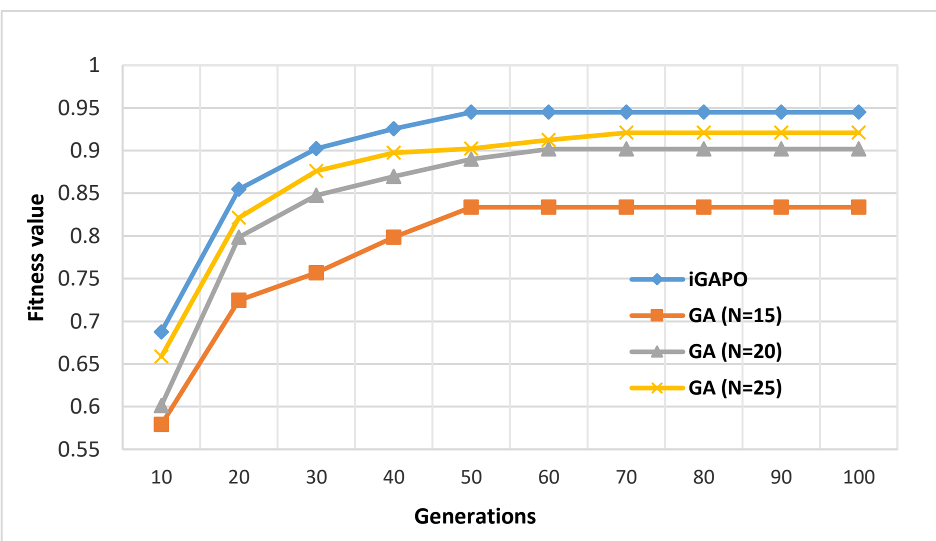


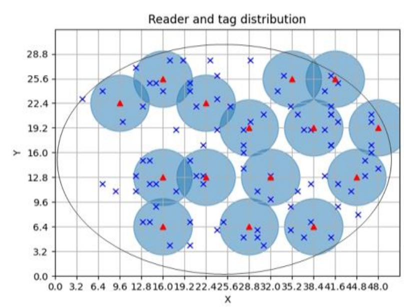
Figure 9: Compare the fitness value of iGAPO with GA

A comparison of GA in Table 2 according to the criteria of fitness value, coverage, interference, and load balance shows that as we increase the number of readers, fitness value also increases in GA. The reason for the increase in fitness value is the improved card coverage. Specifically, with 15 readers, the coverage only reached 76.67%. However, it increases to 91.11% with 20 readers and 96.67% with 25 readers. Increasing the number of readers also leads to an increase in noise values due to increased overlap of reader regions. As shown in Figure 10(a), with 15 readers there are only 4 tags in the interference area, but with 20 readers in Figure 10(b) there are 7 tags, and with 25 readers in Figure 10(c), 10(d), there are 11 tags. Increasing the number of readers also leads to a decrease in load balance, with 15 readers reaching 91.25%, while with 20 readers, this number drops to 85.32%, and 82.66% with 25 readers.

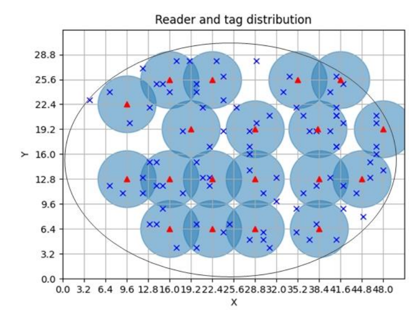
Table 2: Comparison of the efficiency of the GA and iGAPO

Algorithm	**N_r**	**fitness**	**f_1**	**f_2**	**f_3**	**Coverage**	**Interference**	**Load balance**
GA	15	0.83362	0.76667	0.955556	0.9125294	76.67%	4.44%	91.25%
	20	0.90176	0.91111	0.922222	0.8532439	91.11%	7.78%	85.32%
	25	0.92087	0.96667	0.877778	0.8265894	96.67%	12.22%	82.66%
iGAPO	21	0.94487	0.95556	0.933333	0.9243659	95.56%	6.67%	92.44%

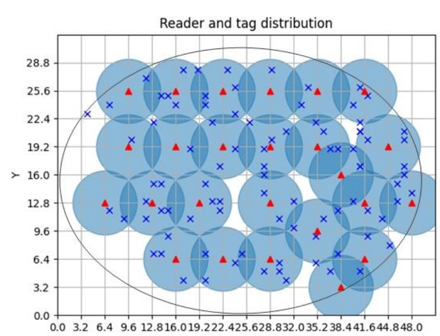
From the results above, we can observe that using the GA for the RNP problem is less efficient. When increasing the number of readers, the fitness value increases, but it comes at the cost of increased interference and reduced load balance. Moreover, in the RNP problem, determining the minimum reader value to achieve the most criteria is of the highest priority. Therefore, we propose using the iGAPO for Phase 3 of the proposed model to address this goal.



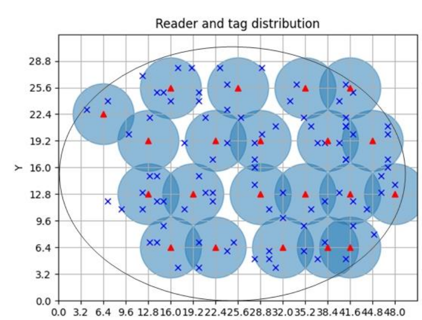
(a) GA with 15 RFID reader



(b) GA with 20 RFID reader



(c) GA with 25 RFID reader



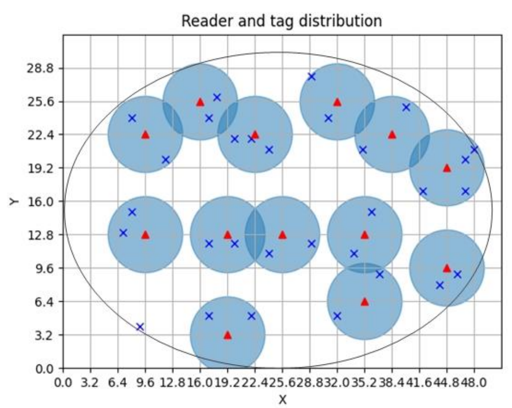
(d) iGAPO with 21 RFID reader

Figure 10: Allocation of reader positions using iGAPO compared to GA

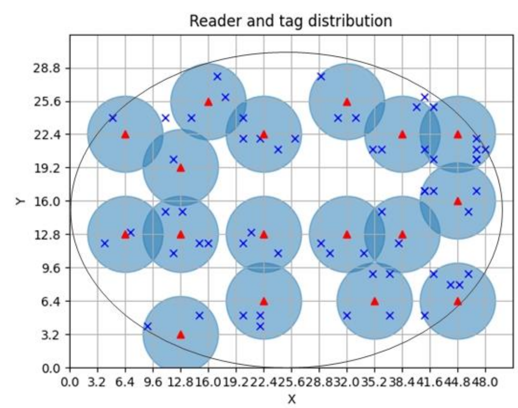
As shown in Table 2, with the iGAPO, the optimal number of readers N_r is 21, which is more efficient compared to using 25 readers with GA. Specifically, the fitness value increases by 2.4%, from 0.92087 to 0.94487. Although the coverage has decreased by 1.1% compared to using 25 readers with GA, the interference has reduced by nearly 50%, and the load balance has improved by almost 10%.

Comparing the Efficiency of the iGAPO as the Number of Tags Varies

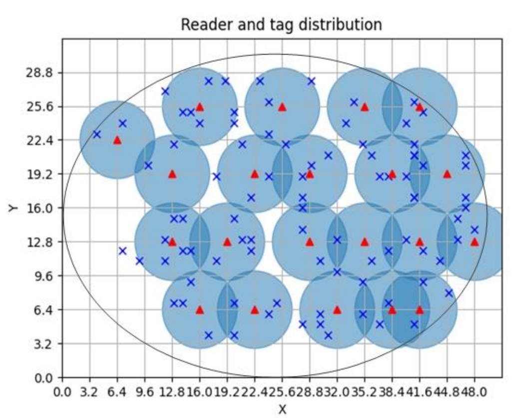
We continued to evaluate the effectiveness of the iGAPO by randomly changing the number of tags from 30 to 120 tags in the workspace, and the results are presented in Table 3. From Table 3, we can see that the iGAPO demonstrates a good ability to adapt to changes in the number of tags. Specifically, when the number of tags is low, the optimal allocation of readers also decreases, and as the number of tags increases, the number of readers also increases to cover the tags effectively. As shown in Figure 11, the iGAPO consistently achieves tag coverage of over 95% in all four cases of varying the number of tags in the workspace. With a large number of tags, an increase in interference and a decrease in load balance are inevitable. However, tag coverage also increases accordingly.



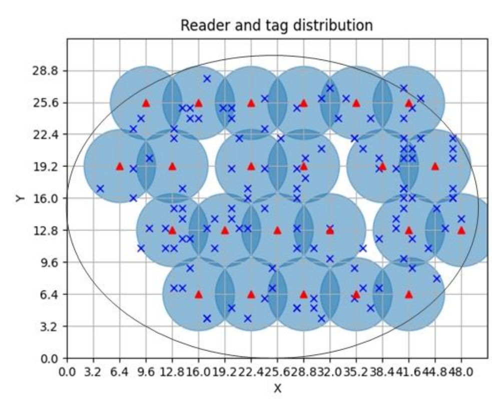
iGAPO with 30 RFID tag



iGAPO with 60 RFID tag



iGAPO with 90 RFID tag



(d) iGAPO with 120 RFID tag

Figure 11: Allocation of reader positions using the iGAPO as the number of tags varies from 30 to 120 tags

Table 3: Comparison of the efficiency of the iGAPO as the number of tags varies

RFID tag	N_r	fitness	f_1	f_2	f_3	coverage	Interference	Load balance
30	13	0.9775196	0.96667	1.00000	0.98759	96.67%	0.00%	98.76%
60	17	0.9617135	0.98333	0.90000	0.95856	98.33%	10.00%	95.86%
90	21	0.9448725	0.95556	0.93333	0.92436	95.56%	6.67%	92.44%
120	25	0.9408239	0.99167	0.88333	0.84578	99.17%	11.67%	84.58%

5 Conclusion

RFID network planning is a problem classified as NP-hard and is often solved using evolutionary methods such as GA, PSO, CS, etc. Unlike previous proposals, where the workspace is typically square or rectangular, real-world workspaces are often arbitrarily shaped. Therefore, in this paper, we propose the RNP-3P model to optimize the quantity and positions of readers allocated based on a grid size in arbitrarily shaped workspaces. Simulation results demonstrate the effectiveness of the RNP-3P model, providing a promising solution for efficiently solving the RFID network planning problem in arbitrarily shaped workspaces, aligning with real-world working environments.

Acknowledgement

This work was supported by Hue University, Vietnam, Grant No. DHH2022-10-26.

References

[1] Bhattacharya, I., & Roy, U.K. (2010). Optimal Placement of Readers in an RFID Network Using Particle Swarm Optimization, *International Journal of Computer Networks and Communications*, *2*(6), 225–234.

[2] Botero, O., & Chaouchi, H. (2011). RFID network topology design based on Genetic Algorithms. *IEEE International Conference on RFID-Technologies and Applications*, 300–305.

[3] Cao, Y., Liu, J., & Xu, Z. (2021). A hybrid particle swarm optimization for RFID network planning. *Soft Computing*, *25*, 5747-5761.

[4] Costa, F., Genovesi, S., Borgese, M., Michel, A., Dicandia, F. A., & Manara, G. (2021). A review of RFID sensors, the new frontier of internet of things. *Sensors*, *21*(9), 3138. https://doi.org/10.3390/s21093138

[5] Feng, H., & Qi, J. (2013). Radio frequency identification networks planning using a new hybrid evolutionary algorithm. *In 15th International Conference on Advanced Communications Technology (ICACT)*, 179-188.

[6] Guan, Q., Liu, Y., Yang, Y., & Yu, Y. (2006). Genetic Approach for Network Planning in the RFID Systems. *Sixth International Conference on Intelligent Systems Design and Applications*, *2*, 567–572.

[7] Huang, H.P., & Chang, Y.T. (2011). Optimal layout and deployment for RFID systems. *Advanced Engineering Informatics*, *25*(1), 4–10.

[8] Jaballah, A., & Meddeb, A. (2017). Self adaptive cuckoo search algorithm for RFID network planning, *2017 Internet Technologies and Applications (ITA)*, 122–127.

[9] Jia, X., Feng, Q., Fan, T., & Lei, Q. (2012). RFID technology and its applications in Internet of Things (IoT). *2nd International Conference on Consumer Electronics, Communications and Networks (CECNet)*, 1282–1285.

[10] Khamayseh, Y.M., Mardini, W., Aldwairi, M., & Mouftah, H.T. (2020). On the Optimality of Route Selection in Grid Wireless Sensor Networks: Theory and Applications. *Journal of*

Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), 11(2), 87-105.

[11] Le, V.H., Dang, T.C., Nguyen, H.Q., & Vo, V.M.N. (2023). An Integrated Model of Placement Optimization and Redundancy Elimination in RFID Network Planning, The 12th Conference on Information Technology and Its Applications. *CITA 2023. Lecture Notes in Networks and Systems, 734*, 342–354.

[12] Suriya, A., & Porter, J.D. (2014). Genetic algorithm based approach for RFID network planning. *TENCON 2014 - 2014 IEEE Region 10 Conference*, 1–5.

[13] Tang, L., Zheng, L., Cao, H., & Huang, N. (2016). An improved multi-objective genetic algorithm for heterogeneous coverage RFID network planning. *International Journal of Production Research, 54*(8), 2227–2240.

[14] Vasquez, M., & Hao, J.K. (2001). A Heuristic Approach for Antenna Positioning in Cellular Networks. *Journal of Heuristics, 7*, 443–472.

[15] Xiong, Y., Giuseppe, V., Occhiuzzi, C., Marrocco, G., Caizzone, S., & Quijano, J.A. (2013). Optimization of multichip RFID tag antenna with genetic algorithm and method of moments. *IEEE Antennas and Propagation Society International Symposium (APSURSI)*, 416–417.

[16] Zhang, Y.H., Gong, Y.J., Gu, T.L., Li, Y., & Zhang, J. (2017). Flexible genetic algorithm: A simple and generic approach to node placement problems. *Applied Soft Computing, 52*, 457–470.

[17] Zhu, W., & Li, M. (2018). RFID reader planning for the surveillance of predictable mobile objects. *Procedia Computer Science, 129*, 475–481.

Author Biography

Van Hoa Le received a Doctor of Computer Science from Hue University, Vietnam, in 2020. He is currently the Head of the Faculty of Event Management and Communication Technology, School of Hospitality and Tourism, Hue University, Vietnam. His research interests include optical packet/burst-based switching networks, RFID technology, sensor systems, fairness, quality of service, Smart Tourism, neural networks, and soft computing.