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RADIO FREQUENCY IDENTIFICATION NETWORK PLANNING USING ASCENDANT HIERARCHICAL CLUSTERING ALGORITHM

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ABSTRACT

Radio Frequency Identification (RFID) is a suitable technology for several application scenarios. However, it faces many issues that need to be addressed. RFID Network Planning (RNP) is one of these challenges, which is studied in this paper. It consists in defining the optimal placement of RFID readers and their communication range. In this study, the RNP issue is considered as a clustering problem. Therefore, it is solved using Ascendant Hierarchical Clustering (AHC) algorithm, such that each cluster head represents a reader. The advantage of our proposed approach is that, in addition to optimizing the RNP, it is capable to determine the optimal number of readers needed to get optimal performances. Simulation results demonstrate that the proposed AHC algorithm performs better than two efficient RNP algorithms from the literature: Particle Swarm Optimization (PSO) and Leaders and Followers (LaF) algorithms. Hence, it is observed that the AHC algorithm is more efficient, scalable and runs faster than PSO and LaF.

KEYWORDS

RFID, Network planning, Hierarchical clustering, Agglomerative hierarchical clustering, Reader placement.

1. INTRODUCTION

Radio Frequency Identification (RFID) is a widely used wireless technology that involves the use of radio waves to track and identify items, products and individuals. It is considered as one of the key technologies in 21st century [1]. Hence, according to [2], the RFID market is expected to reach more than 36 billion US Dollars by 2030. A typical RFID system is composed of three kinds of components: tags, readers and a host computer. RFID tags are small electronic devices consisting on a chip and an antenna. Each tag is embedded in or attached to the object to track and stores data that can be read by an RFID reader. Based on their functionality, RFID tags can be of three types: passive, active and semi-passive. Passive RFID tags are not equipped with a power source; hence, they are powered and activated by the energy transmitted by the RFID reader. On the other hand, active RFID tags, unlike passive tags, do not rely on the energy transmitted by the RFID reader, but they have their own power source. Semi-passive RFID tags still depend on the energy sent by the reader. However, this energy is used only for communication and they use their own power source to power their internal circuitry. An RFID reader is a device used to collect information from the tags within its communication range. The role of the host computer, as a component of an RFID system, is to process, analyze and store the data received from the RFID readers.

The fact that RFID systems eliminate the need for direct physical contact to track and identify objects makes them very useful in a wide range of application fields, including:

- Supply Chain Management: it is used in inventory management in warehouses and distribution centres to improve inventory accuracy.
- Transportation and Logistics: RFID technology is also involved in many transportation and logistics operations, such as tracking and tracing goods, managing shipping containers and monitoring vehicle movements.
- Retail: it is used for item-level tracking.
- Healthcare: RFID systems can also be used to enhance patient safety by monitoring patients and tracking medical equipment [3] [4].
- Manufacturing: it is used to improve the efficiency and enable better quality control in asset tracking, inventory management and process control in manufacturing facilities.

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- Access Control and Security: RFID cards can provide a suitable tool to control and secure the access to buildings and restricted areas.

Furthermore, RFID technology can be integrated with an IoT system by connecting RFID systems to the internet.

Even though RFID technology is widely used in many application areas, several challenges and issues are still open and new solutions are needed and/or current solutions need improvements. RFID Network Planning (RNP) is one of these issues that need to be considered and addressed before the deployment of such networks. The RNP issue refers to the process of defining the appropriate network parameters, such that the performance of the network will be optimized. Usually, this planning problem involves three tasks: i) defining the optimal number of readers, ii) defining the adequate readers' positions and iii) defining the optimal transmission power of every reader. The main objectives when dealing with the RNP issue are maximizing tag coverage, minimizing interferences and minimizing cost (both capital and operational). It has been proven in the literature that the RNP issue is NP-hard [5].

In this paper, we apply the Ascendant Hierarchical Clustering (AHC) algorithm, also known as agglomerative hierarchical clustering, to solve this RNP issue. AHC algorithm is a flexible approach for dataset clustering and has applications in various fields, such as biology, social sciences and marketing, among others. Hence, this work aims to optimize five parameters: number of readers, tag coverage, interferences, power and power loss.

Several algorithms have been proposed to tackle the RNP issue. Most of them are based on metaheuristic algorithms. Guan et al. [5] have proposed the first algorithm that solves the RNP issue using genetic algorithm. Particle Swarm Optimization (PSO) was also applied in [1, 6, 7] to solve the RNP issue. In [7], a multi-swarm optimizer, called PS²O, has been proposed to solve the RNP issue by considering the following objectives: tag coverage, reader collision, economic efficiency and load balance. Hence, multiple populations of the PSO algorithm are combined in a hierarchical interaction topology. Furthermore, another PSO-based approach has been proposed in [6]. This algorithm, called HPSO-RNP, is a combination between PSO with K-means and virtual force algorithms. In [8], Genetic algorithm has been applied to solve the RFID network-planning problem based on directional and omnidirectional antenna readers. In this approach, a reader-elimination method has been introduced in order to remove unnecessary readers (redundant readers) from the network. Two metrics have been considered while addressing this issue: tag interference and reader-load balance. In addition, Zhao et al. [9] have applied a multi-objective firefly algorithm (FA) to solve the RNP issue with uncertainty. Similarly, authors have considered the optimization of three objectives: tag coverage, deployment cost and interference level. An improved version of FA algorithm has been used in [10] to address the same RNP issue. Moreover, another algorithm called Mayfly Sparrow Search in [11] tries to optimize four objectives : tag coverage, interference, power and load balance. M. Shokouhifar [12] has proposed a combination of whale optimization algorithm and simulated annealing to solve the RNP issue used to track medical assets in hospital environments. This solution considers the optimization of five parameters : coverage, cost, interference, collision and power. Recently, artificial neural networks [13], leaders and followers algorithm [14] and biogeography-based optimization [15] have been applied to solve the RNP issue.

Although the first works addressing the RNP issue have been designed since about two decades and several algorithms and solutions have been proposed to solve this issue, the need for new solutions is still required to address multiple objectives and the scalability of the RNP solutions. Hence, in this paper, the RNP issue is seen as a clustering problem, such that: the tags are the points to split into clusters, clusters are the RFID readers and the centres of clusters are the positions of the readers. Accordingly, we propose, in this paper, to solve the RNP issue using Ascendant Hierarchical Clustering (AHC) algorithm. The idea behind this algorithm is very simple. At the beginning, every tag is considered as a cluster. Then, at every iteration, the closest clusters are merged into larger clusters. Unlike existing algorithms, AHC deals with the RNP issue very fast and has a linear execution-time complexity.

The contributions of this paper are summarized as follows :

1. We propose a model for RFID system and a mathematical formulation to the multi-objective RNP (MORNP) problem. Hence, five optimization objectives have been considered: number of readers, tag coverage, interferences, power and power loss.

2. We design an approach, called AHC-MORNP, based on the AHC algorithm to deal with the MORNP problem.
3. We have implemented, evaluated and then compared the performance of the proposed approach with those of two RNP algorithms from the literature: PSO [7] and LaF [14].

The remainder of this paper is organized as follows: In the next section, the model of the system will be given, then a mathematical formulation of the RNP problem will be proposed. Section 3 will provide an explanation of the proposed Ascendant Hierarchical Clustering (AHC) algorithm and how it is applied to solve the considered RNP problem. The evaluation process and the simulation results are presented and described in Section 4. Finally, some conclusions and perspectives are provided in Section 5.

2. SYSTEM MODEL AND PROBLEM FORMULATION

This section will describe how the system is modelled. Then, it describes the mathematical formulation of the problem. Therefore, let us first describe the symbols used in this paper, as illustrated in Table 1.

Table 1. List of symbols and parameters used in this paper.

Notation	*Description*
Inputs	
t_i	The *i*-th tag
r_j	The *j*-th reader
n	Total number of tags
m	Maximum number of readers
Γ	The deployment area
W	Deployment area width
H	Deployment area height
B_t	The *t*-th boundary of the deployment area
(x_t, y_t)	Coordinates of the *t*-th tag
ρ_{Min}	Minimum communication radius of readers
ρ_{Max}	Maximum communication radius of readers
Model variables	
d_{rt}	Euclidean distance between tag t and reader r
δ_{rt}	Defines whether tag *t* is inside the communication range of *r*
φ_{rj}	Defines whether a reader *r* is inside the interference range of another reader *j*
C_{rt}	Defines whether tag *t* is covered by reader *r*
Outputs	
k	Number of selected readers
(x_r, y_r)	Coordinates of the *r*-th reader
σ_j	Interference radius of the *j*-th reader
ρ_j	Communication radius of the *j*-th reader
Objective variables	
$DR(G)$	Number of deployed readers in the RFID network represented by the graph G
$Cov(G)$	Coverage ratio of the RFID network represented by the graph G
$Interf(G)$	Interference of the RFID network represented by the graph G
$Pow(G)$	Total power consumed by the RFID network represented by the graph G
$PLoss(G)$	Power lost by the RFID network represented by the graph G
AHC symbols	
c_i	*i*-th cluster
S_{ij}	Similarity measure between clusters c_i and c_j.

The RFID system is designed under the following assumptions:

- All tags are passive due to their low cost [16], meaning that they are powered by the energy transported by the radio signals transmitted by the RFID readers.
- The RFID system is deployed on a 2D rectangular area.
- The RFID readers can be placed anywhere on the deployment area.
- Every node of the network (reader or tag) has one omnidirectional antenna.

- The RFID readers are heterogeneous in terms of communication range.

2.1 System Model

We consider a 2D rectangular deployment area Γ with a width *W* and a height *H*. The RFID network is represented as a graph G(V, E), where V is the set of vertices or nodes and E is the set of edges. Additionally, there are two kinds of nodes in the network: tags and readers. Hence, $V = T \cup R$, such that:

- The set $T = \{t_1, t_2, \dots, t_n\}$ of n passive tags attached to the objects to be tracked or identified. We consider (x_t, y_t) as the coordinates of the *t*-th tag ($1 \leq t \leq n$).
- The set $R = \{r_1, r_2, \dots, r_m\}$ of available RFID readers. The aim of the RNP issue is to find the best number of readers *k* ($k \leq m$) and their positions (x_r, y_r) on the deployment area Γ ($1 \leq r \leq k$). In addition, it also aims to find the best interrogation range ρ_r of every reader *r* to meet the requirements, where $\rho_{Min} \leq \rho_r \leq \rho_{Max}$, $r \leq k$.

2.2 Problem Formulation

In this paper, the RNP problem considers the optimization of five objectives that are formulated as follows:

2.2.1 Coverage

Mainly, the most important requirement when addressing the RNP issue is to cover the maximum number of tags. Hence, we define the coverage *Cov(G)* of the graph G, representing our RFID system, as follows:

$$Cov(G) = \frac{\sum_{t=1}^{n}\left(\sum_{r=1}^{k}(C_{rt})\right)}{n} \quad (1)$$

where:

$$C_{rt} = \begin{cases} 1 & if\ tag\ t\ is\ covered\ by\ reader\ r. \\ 0 & Otherwise \end{cases} \quad (2)$$

and $\sum_{r=1}^{k}(C_{rt}) \leq 1, \ \forall t \in \{1, \dots, n\}$.

2.2.2 Interference

In addition to coverage, the aim of this work is also to minimize the interferences caused by the nodes of the RFID network *G*. Interferences are proportional to the density of the network [17]. Hence, the higher the density, the greater the number of interferences. In RFID, there are two kinds of interferences: interference between two or more close readers situated inside their communication range (reader interference) and interference caused by two or more readers covering the same tag (tag interference) [11]. Therefore, Equation (3) defines how interference metric is computed.

$$Interf(G) = \frac{\sum_{t=1}^{n} TI(t) + \sum_{r=1}^{k} RI(r)}{m + n} \quad (3)$$

where *TI(t)* defines whether interferences occurred at the tag *t*. *TI(t)* is computed according to the following equation:

$$TI(t) = \begin{cases} 1 & if\ \left(\sum_{r=1}^{k} \delta_{rt}\right) > 1 \\ 0 & Otherwise \end{cases}, \quad (4)$$

$$\delta_{rt} = \begin{cases} 1 & if\ d_{rt} \leq \rho_r \\ 0 & Otherwise \end{cases}, \quad (5)$$

and *RI(r)* defines whether interferences occurred at the reader *r* and is computed according to the following equation:

$$RI(r) = \begin{cases} 1 & if\ \left(\sum_{j=1, j\neq r}^{k} \varphi_{rj}\right) > 0 \\ 0 & Otherwise \end{cases}, \quad (6)$$

$$\varphi_{rj} = \begin{cases} 1 & if\ d_{rj} \leq \sigma_j \\ 0 & Otherwise \end{cases} \quad (7)$$

2.2.3 Power

The transmitted power by all readers needs also to be minimized when solving the RNP problem. Based on the Friis transmission equation [18], the power received at a tag is calculated as follows:

$$P_{rec} = P_{tr} \,.\, G_{rec} \,.\, G_{tr} \,.\, (\frac{\lambda}{4\,\pi\,R})^2 \tag{8}$$

where P_{rec} is the received power, P_{tr} is the transmitted power, G_{rec} is the receiver-antenna gain, G_{tr} is the transmitter-antenna gain, λ is the wavelength and *R* is the distance between the reader and the tag.

According to eq. (8), the only factor that can affect the power received by a tag or a reader is the distance between them, which represents the radius of the reader's antenna. Therefore, to optimize the transmission power of a reader while dealing with the RNP issue, it is more convenient to minimize the radius of the reader ρ_j, where $\rho_{Min} \leq \rho_j \leq \rho_{Max} \quad j \leq k$.

Then, in this work, the total transmission power of an RFID network is defined as a function of the transmission radius, as shown in the following equation:

$$Pow(G) = \frac{\sum_{r=1}^{k} \rho_r}{m * \rho_{Max}} \tag{9}$$

2.2.4 Power Loss

There is another way to save additional power in addition to the power saved previously. In this work, we also consider the minimization of the power lost when the reader is very close to one of the boundaries of the deployment area. Therefore, we define the power loss as follows:

$$PLoss(G) = \frac{\sum_{j=1}^{k} \sum_{t=1}^{4} PL(r_j, B_t)}{m \,.\, (2 * \rho_{Max})} \tag{10}$$

where:

$$PL(r_j, B_t) = \begin{cases} \rho_j - d_{jt} & if \;\; \rho_j - d_{jt} > 0 \\ 0 & Otherwise \end{cases} \tag{11}$$

2.2.5 Number of Deployed Readers

It is also very important to reduce the number of used readers. However, most of the related works did not consider the automatic adjustment of the number of readers. Hence, we define *DR(G)*, the ratio of the number of readers, as follows:

$$DR(G) = \frac{\sum_{j=1}^{m} a_j}{m} = \frac{k}{m} \tag{12}$$

where:

$$a_j = \begin{cases} 1 & if\ the\ reader\ r_j\ is\ selected \\ 0 & Otherwise \end{cases} \tag{13}$$

2.2.6 Objective Function

The RNP issue addressed in this paper is a multi-objective problem consisting in simultaneously optimizing five conflicting objectives. However, in our work, we have transformed the multi-optimization problem into a single optimization problem, as most works from the literature in this field do, by adopting a weighted summation of the five objectives. Even though converting a multi-objective problem into a single-objective problem can lead to some limitations, such an approach presents several advantages:

1) It provides a simplicity and efficiency in solving the problem.
2) It allows the exploration of trade-offs between different objectives.
3) It facilitates decision-making by providing a single solution that can be easily compared with other algorithms.

In addition, by aggregating the five objectives into a single objective function, the users will have the ability to adjust the weights, which represent the importance given to every objective, according to their needs and their financial and technical constraints. Thus, the objective function used to evaluate the quality of solutions is defined according to the Equation (14):

$$f(G) = w_1.\big(1 - cov(G)\big) + w_2.Interf(G) + w_3.Pow(G) + w_4.PLoss(G) + w_5.DR(G) \qquad (14)$$

where: $\sum_{i=1}^{5} w_i = 1$ and $0 \le w_i \le 1 \quad i \in \{1,2,3,4,5\}$.
It is evident that the described RNP issue can be considered as a minimization problem as follows:

$$\mathbf{Min}_{G} \Big(w_1.\big(1 - cov(G)\big) + w_2.Interf(G) + w_3.Pow(G) + w_4.PLoss(G) + w_5.DR(G)\Big)$$

Subject to

$$w_1 + w_2 + w_3 + w_4 + w_5 = 1$$

$$0 \le w_i \le 1\ ;\ \forall\, i \in \{1,2,3,4,5\}$$

$$0 \le x_r \le W\ ;\quad \forall r \in \{1,\dots,k\}$$

$$0 \le y_r \le H\ ;\quad \forall r \in \{1,\dots,k\}$$

$$\rho_{Min} \le \rho_r \le \rho_{Max}\ ;\quad \forall r \in \{1,\dots,k\}$$

$$0 \le \Big(\sum_{r=1}^{m} C_{rt}\Big) \le 1\ ;\forall\, t \in \{1,\dots,n\},\quad \forall r \in \{1,\dots,k\}.$$

3. PROPOSAL

In this paper, we address the problem of RFID network planning by using AHC algorithm. Hence, a brief description of this algorithm is first provided.

3.1 Ascendant Hierarchical Clustering Algorithm

Ascendant hierarchical clustering, also known as agglomerative hierarchical clustering, is a bottom-up clustering method widely used to group similar data together. It is a widely used clustering algorithm in data analysis and machine learning. The basic idea behind AHC is very simple. It starts by creating as many clusters as data points and then assigning each of these data points to a single cluster (each cluster contains one data point). Then, it performs an iterative merging of the closest pair of clusters in a single larger cluster. This process of merging is based on a similarity measure between clusters defined beforehand.

The key operations of AHC algorithm are straight forward:

1. Let each data point be a cluster,
2. Compute the similarity (proximity) matrix,
3. Merge the two closest clusters,
4. Update the similarity matrix,
5. Repeat steps 3 and 4 until only a single cluster remains.

Algorithm 1: AHC algorithm for RNP problem

Inputs: X: Set of input data (tags)
X_Size : Size of the instance (number of tags)
Output: $Best_G$: Best Clustering
G_Size : number of clusters
Variables : S_{ij}: Similarity matrix
G: Set of Clusters

```
1 Function AHC()
2    G ← ∅
3    For i ← 1 to n do
4       G_i ← {X_i}          //Create a cluster for each data point
5       G ← G + G_i          // Add G_i to the set of clusters
6       For j ← (i + 1) to n do
7          S_ij ← Similarity(i, j)
8          S_ji ← S_ij
9       End For
```

```
    F_i ← f(G)          // using eq. (14)
    Best_G ← G
    Best_F ← F_i
  End For
  G_Size ← n
  While G_Size > 1 do
    (i', j') ← Argmin_(i,j)(Similarity(i, j)
    //*** Merge clusters G_i' and G_j' into cluster G_k***//
    G_k ← G_i' ∪ G_j'
    G ← G + G_k − G_i' − G_j'
    G_Size ← G_Size − 1
    For i ← 1 to G_Size do
      S_ki ← Similarity(k, i)
      S_ik ← S_ki
    End For
    F_i ← f(G)          // using eq. (14)
    If F_i < Best_F then
      Best_G ← G
      Best_F ← F_i
    End If
  End While
  Return Best_G
End
```

3.2 AHC Algorithm Applied to RNP Issue

The described RNP issue can be considered as a clustering problem. In fact, the tags are the objects to make in clusters and every cluster represents a reader, such that the centre of gravity of the clusters defines the position of the reader and the radius of the cluster determines the communication range (power) of the reader. From this observation, we have solved the RNP problem using a clustering algorithm. In the following, a detailed description of the proposed approach to solve the considered RNP problem is given. This approach is based on hierarchical clustering. There exists two categories of hierarchical clustering: Ascendant Hierarchical Clustering (AHC) and Descendant Hierarchical Clustering (DHC). In this work, we apply the AHC method to solve the above RNP problem. The detailed pseudo-code of the AHC algorithm is shown in Algorithm 1.

To be more efficient, the solution obtained from this algorithm is then adjusted by removing the readers that are covering less than the defined threshold of the number of tags. Furthermore, the radius of some readers is adjusted to fit the maximum radius when it exceeds this value.

3.2.1 Similarity Measure

There are different ways to measure the similarity between two clusters. The most common one is the Euclidean distance. In addition, it is very important to determine a linkage criterion, which defines the way to compute the distance between two clusters based on the links between their constituent data points. Accordingly, there are several approaches to define this linkage, such as: minimum (single) linkage, maximum (complete) linkage and average linkage. In this paper, we define the distance between two clusters as the Euclidean distance between their centres of gravity. It is defined as follows:

$$S_{ij} = D(o_i, o_j) = \sqrt{\sum_{k=1}^{d} (x_k^i - x_k^j)^2} \tag{15}$$

where: S_{ij} is the similarity measure between clusters c_i and c_j. D is the Euclidean distance and o_i and o_j are the centers of gravity of cluster c_i and cluster c_j, respectively.

4. PERFORMANCE EVALUATION

To evaluate the performance of the proposed AHC algorithm, we have proceeded by simulation. Hence, the proposed AHC algorithm has been compared to two algorithms from the literature: PS^{2}O [7] and

LaF [14]. PS^{2}O [7] is commonly used for comparing new proposed RNP algorithms, while LaF algorithm [14] was proposed in 2021. Furthermore, a simulator has been developed using C++ language. This simulator includes the following features:

- Implementation of the mathematic model of the RNP problem.
- Implementation of three RNP algorithms: AHC, PSO and LaF.
- Implementation of a visualization tool.
- Implementation of dataset generator.

The simulation procedure as well as the obtained results are described in the following part.

4.1 Simulation Parameters

The parameters used during the simulation as well as their values are summarized in Table 2.

Table 2. Simulation parameters and their values.

Parameter	*Possible values*	*Default*
H, W	{20, 30, 40, 50, 60}	30
n	{50, 100, 200, 300, 400}	100
m	{50, 100, 200, 300, 400}	100
ρ_{Min}	1 m	1 m
ρ_{Max}	5 m	5 m
w_1	[0, 1]	0.2
w_2	[0, 1]	0.15
w_3	[0, 1]	0.05
w_4	[0, 1]	0.1
w_5	[0, 1]	0.5
p		30
T	10 000	10 000
L	40	40
S	2m	2m
#runs		20

The datasets used during the simulation have been generated randomly. In fact, 200 datasets representing 10 scenarios have been generated according to the parameters illustrated in Table 3. Mainly, these datasets have been generated using two tag distributions: uniform and clustered. Hence, for every scenario, 20 datasets are generated using the same parameter values.

Table 3. Parameter settings of the RNP instances.

Scenario	*Tag distrib.*	*Field*	*#Tags*	*#MaxReaders*
R50	Uniform	20 x 20	50	50
R100	Uniform	30 x 30	100	100
R200	Uniform	40 x 40	200	200
R300	Uniform	50 x 50	300	300
R400	Uniform	60 x 60	400	400
C50	Clustered	20 x 20	50	50
C100	Clustered	30 x 30	100	100
C200	Clustered	40 x 40	200	200
C300	Clustered	50 x 50	300	300
C400	Clustered	60 x 60	400	400

4.2 Results and Discussion

In the following part, we illustrate and describe the results obtained from simulations. Hence, Figure 1 shows the implemented simulator. The latter includes algorithm selection, parameter setting and obtained results in terms of different objectives and metrics. Figure 2 (Figure 4, respectively) illustrates the visualization of the solutions found by AHC, PSO and LaF while considering the parameters shown in Figure 1 (Figure 3, respectively).

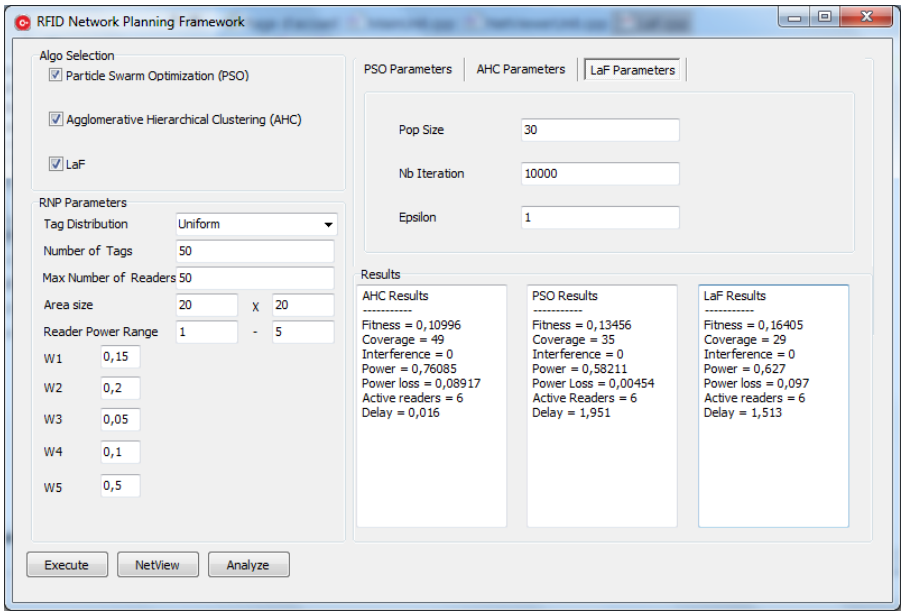
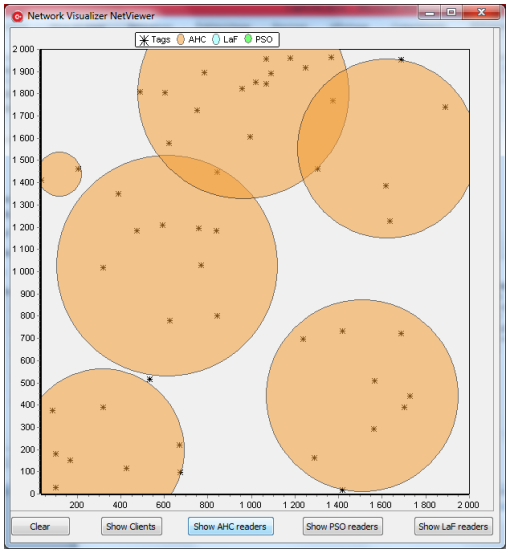
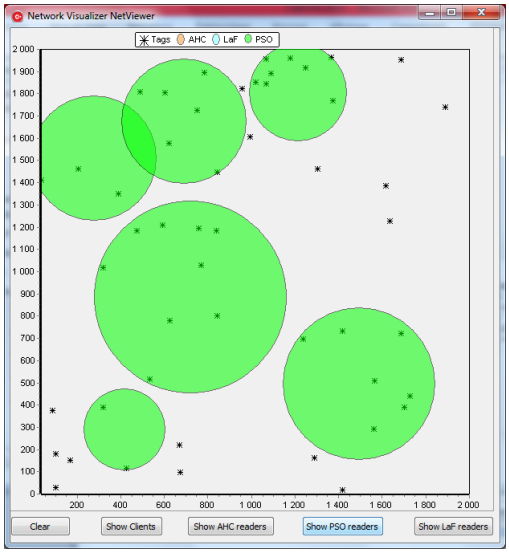


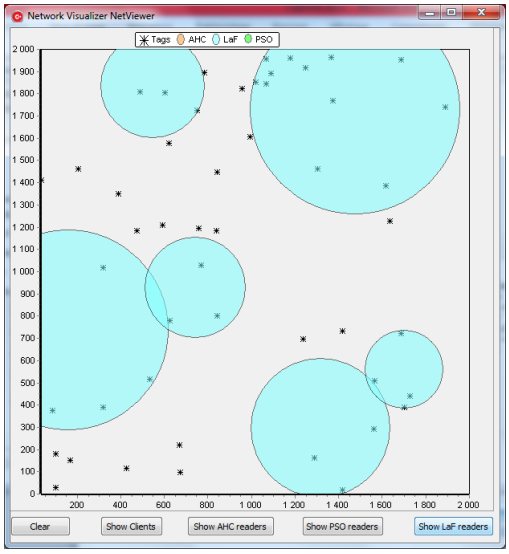
Figure 1. Parameter setting for an R50 instance.



(a) AHC



(b) PSO



(c) LaF

Figure 2. Results obtained by AHC, PSO and LaF for an R50 instance.

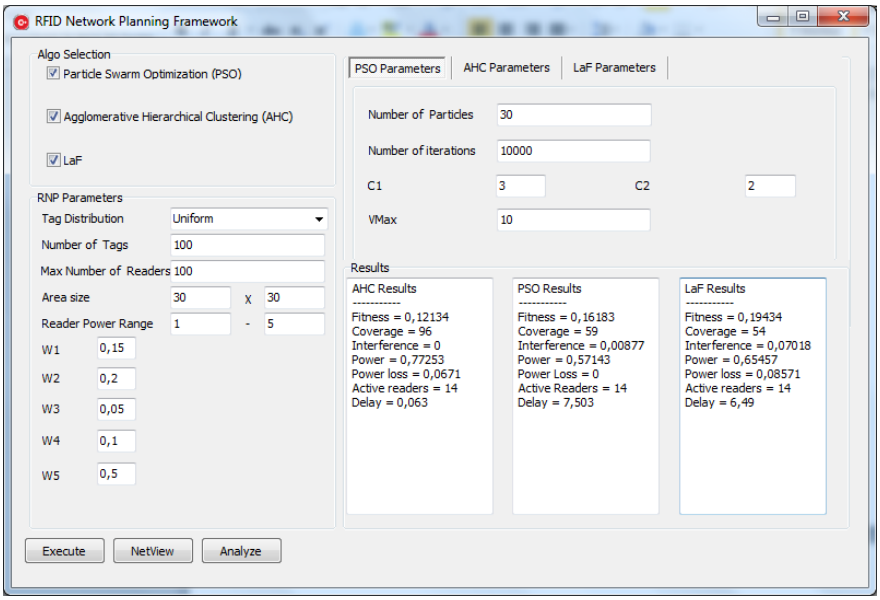
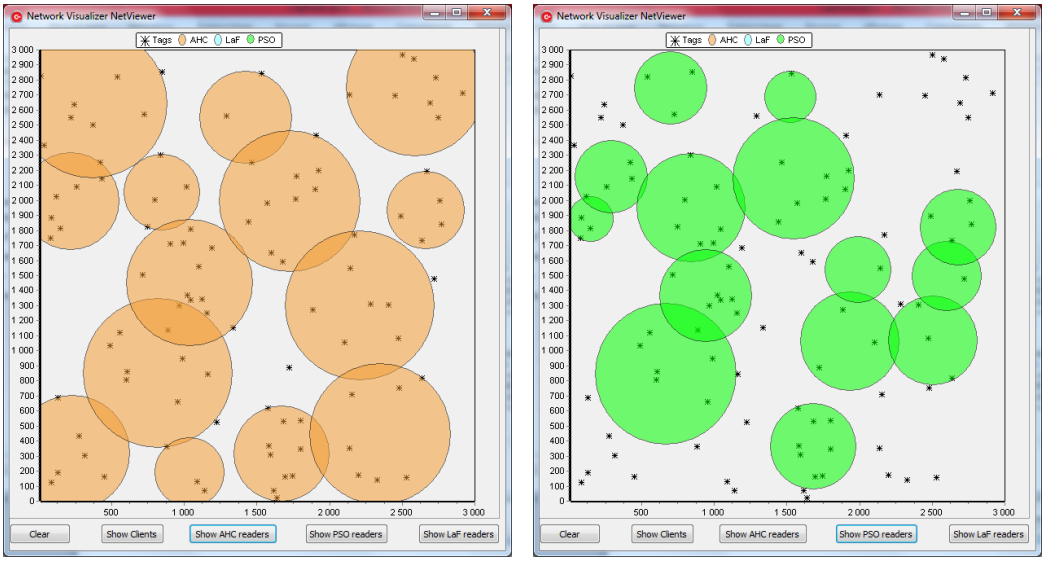
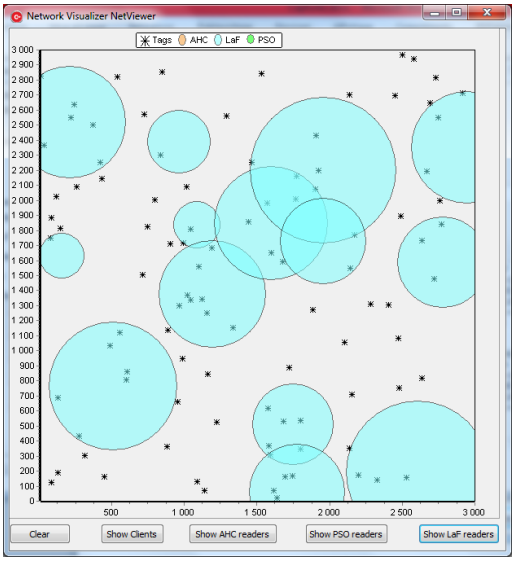


Figure 3. Parameter setting for an R100 instance.



(a) AHC (b) PSO



(c) LaF

Figure 4. Results obtained by AHC, PSO and LaF for an R100 instance.

4.2.1 Evaluating the Impact of Varying Objective Weights

Even though our work aims at finding a good (eventually best) solution to the considered RNP problem regardless of the values of weights, it is very important to study the impact of varying the values of these weights on the quality of the solution and the performance of the system. Thus, Table 4 shows the different weight settings used to measure the impact of these settings on the performance of the system. In fact, the greatest the value of weight, the more importance is given to the corresponding objective. Therefore, weight setting WS #1 gives the same importance to all metrics, while the other settings define different ascendant orders of objective importance.

Table 4. Different weight settings.

	Weight settings					
	WS #1	*WS #2*	*WS #3*	*WS #4*	*WS #5*	*WS #6*
w_5 *(Selected readers)*	0.2	0.5	0.05	0.1	0.15	0.2
w_1 *(Coverage)*	0.2	0.2	0.5	0.05	0.1	0.15
w_2 *(Interference)*	0.2	0.15	0.2	0.5	0.05	0.1
w_3 *(Power)*	0.2	0.1	0.15	0.2	0.5	0.05
w_4 *(Power loss)*	0.2	0.05	0.1	0.15	0.2	0.5

Table 5 illustrates the results obtained when varying weight setting according to Table 4 and using the scenario R50. The results obtained represent average values of 20 randomly generated instances using the same parameter setting. Hence, these results demonstrate clearly that the behavior of the three algorithms changes according to the weight settings all algorithms adapt to the user needs. However, in practice, selected readers, coverage and interference are, generally, given more importance by setting their weights to higher values. Accordingly, the weights of these metrics are defined according to Table 1.

Table 5. Evaluating the impact of objective weights.

Metric	*Weight Setting*	*AHC*	*PSO*	*LaF*	*Metric*	*Weight setting*	*AHC*	*PSO*	*LaF*
Fitness	*WS #1*	0.129	0.171	0.235	Power	*WS #1*	0.3004	0.3506	0.4241
	WS #2	0.147	0.158	0.201		*WS #2*	0.6092	0.4344	0.5329
	WS #3	0.058	0.146	0.210		*WS #3*	0.2294	0.4137	0.4658
	WS #4	0.093	0.160	0.235		*WS #4*	0.2470	0.3148	0.4039
	WS #5	0.183	0.211	0.293		*WS #5*	0.2224	0.2795	0.3925
	WS #6	0.080	0.099	0.140		*WS #6*	0.4178	0.4065	0.4879
Coverage	*WS #1*	50	38.7	36.75	Power loss	*WS #1*	0.0170	0.0143	0.0643
	WS #2	50	34.1	31.5		*WS #2*	0.0613	0.0119	0.0673
	WS #3	50	48.4	45.9		*WS #3*	0.0116	0.0471	0.1041
	WS #4	50	31.4	33.85		*WS #4*	0.0141	0.0106	0.0957
	WS #5	50	34.85	37.8		*WS #5*	0.0103	0.0090	0.0602
	WS #6	50	36.05	34.1		*WS #6*	0.0247	0.0045	0.0368
Interference	*WS #1*	0	0.0804	0.1964	Selected readers	*WS #1*	16.5	16.5	16.5
	WS #2	0.0008	0.0128	0.0446		*WS #2*	8.05	8.05	8.05
	WS #3	0	0.2481	0.3606		*WS #3*	23.1	23.1	23.1
	WS #4	0	0.1103	0.1893		*WS #4*	20.9	20.9	20.9
	WS #5	0	0.2017	0.3315		*WS #5*	23.35	23.35	23.35
	WS #6	0.0008	0.0572	0.1221		*WS #6*	11.6	11.6	11.6

4.2.2 Fitness

The fitness value is the most important parameter that allows evaluating the performance of any given RNP algorithm. Table 6 shows the obtained fitness for the three algorithms according to different scenarios. The results shown in Table 6 demonstrate that the proposed AHC algorithm clearly outperforms the two PSO and LaF algorithms. In addition, AHC algorithm succeeded in maintaining almost the same performance (between 0.109 and 0.118 for uniform tag distribution scenarios and between 0.088 and 0.092 for clustered tag distribution scenarios). The fitness of PSO and LaF increases when increasing the number of tags. Consequently, AHC algorithm is more scalable than PSO and LaF algorithms when addressing the RNP problem.

Table 6. Obtained fitness according to different scenarios.

Scenario	*AHC*			*PSO*			*LaF*		
	Worst	*Average*	*Best*	*Worst*	*Average*	*Best*	*Worst*	*Average*	*Best*
R50	**0.127**	**0.118**	**0.105**	0.141	0.128	0.115	0.171	0.157	0.141
R100	**0.124**	**0.117**	**0.109**	0.158	0.144	0.126	0.184	0.170	0.151
R200	**0.114**	**0.109**	**0.103**	0.163	0.151	0.137	0.183	0.175	0.168
R300	**0.114**	**0.109**	**0.104**	0.172	0.161	0.148	0.190	0.183	0.171
R400	**0.115**	**0.111**	**0.107**	0.183	0.168	0.150	0.194	0.186	0.178
C50	**0.106**	**0.089**	**0.065**	0.120	0.096	0.069	0.140	0.123	0.103
C100	**0.102**	**0.092**	**0.073**	0.147	0.120	0.085	0.174	0.152	0.130
C200	**0.099**	**0.088**	**0.082**	0.148	0.128	0.105	0.169	0.157	0.140
C300	**0.101**	**0.090**	**0.081**	0.155	0.143	0.129	0.175	0.166	0.154
C400	**0.099**	**0.091**	**0.087**	0.164	0.150	0.130	0.188	0.174	0.166

4.2.3 Coverage

Table 7 illustrates the evolution of the number of tags covered by RFID readers according to 10 scenarios containing 20 instances each. Again, AHC algorithm outperforms PSO and LaF algorithms by covering more RFID tags. Hence, AHC algorithm covers between 96.4% and 97.9% tags, while PSO algorithm covers between 46% and 76% tags and LaF algorithm covers between 43% and 67% tags. The AHC algorithm is designed to cover all tags; however, when a reader is covering a much less number of tags, it is removed. In addition, the radius of a reader may be decreased to fit the defined threshold, which means that few tags may remain not covered.

Table 7. Obtained coverage according to different scenarios

Scenario	*AHC*			*PSO*			*LaF*		
	Worst	*Average*	*Best*	*Worst*	*Average*	*Best*	*Worst*	*Average*	*Best*
R50	**42**	**48.95**	**50**	20	38	46	17	33.8	45
R100	**88**	**97.05**	**100**	37	64.55	80	38	52.8	67
R200	**180**	**193.15**	**200**	82	118	158	72	100.85	122
R300	**279**	**289.15**	**299**	115	154.4	179	103	135.65	159
R400	**368**	**386.25**	**396**	149	190.75	245	142	173.9	216
C50	**43**	**48.95**	**50**	24	38	46	28	33.8	45
C100	**92**	**97.05**	**100**	48	64.55	80	32	52.8	67
C200	**181**	**193.15**	**200**	88	118	158	79	100.85	122
C300	**280**	**289.15**	**299**	119	154.4	179	118	135.65	159
C400	**369**	**386.25**	**396**	140	190.75	245	137	173.9	216

4.2.4 Interference

Interferences should also be minimized when addressing the RNP issue. Table 8 illustrates the obtained interference for the three algorithms according to 10 scenarios. This table shows, once again, that overall, our proposed algorithm is better than PSO and LaF algorithms in terms of interference. Indeed, AHC algorithm encourages merging close clusters (readers), resulting in distant clusters and reduced overlaps. Consequently, interference is minimized.

Table 8. Obtained interference value according to different scenarios.

Scenario	*AHC*			*PSO*			*LaF*		
	Worst	*Average*	*Best*	*Worst*	*Average*	*Best*	*Worst*	*Average*	*Best*
R50	**0**	**0**	**0**	0.017	0.00085	**0**	0.054	0.01930	**0**
R100	**0.009**	**0.00045**	**0**	0.061	0.00790	**0**	0.086	0.03015	0.009
R200	**0.004**	**0.00020**	**0**	0.054	0.01645	**0**	0.093	0.04395	0.013
R300	**0**	**0**	**0**	0.091	0.0318	0.003	0.124	0.06255	0.018
R400	**0.002**	**0.00010**	**0**	0.049	0.02655	0.007	0.091	0.05875	0.020
C50	0.018	0.00180	**0**	**0**	**0**	**0**	0.055	0.01010	**0**
C100	0.018	0.00225	**0**	**0.009**	**0.00135**	**0**	0.062	0.02195	**0**
C200	**0.009**	**0.00145**	**0**	**0.009**	0.00415	**0**	0.070	0.03025	**0**
C300	**0.006**	**0.00105**	**0**	0.042	0.01140	**0**	0.086	0.0399	0.006
C400	**0.005**	**0.00085**	**0**	0.051	0.01980	0.002	0.115	0.05445	**0**

4.2.5 Power

The results shown in Table 9 describe a comparison between the transmitted powers of AHC, PSO and LaF algorithms. Since we are giving more importance to the coverage in the objective function, our proposed algorithm is making more effort to maximize coverage and minimize the number of readers. To achieve this goal, clusters should be larger, such that more tags are included and fewer readers are used. For this reason, AHC algorithm needs more power than PSO and LaF algorithm.

Table 9. Obtained power according to different scenarios.

Scenario	*AHC*			*PSO*			*LaF*		
	Worst	*Average*	*Best*	*Worst*	*Average*	*Best*	*Worst*	*Average*	*Best*
R50	0.858	0.696	0.556	**0.560**	**0.441**	**0.324**	0.667	0.495	0.353
R100	0.867	0.723	0.598	0.631	**0.462**	**0.320**	**0.617**	0.542	0.456
R200	0.810	0.740	0.674	0.673	**0.509**	**0.413**	**0.625**	0.557	0.477
R300	0.792	0.729	0.658	**0.561**	**0.516**	**0.442**	0.651	0.571	0.477
R400	0.810	0.750	0.691	**0.595**	**0.533**	**0.463**	0.615	0.567	0.512
C50	0.482	0.633	0.857	**0.306**	**0.508**	**0.717**	0.373	0.584	0.814
C100	0.541	0.630	0.819	0.414	**0.510**	**0.649**	**0.396**	0.546	0.686
C200	0.562	0.658	0.792	0.443	**0.536**	**0.681**	**0.441**	0.594	0.710
C300	0.579	0.667	0.784	**0.412**	**0.534**	**0.608**	0.498	0.573	0.634
C400	0.576	0.677	0.765	**0.462**	**0.530**	**0.612**	0.500	0.592	0.660

4.2.6 Power Loss

Measuring the power lost outside the boundaries of the deployment area is another way to measure the efficiency of any RNP algorithm, as illustrated in Table 10. As shown in this table, PSO algorithm outperforms both AHC and LaF algorithms. Furthermore, AHC and LaF algorithms have, approximately, equivalent performances in terms of power loss.

Table 10. Obtained power loss according to different scenarios.

Scenario	*AHC*			*PSO*			*LaF*		
	Worst	*Average*	*Best*	*Worst*	*Average*	*Best*	*Worst*	*Average*	*Best*
R50	0.127	0.0774	0.0420	**0.0350**	**0.0071**	**0**	0.118	0.0602	**0**
R100	0.123	0.0588	0.0240	**0.0120**	**0.0036**	**0**	0.162	0.0566	0.013
R200	0.075	0.0477	0.0290	**0.0220**	**0.0059**	**0**	0.088	0.0418	0.015
R300	0.064	0.0368	0.0200	**0.0100**	**0.0024**	**0**	0.064	0.0353	0.013
R400	0.046	0.0328	0.0210	**0.0100**	**0.0031**	**0**	0.043	0.0253	0.007
C50	0.151	0.0751	0.0170	**0.0550**	**0.0173**	**0**	0.150	0.0737	**0**
C100	0.088	0.0401	0.0050	**0.0520**	**0.0078**	**0**	0.138	0.0465	0.011
C200	0.078	0.0422	0.0150	**0.0300**	**0.0067**	**0**	0.137	0.0445	0.001
C300	0.059	0.0336	0.0080	**0.0120**	**0.0027**	**0**	0.065	0.0343	0.013
C400	0.035	0.0253	0.0110	**0.0090**	**0.0020**	**0**	0.058	0.0278	0.010

4.2.7 Number of Readers

The proposed AHC algorithm is characterized by its ability to determine the adequate number of readers required to achieve good performance of the RFID system. Therefore, Figure 5 illustrates the impact of increasing the number of tags on the number of readers required to cover them. Indeed, the number of readers increases when increasing the number of tags. However, clustered scenarios require less readers than uniform scenarios. When tags are grouped in clusters, it is easy to find fewer readers to cover them. On the other hand, when tags are uniformly distributed on the deployment area, more readers are needed to cover them.

4.2.8 Execution Time

Figure 6 illustrates the execution time of all algorithms when increasing the number of tags. The most important observation from this figure is that our proposed AHC algorithm maintains, almost, the same

execution time when increasing the number of tags. It is observed that AHC algorithm gives the result in less than 4 seconds even with large instances, while PSO and LaF algorithms can run in more than 240 seconds when the number of tags exceeds 200. These results demonstrate that AHC algorithm is more scalable than PSO and LaF algorithms.

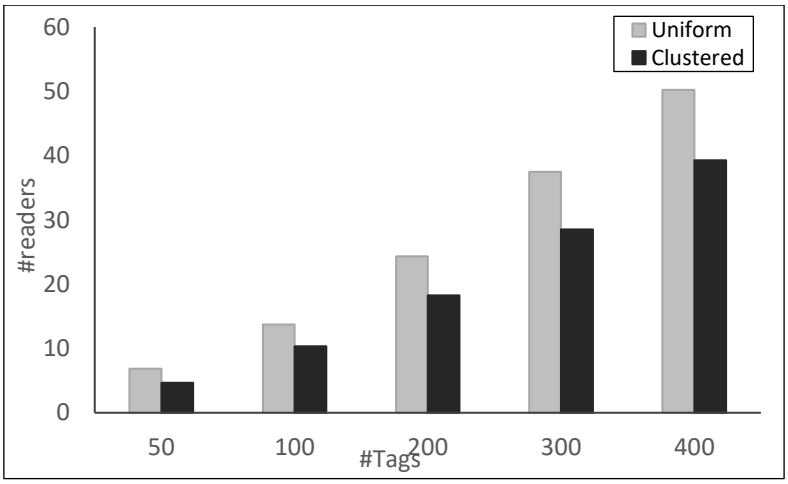


Figure 5. Number of deployed readers according to different scenarios.

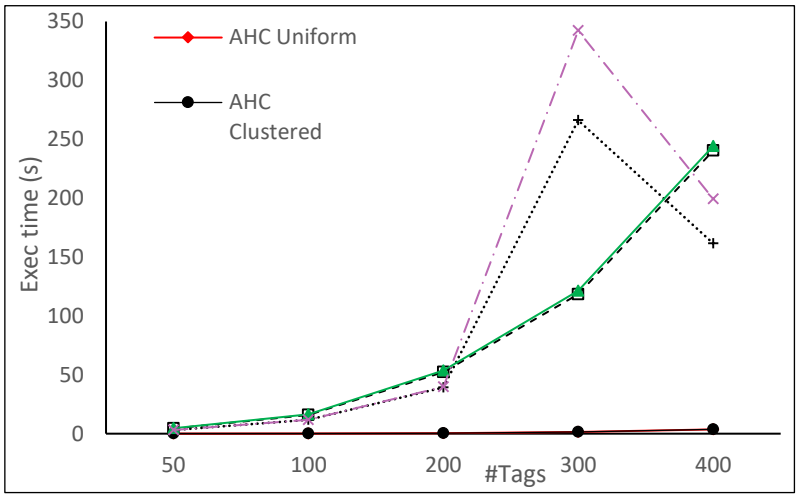


Figure 6. Execution time according to different scenarios.

5. CONCLUSION

In this paper, we have addressed the problem of RFID network planning (RNP) by considering the optimization of five parameters: coverage, interference, power, power loss and number of readers. We have considered the RNP as a clustering problem by grouping the closer tags into the same clusters. Hence, an ascendant hierarchical clustering (AHC) algorithm has been proposed to solve this issue. The results obtained have demonstrated that the proposed AHC algorithm outperforms PSO and LaF algorithms.

In the future, we expect to consider other variants of the problem, such as introducing obstacles. In addition, we expect to apply other algorithms, like Descendant Hierarchical Clustering, to solve this issue.

REFERENCES

[1] B. Niu, E. C. Wong, Y. Chai and L. Li, "RFID Network Planning Based on MCPSO Algorithm," Proc. of the 2009 2nd Int. Symposium on Information Science and Engineering, pp. 8-12, Shanghai, China, 2009.

[2] "RFID Market," [Online], Available: https://www.marketsandmarkets.com/Market-Reports/rfid-market-446.html, 2022.

[3] C. Zhao, J. Zhu, Z. Xu, S. Chen, F. Chen and T. Wang, "Wear-free Indoor Fall Detection Based on RFID and Deep Residual Networks," International Journal of Communication Systems, vol. 36, no. 10, 2023.
[4] C. Zhao, F. Xiong, T. Wang, Y. Wang, F. Chen and Z. Xu, "Wear-free Gesture Recognition Based on Residual Features of RFID Signals," Intelligent Data Analysis, vol. 26, no. 14, pp. 1051-1070, 2022.
[5] Q. Guan, Y. Liu, Y. Yang and W. Yu, "Genetic Approach for Network Planning in the RFID Systems," Proc. of the 6th Int. Conf. on Intelligent Systems Design and Applications, Jian, China, 2006.
[6] Y. Cao, J. Liu and Z. Xu, "A Hybrid Particle Swarm Optimization Algorithm for RFID Network Planning," Soft Computing, vol. 25, pp. 5747-5761, 2021.
[7] H. Chen, Y. Zhu, K. Hu and T. Ku, "RFID Network Planning Using a Multi-swarm Optimizer," Journal of Network and Computer Applications, vol. 34, no. 13, pp. 888-901, 2011.
[8] Z. Zhang, J. Ren, Z. Dai, B. Zhang, L. Wu and Z. Wu, "Research on RFID Network Planning Based on Directional and Omnidirectional Antenna Readers," Proc. of the Int. Conf. on Natural Computation, Fuzzy Systems and Knowledge Discovery, pp. 1192-1202, Xi'an, China, 2020.
[9] C. Zhao, C. Wu, J. Chai, X. Wang, X. Yang, J.-M. Lee and M. J. Kim, "Decomposition-based Multi-objective Firefly Algorithm for RFID Network Planning with Uncertainty," Applied Soft Computing, vol. 55, pp. 549-564, 2017.
[10] M. Tuba, N. Bacanin and A. Alihodzic, "Firefly Algorithm for Multi-objective RFID Network Planning Problem," Proc. of the 2014 22nd Telecom. Forum Telfor (TELFOR), pp. 95-98, Belgrade, Serbia, 2014.
[11] J. Zhang, J. Zheng, X. Xie, Z. Lin and H. Li, "Mayfly Sparrow Search Hybrid Algorithm for RFID Network Planning," IEEE Sensors Journal, vol. 22, no. 116, pp. 16673-16686, 2022.
[12] M. Shokouhifar, "Swarm Intelligence RFID Network Planning Using Multi-antenna Readers for Asset Tracking in Hospital Environments," Computer Networks, vol. 198, p. 108427, 2021.
[13] M. Maimouni and B. Abou El Majd, "New Hybrid Approach Based on Artificial Neural Networks for RFID Network Planning with Random Redundant Antenna Elimination," Proc. of the 2021 3rd Int. Conf. on Transportation and Smart Technologies (TST), pp. 24-29, Tangier, Morocco, 2021.
[14] T. Mathaba, "Multi-objective Optimal RFID Reader Deployment Using a Leaders and Followers Algorithm," Computers & Electrical Engineering, vol. 94, p. 107323, 2021.
[15] E. G. Zahran, A. A. Arafa, H. I. Saleh and M. I. Dessouky, "A Self Learned Invasive Weed-mixed Biogeography Based Optimization Algorithm for RFID Network Planning," Wireless Networks, vol. 26, no. 16, pp. 4109-4127, 2020.
[16] A. Jaballah and A. Meddeb, "A New Variant of Cuckoo Search Algorithm with Self Adaptive Parameters to Solve Complex RFID Network Planning Problem," Wireless Networks, vol. 25, pp. 1585-1604, 2019.
[17] H. Chen, Y. Zhu and K. Hu, "Multi-colony Bacteria Foraging Optimization with Cell-to-cell Communication for RFID Network Planning," Applied Soft Computing, vol. 10, no. 12, pp. 539-547, 2010.
[18] O. Franek, "Phasor Alternatives to Friis' Transmission Equation," IEEE Antennas and Wireless Propagation Letters, vol. 17, no. 11, pp. 90-93, 2017.

ملخص البحث:

يمثّل تحديد التّردُّدات الرّاديوية (RFID) تكنولوجيا ملائمة للعديد من سيناريوهات التّطبيق. إلّا أنّه ينطوي على العديد من المسائل التي تحتاج للتّعامل معها. ويُعَدّ تخطيط شبكات تحديد التّردُّدات الرّاديوية أحد التّحدّيات التي تتناولها هذه الورقة بالدّراسة، وتتمثل تلك المسألة في المَوْضَعَة المثالية لقارئات تحديد التّردّدات الرّاديوية، ومدى الاتّصال. في هذه الدّراسة، جرى اعتبار المسألة المشار إليها أعلاه مسألة عَنْقَدة؛ فقد تمّت معالجتها باستخدام خوارزمية عَنْقَدَة هرمية تصاعُدية (AHC)، بحيث يمثّل رأس كلّ عنقود إحدى القارئات. وتتميز الطّريقة المقترحة هُنا بأنّها –بالإضافة الى تحقيقها التّخطيط المثالي لشبكات التّردّدات الرّاديوية- تعمل على تحديد العدد المثالي للقارئات اللّازم لتحقيق أفضل أداء.

وقد أثبتت التّجارب عبْر المحاكاة أنّ الخوارزمية المستخدمة في هذه الدّراسة تفوّقت على اثنتيْن من الخوارزميات الواردة في أدبيّات الموضوع (PSO و Laf). فقد ثبت أن الخوارزمية المستخدمة في هذه الدّراسة (AHC) أكثر فاعلية، وأكثر قابلية للتوسيع، وتعمل على نحوٍ أسرع عند مقارنتها بالخوارزميتيْن الأُخرَيَيْن.

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