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An Approach to Hopfield Network-Based Energy-Efficient RFID Network Planning

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Abstract**:** *Radio Frequency IDentification* (*RFID*) *Network Planning* (*RNP*) *is the problem of placing RFID readers in a working area where a tag is interrogated by at least one reader and at the same time satisfies some constraints such as minimum number of placed readers, minimal interference, and minimal outside coverage. The RNP optimization has been proven NP-hard; thus, natural-inspired approaches are often used to find the optimal solution. The paper proposes an energy-efficient RNP approach in which the positions of placed readers are optimized by a Hopfield network, and the energy efficiency is achieved through a placement area restriction technique. A mechanism of redundant reader elimination is also added to minimize the number of placed readers. Simulation results show that the Hopfield network-based energy-efficient RNP approach achieves the maximum tag coverage and energy efficiency by reducing interference, outside coverage, and the number of placed readers.*

Keywords**:** *RFID Network Planning* (*RNP*), *Energy efficiency, Optimization, Hopfield network, Redundant reader elimination.*

1. Introduction

Radio Frequency IDentification (RFID) is the most known automatic identification technology widely deployed in Internet of Things (IoT) systems. An RFID system consists of RFID readers connected to form an RFID network, which can monitor tags or tagged objects in a working area. A server (host) is connected to the RFID network to store and process the collected data. The tags in an RFID system can be active, i.e., having their power source, or passive, i.e., not being powered by any source. With the latter, passive tags must harvest the energy from reader interrogation pulses to return their data [1, 2].

To maximize the coverage of a working area, the RFID network needs to be well-designed, and a good location for readers is essential. An RFID network is said to be well deployed if a tag is interrogated by at least one reader. The primary objective of RFID Network Planning (RNP) is to achieve maximum coverage.

Some additional constraints can be included, such as the minimum number of placed readers, the minimum interference, and the minimum outside coverage [3]. In the paper, the energy efficiency is of interest.

Energy efficiency in the RNP problem refers to minimizing the energy consumption of the deployed RFID network. The energy consumption of an RFID network mainly comes from the tag interrogation of readers, including the power for sending the interrogation command, the power for holding the downlink carrier on which the tag returns its response, and the energy for receiving/reading the tag's data. If only one reader covers a tag, the reader only consumes energy for interrogating the tag. However, if multiple readers cover a tag, i.e., the tag is in the overlap area, these readers interrogate the tag simultaneously. There is a waste of energy due to redundant interrogation. Therefore, minimizing the number of tags in the overlap area, called overlapped tags, increases energy efficiency.

Readers placed at the edges of a working area result in outside coverage, which is not helpful for tag monitoring. Meanwhile, the reader still has to expend energy to maintain outside coverage. Therefore, placing the readers with minimal outside coverage increases energy efficiency.

The number of readers placed also indirectly affects the energy efficiency of an RFID network. As the number of readers increases, the coverage outside the working area and the size of the overlap area may also increase, potentially increasing the number of overlapped tags. Reducing the number of readers placed thus also contributes to energy efficiency.

The paper proposes an approach of Hopfield network-based energy-efficient RNP, in which the reader placement location is optimized by a Hopfield network, and the energy efficiency is achieved through a placement area restriction technique. A mechanism of redundant reader elimination is integrated into the optimization process to minimize the number of placed readers. Simulation results demonstrate that the Hopfield network-based RNP outperforms similar RNP approaches in terms of coverage rate and energy efficiency.

The main contributions of the paper include:

- Proposing an energy efficiency model for the RNP problem, in which the energy-efficient RNP problem is formulated as an RNP problem with the maximum number of covered tags and the minimum energy consumption.
- Converting the energy-efficient RNP problem and related constraints into the energy function of a Hopfield network.
- Proposing a placement area restriction technique to eliminate overlap area and outside coverage, which is integrated into the Hopfield network-based optimization process.
- Using a mechanism of redundant reader elimination to minimize the number of placed readers.

The remainder of the paper is organized as follows. Section 2 reviews research in the past ten years on nature-inspired approaches to solving the RNP problem. Based on the analysis and evaluations, a Hopfield network-based energy-efficient RNP approach is proposed in Section 3, including the case study, the energy efficiency model of the energy-efficient RNP problem, and the Hopfield network-based energy-efficient RNP optimization. Next, Section 4 describes the simulation and result analysis. Finally, Section 5 presents the conclusion.

2. Related works

RFID Network Planning is an essential issue in deploying RFID applications. RNP is also a challenging problem because it needs to satisfy many constraints. RNP optimization has proved NP-hard [4], and nature-inspired approaches are receiving much attention in solving it [5]. Some typical approaches can be listed as Particle Swarm Optimization (PSO) Algorithm [6], Genetic Algorithm (GA) [4], Artificial Bee Colony (ABC) Algorithm [7], Firefly Algorithm [8], Cuckoo Search (CS) Algorithm [9], and Chicken Swarm Optimization (CSO) Algorithm [10]. Furthermore, other combination approaches are also proposed to enhance further the efficiency of solving the RNP problem. The section presents a review of notable studies in the past ten years.

GA and PSO attract the most attention in improving the efficiency of RNP solutions. Combinations of PSO and GA with each other or other techniques are, therefore, the majority in number. The first combination of GA and PSO, called multi-community GA-PSO, was proposed by Feng and Qi [11] to solve the RNP problem of large-scale systems. The main idea is to divide the single population of PSO into several colonies and use genetic selection and mutation strategies to improve the dynamic rules of the particle swarm. Simulation results show that the multi-community GA-PSO achieves a superior solution to the standard PSO.

PSO can be combined with a Tentative Reader Elimination (TRE) operator as proposed in [12], which is called PSO-TRE. To minimize the number of readers needed, the TRE operator temporarily deletes readers during the PSO process and can restore deleted readers after a few generations if the deletion reduces tag coverage. By using TRE, PSO-TRE can adaptively adjust the number of readers used to improve the overall performance of the RFID network. Furthermore, the mutation operator is embedded into the algorithm to improve the success rate of TRE. To evaluate the effectiveness, six requirements of RNP and real-world RFID operation scenarios are considered. Experimental results show that PSO-TRE achieves higher coverage and uses fewer readers than some compared algorithms.

PSO can also be combined with differential evolution strategies as in [13], which forms the Differential Evolutionary Particle Swarm Optimization (DEEPSO) model [14]. Operationally, on the one hand, DEEPSO relies on past information of the optimization process to generate new solutions and replaces individual memory with collective memory to improve sensitivity in the optimization context. On the other hand, DEEPSO has a self-adaptive property thanks to the self-adaptive recombination operator. With the combination, DEEPSO-based RNP has improved global convergence and particle diversity and can avoid falling into local convergence. Through simulation results, DEEPSO-based RNP outperforms standard PSO-based RNP.

In [15], Cao, Liu and Xu proposed a hybrid PSO algorithm combining k-Means clustering with virtual force. The hybrid algorithm, called HPSO-RNP, can automatically search for the number of readers and initialize reader coordinates through the k-Means Algorithm. Virtual Force (VF) is incorporated into the random motion to adjust the reader's position during the search process of PSO. Four objective functions are considered hierarchically. The results show that HPSO-RNP outperforms existing methods in RFID network planning in terms of the number of readers, interference, energy, and load balancing.

GA is also combined with another technique to optimize the RNP solution search results. Instead of acting as a part of the PSO process as in [11], GA can be combined with Simulated Annealing, called GA-SA [16], in a two-stage process. First, GA initiates the optimization process in the first stage, and the results are the input parameters for SA in the second optimization stage. The GA-SA model has exploited the advantages of the two methods while bypassing their disadvantages. Through three experiment deployment scenarios at an emergency department of a hospital, simulation results show that GA-SA increases the coverage and reduces the total cost compared to some previous models.

GA can also be integrated with the Redundant Reader Elimination (RRE) technique in a two-stage process (called GA-RRE) to minimize the number of readers placed in RNP [17]. GA first finds the optimal position of readers in terms of maximum tag coverage, minimum number of readers used, and minimum interference. For the RRE technique, a policy is proposed to eliminate the redundant readers without or with little impact on the tag interrogation efficiency. The number of candidate readers is limited to reduce the computational complexity. The working area is gridded, where each cell is a candidate position to place a reader. Simulation results show that, with some cases of investigated cell sizes, GA-RRE performs better regarding tag coverage, interference, and number of placed readers.

In addition, some combinations of different nature-inspired algorithms have also been proposed. Typically, Yixuan et al. [18] proposed a hybrid Gray Wolf-Optimized Cuckoo Search (GWO-CS) Algorithm, which uses an input representation based on a random gray wolf search and evaluates tag density and location to determine the combined performance of the reader's propagation area. Compared with PSO, CS, and GWO under the same experimental conditions, the coverage of GWO-CS is 9.306% higher than PSO, 6.963% higher than CS, and 3.488% higher than GWO. The results show that GWO-CS improves the global search coverage and the local search depth.

Another hybrid method, which is a combination of Redundant Antenna Elimination (RAE) and Neural Network Algorithm (NNA), called RAE-NNA, was proposed by Maimouni, Majd and Bouya [19], in which RAE focuses on optimizing the RNP problem by eliminating redundant antennas and NNA minimizing the difference between the target solution and the forecasted solutions. The study also examines a combination of RAE and GA (RAE-GA) to compare with RAE-NNA regarding convergence and quality of the solutions found. The results demonstrate the effectiveness and reliability of RAE-NNA in solving the RNP problem and designing cost-effective networks by minimizing the number of antennas and collisions between antennas and maximizing coverage.

Table 1 describes a short comparison between combination approaches.

Table 1. A short comparison between combination approaches

Problem	Problem statement	Methodology	Evaluations
GA-PSO [11]	Optimizing the RNP problem with coverage, interference, and load balancing constraints	– Combine GA and PSO – Divide the single population into several colonies and use genetic selection and mutation strategies to improve the dynamic rules of the particle swarm	GA-PSO performs better than PSO regarding coverage, power, and interference
PSO-TRE [12]	Solve the RNP problem with four optimization goals: tag coverage, number of readers, interference, and the sum of transmitted power	The TRE operator is embedded into the PSO process to remove redundant readers without reducing coverage	PSO-TRE achieves 100% coverage, zero interference, and equivalent power consumption, and uses 30% more readers when compared to traditional PSO
DEEPSO [14]	Increases the performance of RNP with minimum reader interference and maximum tag coverage	– combine DE and PSO – DEEPSO relies on past information of the optimization process to generate new solutions and proposes to replace individual memory with collective memory to improve the sensitivity of the optimization context	Compared with PSO, the fitness value of DEEPSO is improved by 3.39%
HPSO-RNP [15]	Optimize RNP by maximizing tag coverage, minimizing interference between readers, minimizing total power, and minimizing load balancing	– k-Means and VF are embedded in PSO – k-Mean initializes the initial position of readers and VF to adjust readers' location during the process of PSO optimization	HPSO-RNP achieves good performance in terms of coverage, interference, total energy, and load balance compared to a multi-objective evolutionary algorithm based on decomposition and a curling algorithm based on kinematics
GA-SA [16]	RNP optimization for tracking assets in a hospital is a multi-objective function of coverage, cost, collision, interference, energy, and path loss	– A hybrid of GA and SA – GA starts with the initial optimization phase, and its found solution is the input parameter of SA in the second optimization phase. SA continues to search for neighbor solutions to detect the optimal one	With three different scenarios in terms of coverage ratio and cost, GA-SA outperforms GA in terms of effectiveness in terms of coverage, cost, collision, interference, energy, and path loss
GA-RRE [17]	Optimize the RNP problem with maximum tag coverage, minimum interference, and reduced number of readers	– GA combines with RRE in a two-stage process – GA first finds the optimal installation location for readers, and RRE then removes redundant readers	GA-RRE performs better regarding coverage ratio, interference, and the number of placed readers
GWO-CS [18]	Solve the RNP problem with requirements of tag coverage, interference, load balancing, and transmission power	– Combine GWO with CS – GWO-CS uses the probability found in the CS Algorithm to update the population, introduce memory preference directional mutation to improve the global search ability of GWO, and avoid it falling into the local optimum	GWO-CS is 9.301% better than PSO, 6.953% better than CS, and 3.488% better than GWO in the case of coverage
RAE-NNA [19]	optimize the RNP problem by maximizing the network coverage, minimizing interference, and eliminating the redundant antennas	– Merge NNA and RAE; – The optimization phase is addressed using an unsupervised method based on ANNs, and RAE plays an auxiliary role in the second phase by eliminating redundant antenna	RAE-NNA reaches perfect solutions in interference, coverage, and the number of antennas when compared to RAE-GA

In summary, given the nature of the NP-hard problem, RNP should be solved by nature-inspired methods such as GA, PSO, CS, GWO, and NNA. Some combinations of nature-inspired algorithms with another technique or another nature-inspired algorithm have also been proposed to find a more effective solution for reader installation. Also, with this goal, the paper proposes a new approach that applies the Hopfield network to determine the optimal placement location for readers. The objective function of the RNP problem is therefore formulated in the form of a Hopfield energy function, and the energy minimization process by the Hopfield network helps to find the optimal placement solution. An RRE technique is also integrated into the Hopfield network-based optimization process to reduce the number of used readers further, thus highlighting the advantages of our combination model. The following section specifically describes our model.

3. Hopfield network-based energy-efficient RNP approach

Energy-efficient RNP is about finding a solution to place RFID readers in a working area to achieve maximum coverage and energy efficiency. The energy consumption in an RFID network mainly comes from the tag interrogation of readers. Ideally, only one reader interrogates a tag, so the total energy consumed is proportional to the number of tags covered. However, as a tag is within the overlap of coverage between two or more readers, these readers simultaneously interrogate the tag. There is an additional energy consumption for excess interrogation. Energy consumption is, therefore, proportional not only to the number of tags covered but also to the number of tags located in the overlap area. Minimizing the number of tags in the overlap area increases the energy efficiency of the RNP problem. The following subsections detail the approach of Hopfield network-based energy-efficient RNP.

3.1. Problem description

The RNP problem can appear in many practical applications, such as monitoring medical devices in a hospital. Accordingly, the working area can have any shape. However, without loss of generality, we can consider a rectangular working area with the dimension of $X \times Y$ m^2, as shown in Fig. 1, where *m* tags (marked by green '×') are evenly and randomly distributed. The objective is to find a distribution of *n-placed* readers (marked with red triangles) that maximizes tag coverage and is energy efficient.

With geographic coordinates in 2-D space, there are infinite possible placement locations, which results in an explosive number of candidate solutions. To reduce the number of options, the working area needs to be gridded where each cell is a possible placement location [19]. Cell size is an essential parameter because if the cell size is large, the number of possible placement locations is small, and the time to determine a placement solution becomes quick. However, the optimality of the solution found is not high. In the case of small cell sizes, the number of placement locations increases, and it takes longer to determine a suitable placement solution. However, the optimality of the solution is significantly improved. Therefore, a compromise between optimality and solution determination time must be considered.

The gridding can be hexagonal or quadrilateral [20]. In the case of quadrilateral gridding (Fig. 2), the cell sizes considered are divisors of the normalized reader coverage diameter (r_n). With the RFID reader coverage radius of $r = 3.69$ m [4], the normalized reader coverage diameter is calculated by $d_n = 2\times3.69\times\cos(45^o) \approx 5.2$ m. The cell sizes considered in the paper include 5.2, 3.9, 2.6, and 1.3 m.

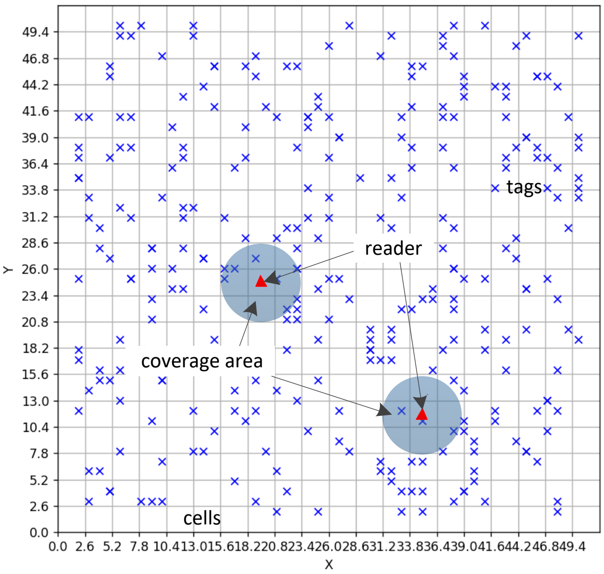


Fig. 1. An example of a gridded working area

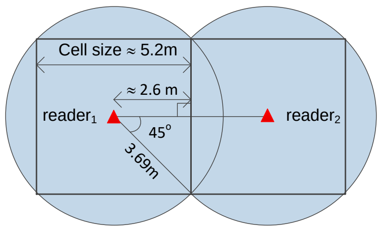


Fig. 2. The ideal distance between two adjacent readers in quadrilateral gridding

With the cell size determined, the number of cell rows and columns of the gridded working area is $N = Y/d_n$ and $M = X/d_n$, respectively. The gridded working area becomes a 2-dimensional cell matrix (as shown in Fig. 1), in which the state of each cell (i, j), $i = 1, ..., N$ and $j = 1, ..., M$, is represented by a variable s_{ij}; $s_{ij} = 1$ if the cell is selected to place a reader, and $s_{ij} = 1$ otherwise.

The primary objective of the RNP problem is to cover the maximum number of tags in a working area, which means the ratio of covered tags to total tags reaches the maximum as

(1) $$\text{maximize } f_1 = \sum_{i,j=1}^{N,M} \sum_{k\neq i,h\neq j}^{N,M} \frac{|T_{ij} \cup T_{kh}|}{m^2} s_{ij} s_{kh}$$

where T_{ij} is the set of tags covered if a reader is placed at cell (i, j); $|T_{ij}|$ is thus the number of tags covered by the reader.

In this paper, energy efficiency is of interest. The following is the energy efficiency model considered in the energy-efficient RNP problem.

3.2. Energy efficiency model of the RNP problem

The energy efficiency of the RNP problem can be interpreted as how to plan an RFID network that maximizes the number of covered tags and, at the same time, minimizes energy consumption. The energy consumption of an RFID network mainly comes from the energy consumption of the readers for tag interrogation. Specifically, a reader spends power on sending the interrogation command to a tag, maintaining the downlink carrier so the tag can harvest power for its response, and, finally, receiving/reading the tag's data [21]. Thus, the energy consumption of an RFID network is proportional to the number of tags covered.

When placing readers in a working area, the coverage of the readers may overlap, and some tags may be in that overlap area. Therefore, these tags are interrogated multiple times, which leads to redundant interrogations and unnecessary energy consumption. Minimizing the number of tags in the overlap area is a measure to increase energy efficiency, as

(2) $$\text{minimize } f_2 = \sum_{i,j=1}^{N,M} \sum_{k\neq i,h\neq j}^{N,M} \frac{\left|T_{ij} \cap T_{kh}\right|}{m^2} s_{ij} s_{kh}$$

where $T_{ij} \cap T_{kh}$ is the number of tags in the overlap of coverage between two readers placed at cell (i, j) and cell (k, h).

The readers placed near the edges of the working area waste their energy due to outside coverage. The outside coverage does not benefit tag interrogation and sometimes even creates vulnerabilities for attacks. Minimizing the number of readers placed near the edges can save energy and maintain the stability of the RFID network from outside intrusions. Consider a reader at cell (i, j) with the distances $d_{ij,k}$ to four edges Z_n, n = 1, ..., 4, the lost energy due to outside coverage, considered in a tag interrogation, which is determined as

(3) $$E_{ij}^{\text{lost}} = \begin{cases} \sum_{k=1}^{4} L(r_{ij}, d_{ij,k}) & \text{if } d_{ij,k} < r_{ij} \\ 0 & \text{otherwise} \end{cases}$$

where r_{ij} is the coverage radius of the reader at cell (i, j) and $L(r_{ij}, d_{ij,k})$ is the energy loss function which is proportional to the outside coverage radius.

In the paper, minimal outside coverage is achieved by a Placement Area Restriction (PAR) technique, in which edge locations (the gray area in Fig. 3) are not selected for reader placement.

Having multiple readers placed in a working area can increase the size of overlap coverage, which results in an increased number of overlapped tags and requires multiple interrogations per overlapped tag. Additionally, increasing the number of placed readers can create unnecessary outside coverage if the readers are located at the edges of the working area. Both overlap area and outside coverage cause wasteful energy consumption. Therefore, minimizing the number of placed readers is necessary, expressed as in

(4) $$\text{minimize } f_3 = \sum_{i,j=1}^{N,M} \frac{s_{ij}}{n}.$$

From Equations (2), (3), and (4), the energy efficiency model of the RNP problem can be expressed as a weighted sum. However, the constraint in Equation (3) is implemented by **a placement area restriction technique**. Combined with Equation (1), the objective function of the energy-efficient RNP problem is determined in the next equation:

(5) $$\text{minimize } f = -a_1 \sum_{i,j=1}^{N,M} \sum_{k\neq i, h\neq j}^{N,M} \frac{|T_{ij} \cup T_{kh}|}{m^2} s_{ij} s_{kh} + a_2 \sum_{i,j=1}^{N,M} \sum_{k\neq i, h\neq j}^{N,M} \frac{|T_{ij} \cap T_{kh}|}{m^2} s_{ij} s_{kh} + a_3 \sum_{i,j=1}^{N,M} \frac{1}{n} s_{ij}$$

where a_n, $n = 1, \ldots, 3$, is the weight of the objective function and constraints, and $\Sigma a_n = 1$.

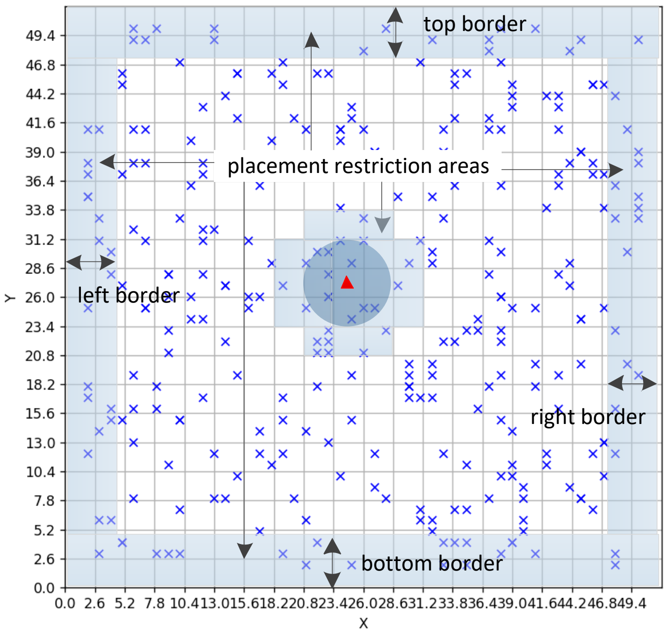


Fig. 3. An example of placement restriction areas (at four edges and around a placed reader)

3.3. Hopfield network-based energy-efficient RNP optimization

The Hopfield network is a recurrent neural network consisting of one fully connected neuron layer. The Hopfield network is generally used in performing auto-association and optimization tasks. The Hopfield network is applied to optimize the energy-efficient RNP problem in the paper.

Considering a Hopfield network of $N \times M$ neurons, its energy function is

(6) $$E = -\frac{1}{2} \sum_{i,j=1}^{N,M} w_{ij} v_i v_j + \sum_{i=1}^{N} \theta_i v_i$$

where v_i and v_j are the activation values of neurons i and j, and w_{ij} is the weight of the connection between neurons i and j.

After each execution cycle, the variance of energy is

$$\Delta E = -\left(\frac{1}{2}\sum_{j=1}^{M} w_{ij}v_j + \theta_i\right)\times \Delta v_i . \tag{7}$$

As shown in [22], ΔE is never positive, which means E never increases, regardless of any variation of Δv_i. That is the Hopfield-based optimization principle, which is "*minimum energy, optimal solution*."

Based on the optimization principle, the function in Equation (5) is rewritten as

$$\begin{aligned} f = {} & \sum_{i,j=1}^{N,M}\sum_{k\neq i,h\neq j}^{N,M} \frac{-a_1\left|T_{ij}\cup T_{kh}\right| + a_2\left|T_{ij}\cap T_{kh}\right|}{m^2} s_{kh}s_{ij} + \sum_{i,j=1}^{N,M}\frac{a_3}{n}s_{ij} - \\ & -\frac{1}{2}\sum_{i,j=1}^{N,M}\sum_{k=1,h=1}^{N,M} 2\frac{a_1\left|T_{ij}\cup T_{kh}\right| - a_2\left|T_{ij}\cap T_{kh}\right|}{m^2} C_{ik}C_{jh}s_{kh}s_{ij} + \sum_{i,j=1}^{N,M}\frac{a_3}{n}s_{ij}, \end{aligned} \tag{8}$$

where C is a constant square matrix, where $C_{ik} = 0$ if $i = k$, otherwise $C_{ik} = 1$.

By comparing Equations (8) and (6), the weight and threshold are obtained as

$$w_{ijkh} = 2\frac{a_1\left|T_{ij}\cup T_{kh}\right| - a_2\left|T_{ij}\cap T_{kh}\right|}{m^2} C_{ik}C_{jh} \text{ and } \theta_{ij} = \frac{a_3}{n}. \tag{9}$$

The proposed Hopfield network for RNP optimization is shown in Fig. 4, where each neuron corresponds to a cell in the working area. A cell is randomly selected to place each reader, corresponding to an input 1 at the corresponding neuron. The weighted sum of the inputs is then calculated to determine the activation level of its neighboring neurons. The neuron with the highest activation determines the corresponding cell to place the reader. The optimization process continues with the subsequent reader placement and stops when there are no more suitable locations to set a new reader or all readers are placed.

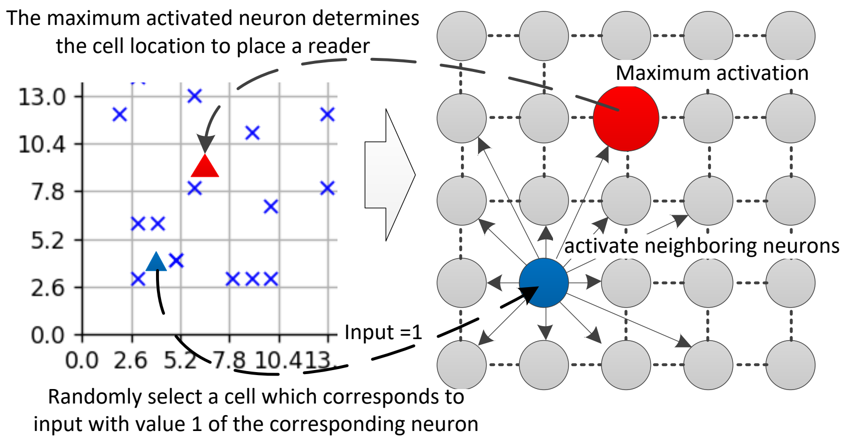


Fig. 4. The Hopfield network for energy-efficient RNP optimization is a matrix of $N\times M$ neurons

The reader placement process must satisfy the constraints in Equations (2) and (3) in that the cells surround a placed reader (with a minimum reader-to-reader distance d_{r2r}) and are at the edges of the working area. (with a normalized radius r_{n}) is not selected to place readers. The placement area restriction mechanism is integrated into the Hopfield network-based energy-efficient RNP optimization process to eliminate outside coverage and reduce overlap area. The integration speeds up the optimization process to find the optimal solution.

The Hopfield network-based energy-efficient RNP optimization process is described by the HNEE-RNP Algorithm.

Algorithm 1. HNEE-RNP Algorithm

Input: n // maximum number of readers that can be placed

M // number of tags in the working area

Output: c // matrix of $n \times m$ cells selected to place readers

Step 1. Initialize the Hopfield network of $n \times m$ with inputs assigned to 0

Step 2. Initialize the weights and the thresholds as Equations (9)

Step 3. Initialize the matrix of $n \times m$ cells (c) corresponding to the Hopfield network

Step 4. Initialize the placement restriction area: the matrix of cells limited to place

Step 5. while ($n > 0$) or (there is no suitable location to place a new reader) **do**

Step 6. Randomly select a cell, which does not belong to the placement restriction area, to place a new reader

Step 7. Activate the neuron corresponding to the selected cell by setting its input to 1

Step 8. Calculates a weighted sum of inputs of each neuron whose corresponding cells are not within placement restriction areas

Step 9. Determine the neuron with the highest activation and the corresponding cell is selected to place a new reader

Step 10. Update the selected cell into the matrix of $n \times m$ cells (c)

Step 11. Update the neighbors of the selected cell into the placement restriction area

Step 12. $n = n - 1$

Step 13. end while

The complexity of the HNEE-RNP algorithm mainly comes from calculating the activation of neurons. With $N \times M$ neurons, the complexity of computing the activations is $O(n \times N^2 \times M^2)$. Accordingly, as the number of neurons corresponding to the number of cells in the gridded working area is large, the algorithm complexity increases.

In the HNEE-RNP Algorithm, the two objectives of maximum tag coverage and minimum energy consumption are prioritized and represented by the higher weights (w_1 and w_2) as in Equation (5). Therefore, the number of placed readers in the optimal solution may be more than necessary, and redundancy occurs. Redundant readers are defined as readers whose elimination does not affect the tag coverage. The Redundant Reader Elimination (RRE) technique in [23] is used to connect to the HNEE-RNP Algorithm to reduce the number of placed readers. The RRE mechanism goes through all placed readers and, for each reader, removes tags that fall within the reader's overlap with other readers. A reader is eliminated if there are no more tags in its coverage. Other readers can interrogate tags belonging to this reader's coverage. The RRE technique reduces the number of redundant interrogations of eliminated readers and thus increases energy efficiency.

4. Simulation and result analysis

Simulation is implemented with Python on a PC Intel(R) Core(TM) i5, 2.40GHz, 8GB RAM. A square-shaped working area is considered, where the gridding is done with different cell sizes and minimum reader-to-reader (r2r) distances. The value d_{r2r} depends on the normalized reader coverage radius (r_{n} = 2.6 m), where two cases, $(3/2)\times r_{\mathrm{n}}$ = 3.9 m and $2\times r_{\mathrm{n}}$ = 5.2 m, are considered. Selecting these parameters ensures that the coverage overlap between two adjacent readers is reduced if any occurs. We consider two cases of even and uneven distribution of tags. The uneven distribution makes tags dense in the lower left corner and gradually sparser towards other corners. Other simulation parameters are described in Table 2.

The simulation objective is to evaluate the efficiency of HNEE-RNPs without and with RRE regarding tag coverage rate, which is the ratio of the number of covered tags to the total tags in the working area and energy efficiency. The HNEE-RNP with RRE (briefly, HNEE-RRE) is also compared with other combinations such as PSO-TRE [12] and GA-RRE [17]. The analyses and comparisons are described in the following subsections.

Table 2. Simulation parameters of HNEE-RNP

No	Parameters	Values
1	Dimension of the working area (m^2)	52×52
2	Number of tags in the working area	300
3	Cell size (m)	5.2, 3.9, 2.6, 1.3
4	Minimum reader-to-reader (r2r) distances (m)	5.2, 3.9
5	Weights of the objective function (a_1) and constraints (a_2, a_3)	0.4, 0.5, 0.1

4.1. Tag coverage rate

Table 3 describes the results of tag coverage rate with different cell sizes (5.2, 3.9, 2.6, and 1.3 m), minimum r2r distances (d_{r2r}) of 3.9 and 5.2, and even and uneven tag distributions. The tag coverage rate achieved is relatively high, in which the smaller the cell size is, the more the tag coverage rate increases due to many placement options.

Table 3. Tag coverage rate with different cell sizes, minimum r2r distances, and tag distributions

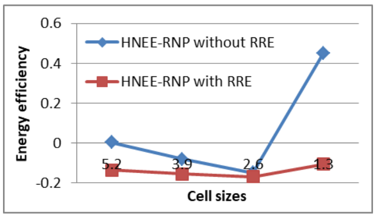
Cell size (m)	Even distribution		Uneven distribution	
	d_{r2r} = 3.9	d_{r2r} = 5.2	d_{r2r} = 3.9	d_{r2r} = 5.2
5.2	0.9967	0.7900	0.9933	0.7807
3.9	0.8967	0.8373	0.9293	0.8333
2.6	0.9473	0.8887	0.9687	0.9220
1.3	0.9873	0.9620	0.9960	0.9687

4.2. Energy efficiency

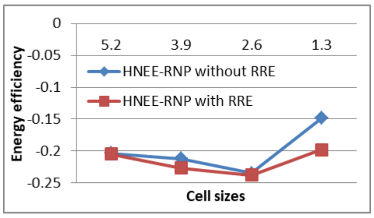
The energy efficiency evaluation criteria are based on Equation (5), where the weights (a_1, a_2, and a_3) are given in Table 2. Different cell sizes (5.2, 3.9, 2.6, and 1.3 m) were investigated, in which each case was performed ten times, and the average value was taken. Simulation results for HNEE-RNP without and with RRE are collected. Fig. 5 shows that HNEE-RNP with RRE achieves the best energy efficiency at cell size 2.6 m for both minimum r2r distances of 3.9 and 5.2 m.

Table 4. The elimination rate with different cell sizes, minimum r2r distances, and tag distributions

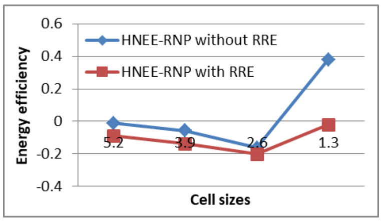
Cell size (m)	Even distribution		Uneven distribution	
	d_{r2r} = 3.9	d_{r2r} = 5.2	d_{r2r} = 3.9	d_{r2r} = 5.2
5.2	0.1859	0	0.1763	0.4930
3.9	0.1282	0.520	0.1622	0.9050
2.6	0.4260	0.150	0.1582	0.1137
1.3	0.3288	0.912	0.3333	0.1638



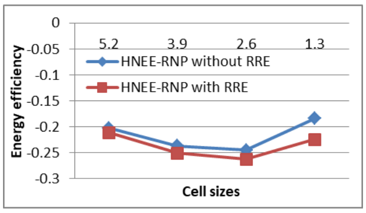
(a) d_{r2r} = 3.9 and even distribution



(b) d_{r2r} = 5.2 and even distribution

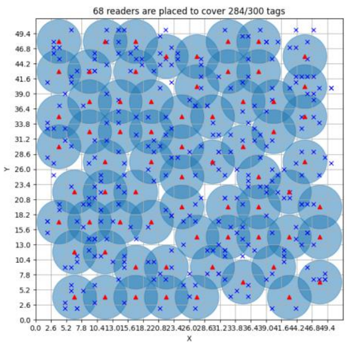


(c) d_{r2r} = 3.9 and uneven distribution

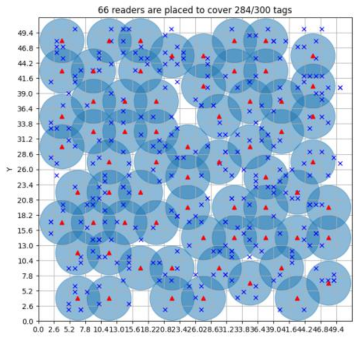


(d) d_{r2r} = 5.2 and uneven distribution

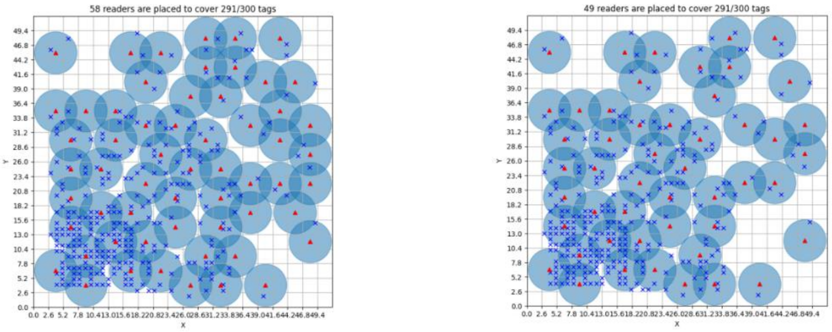
Fig. 5. Comparison of the energy efficiency of HNEE-RNP without and with RRE



(a) Even distribution and without RRE



(b) Even distribution and with RRE



(c) Uneven distribution and without RRE (d) Uneven distribution and with RRE

Fig. 6. Comparison of the energy efficiency of HNEE-RNPs with and without RRE

Fig. 5 also shows that RRE improves energy efficiency for even and uneven tag distributions. The elimination rate, which is the ratio of the number of eliminated redundant readers to total placed readers, for different cell sizes is varied (Table 4), in which the finer the gridding is, the more the candidate placement locations and the placed readers are. Increasing placed readers creates many redundant readers, so the number of readers eliminated increases significantly.

Fig. 6 intuitively shows the reader placement results and the effectiveness of the RRE technique in reducing redundant readers for even distribution (Fig. 6a-b) and uneven distribution (Fig. 6c-d).

4.3. Optimality and runtime

The optimization process is based on the principle of Hopfield network energy minimization. Specifically, with the cell size of 2.6 m and the minimum r2r distance of 3.9 m, the energy varies through the optimization process, as shown in Fig. 7. It is clear that the Hopfield energy gradually decreases through each step of searching the placement location for each reader and saturates when no suitable location can be found. Not increasing the Hopfield network energy ensures that the reader placement results are guaranteed to be optimal.

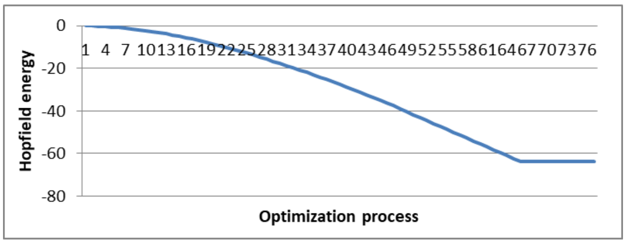


Fig. 7. The Hopfield energy decreases with the optimization process and saturates at the end

When comparing the runtime, Fig. 8 shows that the runtime is inversely proportional to cell size. In other words, the smaller the gridding is, the larger the number of cells is. Therefore, the runtime increases quite quickly when the cell size becomes small.

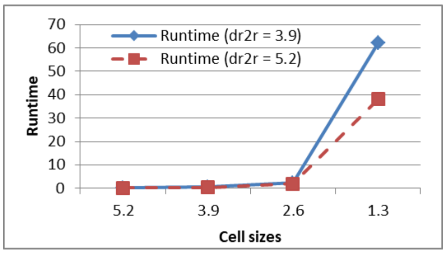


Fig. 8. Runtime increases rapidly as cell size decreases

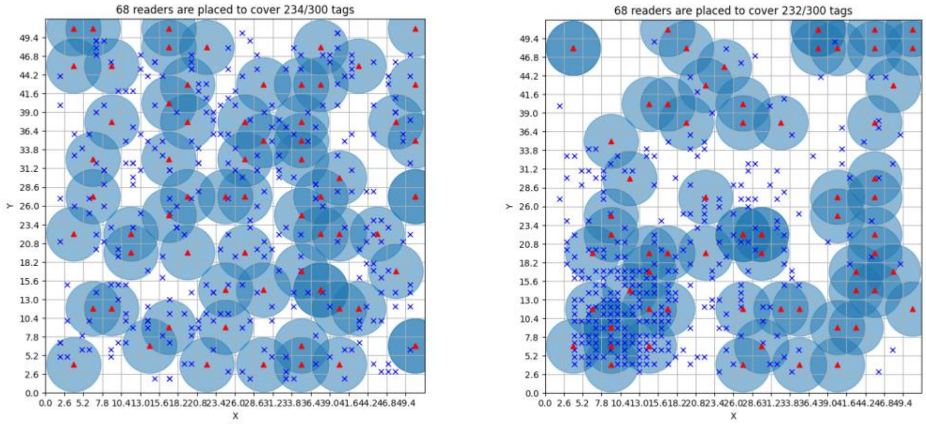
4.4. Comparing HNEE-RRE with PSO-TRE and GA-RRE

HNEE-RRE achieves the best results with a cell size of 2.6 m and a minimum r2r distance of 3.9 m. These parameters are then used to simulate PSO-TRE and GA-RRE. The fitness function of PSO-TRE and GA-RRE is the energy efficiency function in Equation (5) with weights as in Table 2. Simulation parameters for PSO-TRE and GA-RRE are described in Table 5.

Table 5. Simulation parameters for PSO-TRE and GA-RRE

No	Parameters	Values
	GA-RRE	
1	Selection operator	Roulette wheel
2	Crossover operator	Single point
3	Mutation operator and probability	At a single gene with a probability of 0.05
4	New generation	30% elite parents and 70% best children
	PSO-TRE	
5	Interaction weight between individual and population (w)	0.7
6	Interaction coefficient between individuals (c_1)	1.5
7	Interaction coefficient for the whole population (c_2)	1.5

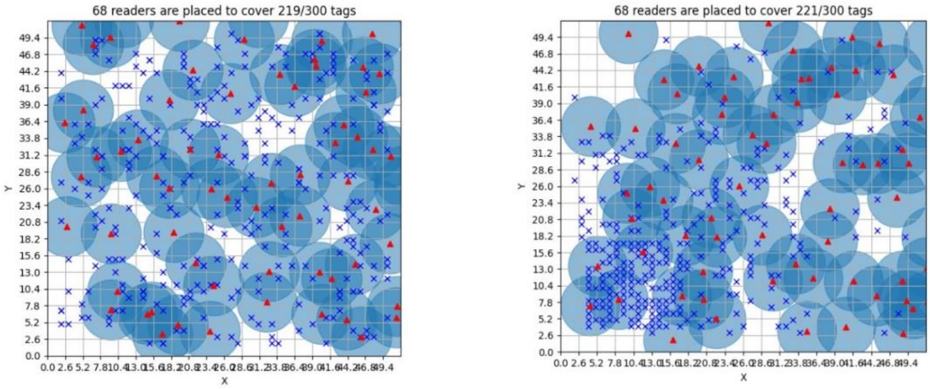
With over 100 generations and a population size of 20, the results in Fig. 9 show that the achieved coverage rate is low. Specifically, with the number of readers used as in HNEE-RRE (68 readers as in Fig. 6a), the coverage rate and the overlap ratio, from the number of overlapped tags to the number of covered tags, are 78% and 37.6%, respectively. The reason is that GA-RRE lacks a mechanism to limit placement at locations close to placed readers, so the size of the overlap area is more significant than that of HNEE-RRE. Furthermore, placing readers near the edges of the working area results in a low tag coverage rate for GA-RRE because the outside coverage is useless. Therefore, the coverage rate of GA-RRE is lower than that of HNEE-RRE. Fig. 9 depicts a visual example of GA-RRE's reader placement results for even and uneven tag distributions.



(a) Even tag distribution (b) Uneven tag distribution

Fig. 9. The reader placement results of GA-RRE with different tag distributions

PSO-TRE achieved the lowest results regarding tag coverage rate, energy efficiency, and optimality. The reason is that the optimization process depends a lot on the particle movement process (solution), and in turn, the particle movement process depends on the appropriate velocity control process when changing the reader positions. As a result, the coverage rate and the overlap ratio, the number of overlapped tags to the number of covered tags, are 72% and 35.5% (Fig. 10.)



(a) Even tag distribution (b) Uneven tag distribution

Fig. 10. The reader placement results of PSO-TRE with different tag distributions

5. Conclusion

The increasingly widespread application and deployment of IoT systems in practice has raised the need to optimize the number of devices used and increase energy efficiency while still ensuring that they cover tagged objects. RNP methods aim to solve this multi-objective problem, where the weights of the objectives/constraints and the trade-offs between them must be considered. The paper proposed an approach of Hopfield-based energy-efficient RNP, in which finding the optimal placement location for readers is performed by a Hopfield network-based optimization process, and a placement area restriction technique is proposed to increase energy efficiency.

The runtime to find an optimal solution for nature-inspired methods is often very long for large working areas and many deployed tags. Applying the optimization principle based on Hopfield network energy reduction makes HNEE-RNP highly adaptive, where later solutions are always better or equal to previously found solutions. HNEE-RNP can return a near-optimal solution if the runtime is limited. To further increase the effectiveness of HNEE-RNP, a technique of redundant reader elimination is also combined with HNEE-RNP. The simulation results show that HNEE-RNP has achieved the best energy efficiency. HNEE-RNP with RRE (HNEE-RRE) also demonstrated superiority over PSO-TRE and GA-RRE in terms of maximum coverage and the best energy efficiency.

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