

Seasonal Agricultural Products Distribution and Traceability System Based on the RFID Internet of Things

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Abstract

Based on the big data and complexity in the identification process of IOT radio frequency, this article puts forward an optimal algorithm for Adaptive Gaussian Traversal Harmony Search IOT radio frequency identification, which aim at solving the problems of high computational complexity and low identification accuracy of traditional algorithm. At first, the network optimization design is carried out based on Harmony Search (HS) algorithm, and in order to solve the problems of standard HS in optimization accuracy, computational complexity and other aspects, control parameters are introduced into the algorithm improvisation process on the basis of traverse characteristics of Gaussian function, so that the pertinence of preliminary and later searches are improved, and meanwhile, theoretical analysis on parameters selection is described; Secondly, the optimization model of IOT radio frequency identification is studied and improved adaptive optimization objectives are put forward to achieve equilibrium optimization of performance indicators; at last, test results are compared to prove the suggested algorithm having high computational accuracy and faster computational speed.

Keywords: *IOT; Radio frequency identification; Logistics; Gaussian traverse; Harmony search; Self-adaptation*

1. Introduction

With the rapid development of IOT (Internet of Things) technology, RFID (Radio frequency identification network) based IOT logistics management has become more and more popular. The RFID system is mainly composed of three parts: Reader module, data management module and electronic tags; in the network, electronic tags and reader module are usually used together. Among them, the rationality of reader module configuration plays a key role in lowering network costs and reducing the configuration conflicts between electronic tag resources and reader module, and it is the focus and crucial topic for the research on radio frequency network optimization in IOT technology. This article mainly studies the RFID network optimization problems by using the HS algorithm, and meanwhile, it considers the optimization of objective function of logistic RFID network by using modified adaptive weighting coefficients. Harmony search algorithm (HS) is an intelligent optimization algorithm which was put forward by Geem and others in 2001 [8], and compared with conventional intelligent optimization algorithm, HS algorithm has the following advantages [9]: (a) In case of generating new harmony, HS algorithm will consider all existing harmonies while Particle Swarm Optimization and other algorithm only consider parent individuals; (b) Hs algorithm adjust the generating method of new harmony according to independent variables; (c) During the improvisation process of HS algorithm, the memory bank can be designed by using random numbers, which in nature is a kind of global random search process.

Based on the advantages of above-mentioned algorithm, this article considers using HS algorithm as basic optimization algorithm, and based on the characteristics of HS

algorithm, it improves the improvisation process by using Gaussian Traverse Function, so as to enhance the pertinence of HS algorithm on real-time information in preliminary and later search, based on which corresponding adjustment will be made on the tracking and search strategies of real-time change of IOT RFID network; meanwhile, regarding the non-adaptability of IOT RFID network model, the article considers using adaptive weights to realize balanced design of IOT RFID network performance indicators.

2. Gaussian Traverse Harmony Search

2.1. Harmony Search

The optimization process of Harmony Search and music production process have many similarities. A couple of music creation concepts are introduced into HS algorithm, mainly including the following algorithm parameters: Harmony memory (HM) and its size (HMS) and harmonic memory reference ratio (HMCR), *etc.*, which are used for storing input vectors, characterizing vector sizes and current music parameter reference rate, $HMCR \in [0,1]$. In addition, there are other parameters, such as pitch adjustment ratio (PAR) and distance width adjustment ratio (bw), *etc.* Detailed procedures of standard harmony search algorithm are as follows [10]:

Step1: (algorithm initialization) input vectors are stored in HM at first, and meanwhile, value range of input vectors are specified. Swarm individuals with a size of HMS are generated based on the following Formula (1), and are stored in HM:

$$x_i^r = x_i^l + rand \times (x_i^u - x_i^l) \quad (1)$$

In Formula (1), x_i^u and x_i^l are the upper and lower limit values of Vector No. in vector individuals.

Step 2: (improvisation process) new vectors are created by means of improvisation: (a) to select an existing vector in HM or to create a new vector based on HMCR is determined by random. (b) if it is determined to select an existing vector, the adjustment will be made on the basis of two parameters, PAR and bw , and see Formula (2) for detailed procedures:

$$\begin{cases} x_i^{new} = x_i^r \pm rand \times bw, & \text{if } rand < PAR \\ x_i^{new} = x_i^r, & \text{if } rand \geq PAR \end{cases} \quad (2)$$

Step 3: (HM update process) To compute the adaptive value of new individual, and compare the value with that of original vector individual, then select the superior individual to participate next generation of evolution according to one-to-one elimination mechanism, so that the HM update process is completed.

Step 4: (algorithm stop discrimination) To check whether the value of existing optimal individual in current memory meet the requirement of algorithm termination, and if it is met, the discrimination is terminated and the superior individual will be output; otherwise, it will jump to Step 2 to continue the improvisation process of next generation.

2.2. Description of Refinement Algorithm

In the improvisation process of HS algorithm, if the conditions of HMCR are met, existing vector individuals in HM will be selected. Then the adjustment will be made based on parameters PAR and bw . Among them, the selection of parameter bw has a profound impact on the performance of HS algorithm, with larger bw values going against further development of the algorithm, smaller values going against the extent exploration of the algorithm, and fixed bw values unable to make automatic adjustment according to the evolution conditions of the algorithm; the above-mentioned disadvantages are obvious and major disadvantages of HS algorithm. The reasonable strategy is selecting larger bw

values in preliminary period and smaller bw values in later period, which can improve the algorithm performance [11]. Control parameter α can be used:

$$\alpha = 1 - \lambda \times iter_{\text{current}} / iter_{\text{max}} \quad (3)$$

At the same time, Gaussian ergodicity can be used for the refinement of improvisation, and it can be used together with the iteration by taking larger probability values and smaller step iteration to further develop existing positions, and by taking larger probability values and larger step iteration to explore the extent of future positions; and based on control parameter α and Gaussian traverse function g , the refinement of creation process is realized:

$$\begin{cases} x_i^{\text{new}} = x_i^r \pm g \times a \times bw, & \text{if } rand < PAR \\ x_i^{\text{new}} = x_i^r, & \text{if } rand \geq PAR \end{cases} \quad (4)$$

In Formula (4), $g \sim N(\mu, \sigma^2)$, the distribution (variance) σ of Gaussian traverse function g has a significant impact on the performance of HS algorithm.

2.3. Theoretical Analysis

In order to facilitate the theory analysis of the algorithm, it is assumed that vector individuals stored in HM are all in one dimensional distribution, with the following forms:

$$HM = x = \{x_1, \dots, x_{HMS}\}^T \quad (5)$$

The adaptive values, to which vector individuals correspond, are all one dimensional vectors, with the following forms:

$$y = \{y_1, \dots, y_{HMS}\}^T \quad (6)$$

The distribution variance of adaptive values of HS algorithm evolution swarm is:

$$E(y(\text{var})) = E\left(\frac{\sum_{i=1}^{HMS} (y^i - \bar{y})}{HMS}\right) = E(\bar{y}^2) - E(\bar{y}^2) \quad (7)$$

where the function,

$$\begin{aligned} E(\bar{y}^2) &= HMCR \cdot \bar{x}^2 + HMCR \cdot PAR/3 \\ &+ (1 - HMCR)(a^2 + ab + b^2)/3 \end{aligned} \quad (8)$$

$$E(\bar{y}^2) = E\left(\left(y^i\right)^2 + \frac{(HMS-1) \cdot (E(y^i))}{HMS}\right)^2 \quad (9)$$

then, the distribution variance of one dimensional adaptive values is:

$$\begin{aligned} E(y(\text{var})) &= \left(1 - \frac{1}{HMS} \cdot HMCR \cdot E(x(\text{var}))\right) \\ &+ HMCR \cdot (1 - HMCR) \cdot \bar{x}^2 + \frac{b\omega^2}{3} \\ &HMCR \cdot PAR + \frac{(1 - HMCR)}{12} (a - b)^2 \end{aligned} \quad (10)$$

In Formula (10), $[a,b]$ is the value range of one dimensional individual x , and $y^{(var)}$ and $y^{(var)}$ correspond to the distribution variance of individual x and its adaptive value y , respectively. When $E(y^{(var)})$ is too large, HS algorithm focuses on exploration, but it is easy to cause algorithm divergence. When $1/HMCR$ is too small and $HMCR \rightarrow 1$, Formula (10) can be reduced to:

$$E(y^{(var)}) = HMCR \left(E(x^{(var)}) + \frac{b\omega^2 \cdot PAR}{3} \right) \quad (11)$$

According to the HS algorithm improvisation process (4), Formula (11) can be rewritten as:

$$E(y^{(var)}) = HMCR \cdot \left(E(x^{(var)}) + \frac{b\omega_0^2 \alpha^2 g^2 \cdot PAR}{3} \right) \quad (12)$$

In Formula (12), the values change along the decrease iteration of parameter α , which is advantageous to convergence $E(y^{(var)})$ and can effectively prevent HS algorithm divergence. After introducing Gaussian parameter g , the creation process complies with Gaussian traverse distribution, which can avoid monotonic decrease of $\alpha^2 g^2$, invigorate the algorithm and effectively balance the exploration and development capabilities of the algorithm.

3. RFID Optimization of GTHS Logistics

3.1. Description of RFID Model

RFID logistics optimization process is essentially a kind of target optimization process; and according to the above descriptions of harmony search algorithm, before using it for the optimization of logistics RFID network, the target function model should be established, and the reasonableness of the model has certain impact on optimization result. Similar to the structure form of target function of common optimization algorithm, Reference [12] makes a profound research on logistics RFID problem and designs an optimization computation target model, but Reference [12] uses the target function with fixed weighting parameter, whose detailed form is:

$$\min f = \gamma_1 f_1 + \dots + \gamma_n f_n \quad (13)$$

In Formula (13), γ_i is the weighting factor (fixed weight) of each performance index, and f_i is the performance index which meets:

$$\sum_{i=1}^n \gamma_i = 1 \quad (14)$$

It is assumed that in IOT RFID network area, the ceiling number of readers is N_{max} , and the actual number of readers is N_R , and the number of electronic tags is N_t , the signal coverage radius of reader module is R_R , and the position is (x_s^i, y_s^i) ; if the network space is A , the optimization feasible region of IOT RFID problem is:

$$(x_s^i, y_s^i) \in A, \forall i \in \{1, \dots, N_R\} \quad (15)$$

If electronic tag j is located at (x_o^j, y_o^j) , it can be defined that:

$$\begin{cases} SN_R = \{1, \dots, N_R\} \\ SN_t = \{1, \dots, N_t\} \end{cases} \quad (16)$$

Then the distance between reader i and electronic tag j in IOT RFID network can be computed by using the formula:

$$d(s_i, o_j) = \sqrt{(x_s^i - x_o^j)^2 + (y_s^i - y_o^j)^2} \quad (17)$$

3.2. Definition of Impact Factor

3.2.1. RFID Network Coverage: If the value range of electronic tags in RFID network is R_T , the identification capability of reader i on electronic tag j is:

$$rder_{i,j} = \begin{cases} 0, R_R + R_T \leq d(s_i, o_j) \\ 1, R_R - R_T > d(s_i, o_j) \\ e^{(-\lambda_1 \alpha_1^{\beta_1} \alpha_2^{\beta_2} + \lambda_2)}, otherwise \end{cases} \quad (18)$$

In Formula (18), the parameters can be defined as: $\alpha_1 = R_T - R_R + d(s_i, o_j)$, $\alpha_2 = R_T + R_R - d(s_i, o_j)$, where, λ_1 is called perception parameter and λ_2 is called noise parameter. Then, the formula of IOT RFID network coverage is:

$$c_o^j = 1 - \prod_{i \in SN_R} (1 - rder_{i,j}) \quad (19)$$

The network coverage index can be defined as:

$$f_1 = \frac{100}{N_t} \sum_{j \in SN_t} c_o^j \quad (20)$$

In order to express it in the form of minimum index, the following formula can be used to make refinement:

$$f_1 = 100 - \frac{100}{N_t} \sum_{j \in SN_t} c_o^j \quad (21)$$

3.2.2. RFID Network Operation Cost: The ceiling number of network readers is N_{\max} and the actual number of reader module in the network is N_R , then cost of readers in RFID network is:

$$f_2 = \frac{N_{\max} - N_R}{N_{\max}} \quad (22)$$

3.2.3. RFID Network Load Balancing: It is very difficult to establish the load balancing mathematical model, but an approximate model can be established by using Monte Carlo sampling. It is assumed that the electronic tag j is located at $o_k^j(x_k^j, y_k^j)$, in which the sampling point No. k corresponds the reader i , then it can be obtained by Formula (18) that $rder_{i,j}^j = 1$, otherwise $rder_{i,j}^j = 0$, and it can be obtained:

$$rder_{i,j}^j = \begin{cases} 0, R_R + R_T < d(s_i, o_j) \\ 1, R_R - R_T \geq d(s_i, o_j) \end{cases} \quad (23)$$

In Formula (23), $k=1, \dots, K$, K is the Monte Carlo sampling point, and then the following conditions are met:

$$R_R - R_T < d(s_i, o_j) \leq R_R + R_T \quad (24)$$

The polar coordinate form of sampling points can be obtained based on the method of concentric circles:

$$(r, \theta) = \begin{cases} (0, 0), \text{ if } \varepsilon_1 = \varepsilon_2 = 0; \left(\varepsilon_1, \frac{\pi \varepsilon_2}{4 \varepsilon_1} \right), \text{ if } \varepsilon_1 > |\varepsilon_2|; \\ \left(\varepsilon_2, \frac{\pi(2 - \varepsilon_1/\varepsilon_2)}{4} \right), \text{ if } -\varepsilon_2 < \varepsilon_1 \leq \varepsilon_2; \\ \left(-\varepsilon_1, \frac{\pi(4 + \varepsilon_2/\varepsilon_1)}{4} \right), \text{ if } \varepsilon_1 \leq -\varepsilon_2 \cup \varepsilon_1 < \varepsilon_2; \\ \left(-\varepsilon_2, \frac{\pi(6 - \varepsilon_1/\varepsilon_2)}{4} \right), \text{ otherwise.} \end{cases} \quad (25)$$

Then, the overlapping degree of sampling point k within the range of electronic tag j is:

$$oer_k = \begin{cases} 0, \sum_{i \in SN_R} rder_{ij}^j \leq 1 \\ \sum_{i \in SN_R} rder_{ij}^j - 1, \sum_{i \in SN_R} rder_{ij}^j \geq 2 \end{cases} \quad (26)$$

and load balancing index can be defined as:

$$f_3 = \prod_{j \in SN_i} \frac{1}{1 + \frac{1}{k} \sum_{i \in SK} oer_k^j} \quad (27)$$

3.3. Adaptive Target Function

In order to solve the integration problem of evaluation indexes of the above-mentioned three IOT RFID network performance, the traditional solution is to comprehensively consider the three indexes by using weighting factor, and establish the comprehensive target function of RFID network, with the detailed form as follows:

$$\min f = \gamma_1 f_1 + \gamma_2 f_2 + \gamma_3 f_3 \quad (28)$$

In Formula (28), γ_1 , γ_2 , γ_3 are weightings, and shall meet following requirement:

$$\gamma_1 + \gamma_2 + \gamma_3 = 1 \quad (29)$$

Target Function (28) can be divided into two situations: one is when f_1 , f_2 and f_3 are in the same order of magnitude, γ_1 , γ_2 , γ_3 can use a same order of magnitude; the other is when f_1 , f_2 and f_3 are in different orders of magnitude or one of them is in a different order of magnitude, then the values of γ_1 , γ_2 , γ_3 should be selected according to the orders of magnitude of f_1 , f_2 and f_3 . But in practical application, the orders of magnitude of f_1 , f_2 and f_3 continuously vary with the performance index characteristics and evolution process, therefore, the target function with fixed weighting cannot reach ideal results. In order to solve this problem, an adaptive weighting selection method is designed as follows:

$$\min f = \frac{f_1 - f_1^{\min}}{f_1^{\max} - f_1^{\min}} + \frac{f_2 - f_2^{\min}}{f_2^{\max} - f_2^{\min}} + \frac{f_3 - f_3^{\min}}{f_3^{\max} - f_3^{\min}} \quad (30)$$

Where, f_i^{\min} and f_i^{\max} are the minimum values and maximum values of No. i Index f_i in current evolution swarm. In the above-mentioned adaptive target function, the hyper-plane defined by index weighting and limiting points shall be updated along with the update of index limiting points, and the final result will be minimum limiting point

gradually approaching final ideal point, so that the optimization of target function is completed.

4. Experimental Analysis

4.1. Algorithm Parameters Impact

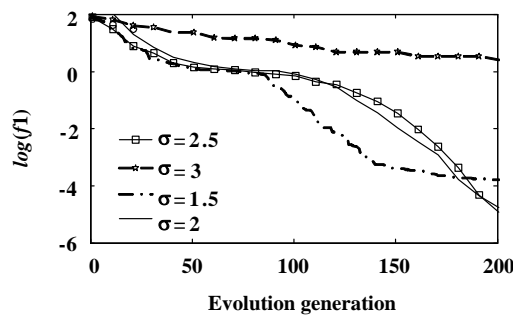
Two standard test functions are selected for the performance test of GTHS algorithm, and the characteristics of the two functions include high dimensions, multi peaks, lots of local extreme points which are strongly seductive to HS individuals; the test functions are as shown in Formula (31), and see Table 1, for the overall optimal values and parameter settings.

$$\begin{aligned}
 f_1(X) &= \sum_{i=1}^n [x_i^2 - 10\cos(2\pi x_i) + 10], \\
 f_2(X) &= \left[\sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos(x_i/\sqrt{i}) + 1 \right] / 4000.
 \end{aligned}
 \tag{31}$$

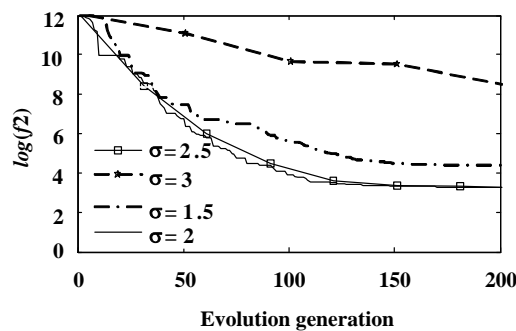
Table 1. Test Function Parameter Settings

f	D	S	P
f1	20	[-5.12, 5.12]	0
f2	20	[-600, 600]	0

In the above-mentioned refinement algorithm, the main way is to add Gaussian traverse parameter g and control parameter α into HS algorithm, and λ has a large impact on parameter α , so does variance σ_g on Gaussian traverse parameter g . Parameter settings: HMS = 100, HMCR = 0.95, PAR = 0.7, iter = 1500, $\lambda = 0.3$. The test results are as shown in Figure 1.



(a) f1 function



(b) f2 function

Figure 1. Effect of Variance Value

It can be seen from the comparison of curves in Figure 1 (a), and (b), when variance $\sigma_g = 2$, HS algorithm has the optimal convergence process. Meanwhile in theory, it can be seen from the analysis of Formula deviation (12), the main function of parameter α is to make the values of parameter bw in a state of monotonic decreasing; larger bw can be used in preliminary stage of the algorithm and smaller bw can be used at later stage, which can balance the exploration and development capabilities in both preliminary and later stages of the algorithm. In spite of this, as the change of bw is too regular, the innovation of this algorithm will be reduced. In this regard, the Gaussian traverse function g is used to enhance the randomness of bw change, but in fact, the value of g is not as large as better, and it can be seen from the analysis of simulation comparing results, $\sigma_g = 2$ is the optimal value.

As a matter of fact, like Figure 2, in terms of Gaussian traverse function $g \sim N(0, \sigma)$, if the Gaussian function variance σ is too small (for example $\sigma = 0.5$), the values of y will be mainly distributed within $[-1, 1]$, showing a peak pattern, and the overall distribution values are comparatively larger. While when variance σ is too large (for example $\sigma = 4$), the value distribution of y will show a flat pattern, mainly within $[-6, 6]$; and the transverse space is expanded while the overall values of y are comparatively smaller. The specific impacts on control parameters: (a) large y values will have larger impact on parameter α , and meanwhile, it will disturb the overall decreasing trend of bw ; (b) small y values will have little impact on parameter α , and cannot show the improvement impact of Gaussian traverse distribution g on control parameter α .

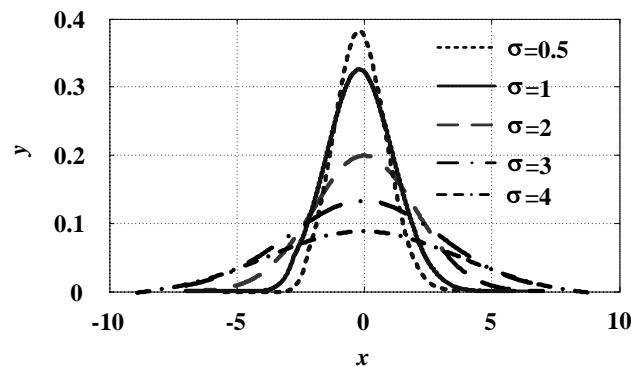


Figure 2. Gauss Distribution for Different σ

4.2. Example of IOT RFID Optimization

According to the experiment setting in Reference [9], the IOT RFID network area is $30\text{m} \times 30\text{m}$ and there are approximately 100 electronic tags randomly distributed in this area, and each reader has a deployment ceiling of $N_{\max} = 20$; electronic tag setting area has a radius parameter uncertainty value of $R_r = 1\text{m}$, and the detection radius of the reader is $R_R = 8\text{m}$; the parameter value of RFID network coverage index is:

$$\begin{cases} \lambda_1 = 1, \lambda_2 = 0 \\ \beta_1 = 1, \beta_2 = 0.5 \end{cases} \quad (32)$$

Three algorithms are selected for the simulation comparing targets, including the adaptive space particle swarm optimization (RPSOAS) [12], combined differential evolution algorithm (CDE) [13] and parameter adaptive differential evolution algorithm (C-MC) [14], and running the RFID network optimization processes of these three algorithms for 50 times to obtain the average value, and the optimal and average values of

RFID network optimization are shown in Table 2, and 3, and the optimal network identification distribution results obtained by means of comparing algorithms are shown in Figure 3. The evolution process convergence curve is as shown in Figure 4.

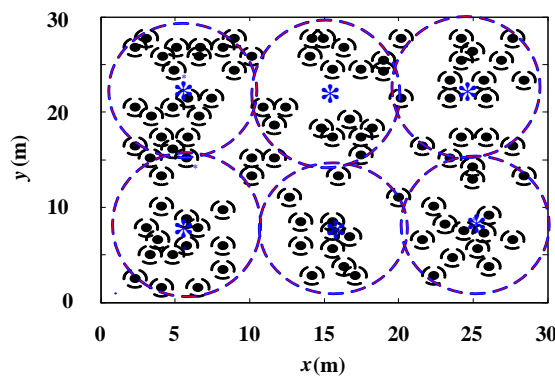
Table 2. Optimal Identification Results

	GTHS	CDE	RPSO AS	C-MC
Coverage rate	72.1356	85.3415	90.9584	83.9128
load balance	0.0123	0.0239	0.8065	0.0553
network cost	0.15	0.32	0.41	0.36
target value	5.2327	8.5368	9.1271	7.4357

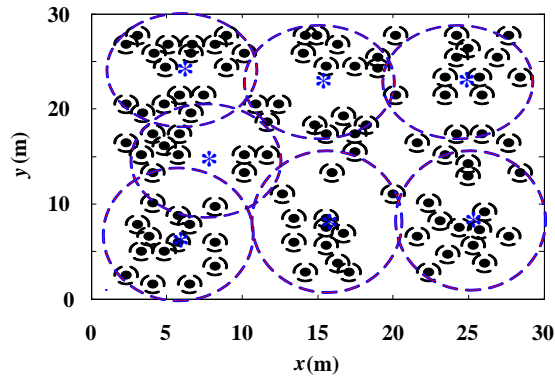
Table 3. Average Recognition Results

	GTHS	CDE	RPSO AS	C-MC
Coverage rate	69.3214	81.1798	86.1918	80.0345
load balance	0.0021	0.0223	0.299	0.0274
network cost	0.127	0.331	0.323	0.226
target value	4.9675	7.8935	8.0679	7.2286

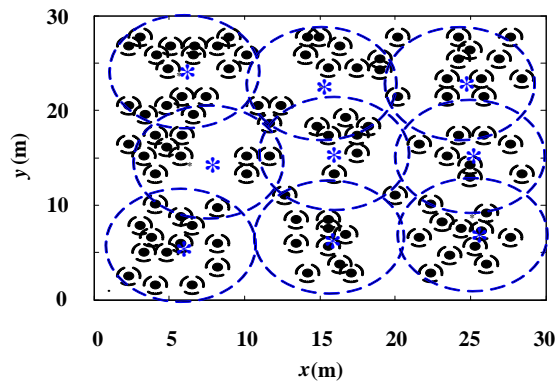
In the simulation results if Figure 3 (a), ~ (d), the RFID network optimal identification conditions of four comparison algorithms, which are GTHS, RPSOAS, CDE and C-MC, are presented, and the black spots "." and surrounding small circles are RFID network electronic tags and their uncertainty regions. The big circles in simulation results represent the detection area of corresponding readers, and "*" represents the readers in RFID network. Table 2, and 3, the average optimization values of the four comparison algorithms which are GTHS, RPSOAS, CDE and C-MC for RFID network target function. Table 2, shows the optimal evolution results, from which it can be seen that in the comparison of optimization results of optimal adaptive values, GTHS algorithm can achieve better optimization result than those of the other three algorithms, while C-MC algorithm ranks the second place, achieving slightly better results than those of RPSOAS and CDE algorithms. Table 3, shows the optimization data of average adaptive values of the above-mentioned four algorithms, and the average value operation results in Table 3 are similar to those in Table 2, with the average value results of GTHS algorithm being better than those of the other three algorithms, and C-MC algorithm ranking the second place, being slightly better than RPSOAS and CDE algorithms. The above experimental data directly proves the feasibility and effectiveness of GTHS algorithm in IOT RFID network identification.



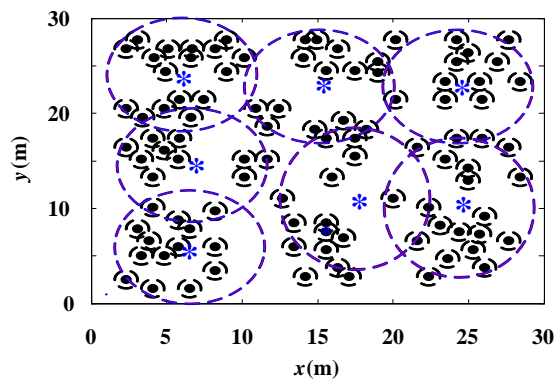
(a) Optimal identification results for GTHS algorithm



(b) Optimal identification results for CDE algorithm

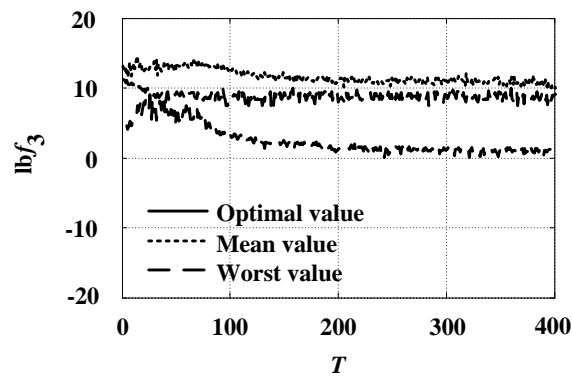


(c) Optimal identification results for RPSOAS algorithm



(d) Optimal identification results for C-MC algorithm

Figure 3. Optimal Identification Results



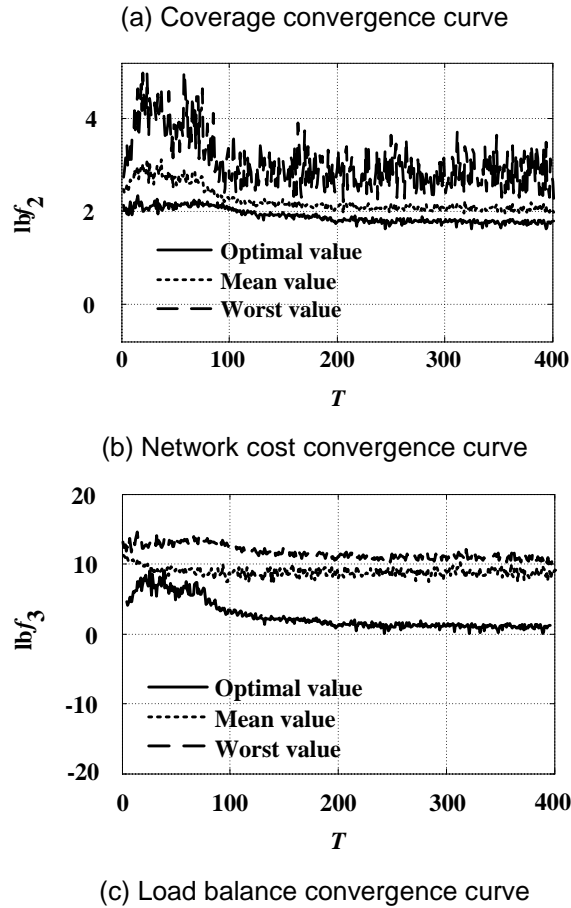


Figure 4. Network Optimization Convergence Curve

Figure 4, shows the optimal, worst and average convergence curves of target adaptive values when GTHS algorithm and adaptive target function are adopted, and in order to present the data differences, the binary logarithm which is commonly used in signal processing is used for data amplification. It can be seen from simulations curves that although the orders of magnitude of three targets' adaptive values are different, GTHS algorithm can achieve synchronous optimization of the three network index after adopting the weighting adaptive for refinement, and meanwhile the phenomenon in Reference [8] that index with larger orders of magnitude merging index with smaller orders of magnitude can be avoided, so that the problem of local extreme points can be prevented.

Table 5, shows the load balancing and adaptive value deviation, from which it can be seen that, under the precondition of different network scales and tag distribution forms, CDE algorithm has better performance in load balancing and adaptive value than PRSOAS and C-MC algorithms, and each of the later two algorithms has advantage and disadvantage in load balancing and adaptive value. Compared with the above three algorithms, GTHS algorithm always has the optimal load balancing and adaptive value, which proves the robustness of GTHS algorithm on network parameters.

Table 5. Load Balance and Fitness Deviation

Network Scale	Tag distribution	Performance index	GTHS	CDE	RPSOAS	C-MC
30×30 m 100 tags	Normal	Load balance	0.0278	0.0371	0.0417	0.3202
		Adaptive value	7.2347	7.6164	7.8598	8.0525
50×50 m	Normal	Load balance	0.0312	0.0386	0.0624	0.3501

Network Scale	Tag distribution	Performance index	GTHS	CDE	RPSOAS	C-MC
250 tags	Random	Adaptive value	7.2156	7.5601	7.753	7.8085
		Load balance	0.0326	0.0394	0.0838	0.3504
		Adaptive value	7.1682	7.4611	7.6617	7.8183
		Load balance	0.0326	0.0384	0.0511	0.3437
100×100 m	Normal	Adaptive value	7.2863	7.5402	7.6073	7.7857
		Load balance	0.0317	0.0352	0.0795	0.3451
1000 tags	Random	Adaptive value	7.0563	7.6296	7.6812	7.8194

5. Conclusion

In order to further improve the accuracy of IOT RFID network optimization, this paper puts forward the innovative design from two aspects: One is to further improve the optimization algorithm performance, which is based on harmony search algorithm, design control parameters and introduce Gaussian traverse distribution function for refinement; the other is improvement of RFID network optimization model, which designs adaptive weighting form target function to realize synchronous evolution of network index, effectively avoiding being trapped in extreme points. The simulation results show that the GTHS algorithm optimization result of adaptive weighting target function is better than those of algorithms in comparing references. The research on radio frequency network optimization of large-scale IOT RFID has very important economic significance; the above-mentioned algorithms also include the researches on this field, but lack of verification under practical environment, and this will be the focus of next step researches.

Acknowledgements

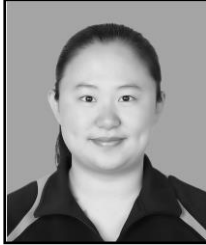
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