DEPLOYMENT APPROACH TO NODES OF THE IOT FOR MONITORING SYSTEMS IN PORTS

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ABSTRACT

In order to solve the conflict between higher monitoring quality and lower application costs of the internet of the things (IoT) monitoring system in ports, a mixed integer non-linear programming model was built. Various key factors, such as network scale, cost, representation level, and the deployment of nodes for the balance degree of the IoT, are comprehensively taken into consideration in this programming model. Furthermore, the quantity and deployment solution was solved through a genetic algorithm; in addition, the selection of nodes was evaluated. Simulation results show that the deployment solution is conducive to solve the quality-cost conflict to some extent. It is also of theoretical significance for the IoT research and design of the monitoring system.

I. INTRODUCTION

Nowadays, with the development of information technology, there are increasing demands in IoT applications in ports. However, IoT applications must consider costs, such as node hardware and software investments, node energy consumption, maintenance, management, and so on. Therefore, how to adopt the intensive way of designing and deploying IoT nodes and the use of a reasonable IoT operational pattern are very important decision-making problems in the popularization and application of IoT.

The research of applying IoT technology to monitoring systems has been very extensive. Bo et al. (2008) designed a monitoring system for product life cycle by integrating the technical advantages of RFID (Radio Frequency Identification) and IoT. He et al. (2011) designed a marine environmental monitoring system based on IoT technology. According to the IoT architecture in forestry data monitoring, Liu et al. (2011) studied sensor positioning algorithms for the detection of forest fires. In the field of transportation, Zhou et al. (2011) proposed a traffic flow measuring system based on IoT. Qin et al. (2008) discussed IoT technology during the container transport of dangerous goods. Mi et al. (2015a, 2015b) proposed a two-stage classification approach for human detection of IoT application in bulk ports.

At present, the wireless sensor network node layout problem is also a hot issue. Ye et al. (2003) elaborated on communication structures for wireless sensor networks, the composition of the sensor nodes, and their possible implementation, then analyzed the advantages and disadvantages of various topologies. Wang (2006) discussed how many nodes were enough to achieve completely seamless coverage for a given detection area. Xu et al. (2008) proposed a p-median layout model of multi sink nodes in a wireless sensor network.

In recent years, improved genetic algorithms have become an effective tool for finding optimal solutions. Wang et al. (2008) proposed an optimal strategy for dynamic node selection with the combination of the Hopfield neural network and genetic algorithm. Fu et al. (2008) proposed a distribution optimization mechanism based on the new quantum genetic algorithm. Li et al. (2010) proposed an optimal cost for a heterogeneous sensor deployment scheme based on the genetic algorithm. The cost of sensor node deployment was used as objective function for optimization computation subjected to network coverage and fault tolerance in order to obtain the suitable types and positions of the sensors. Jia et al. (2009a, 2009b) made use of the improved NSGA-II in order to solve the node deployment of multi-objective optimization problem. An advantage of the new quantum genetic algorithm over the conventional genetic algorithm was demonstrated in simulation result; thus, it can effectively enhance the sensing ability of the whole network. In addition to the genetic algorithm, Lin et al. (2005) used the simulated annealing algorithm in order to solve the deployment issues of grid-based sensor node. Using the weighted average method, Zhou et al. (2010) developed an objective function with which to maximize network coverage and minimize the number of nodes, and they developed an optimal coverage configuration based on the artificial fish swarm algorithm.

Although the deployment problems for wireless sensor network nodes have drawn extensive attention, many scholars
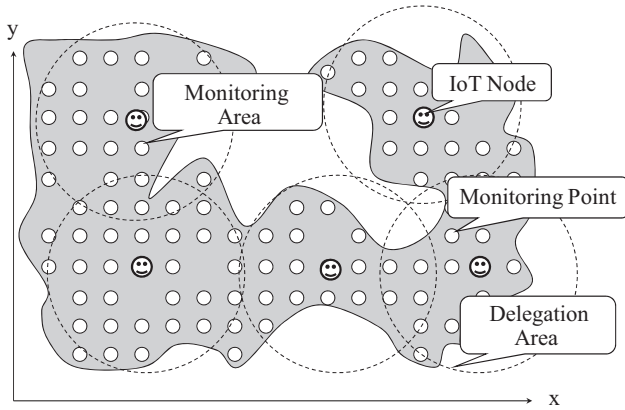
Fig. 1. Conceptual view of IoT data acquisition.

only focus on single-objective deployment problems, such as problems of total cost, total coverage, total energy consumption, and so on. Few studies have considered several objectives in research about the decision-making deployment problem. Moreover, past studies have not considered the equilibrium in monitoring tasks among different monitoring nodes, which makes some nodes take overburdened tasks while others take very few tasks. Actually, in the practical application of port IoT monitoring, the monitoring is a sampling area task because the complete coverage is impossible. Thus, equilibrium and representativeness of samples are of great importance. This study will improve the above defects. This study proposes solutions for node selection and layout in the monitoring area of IoT. It tries to solve node quantity and location problems by using a nonlinear, multi-objective optimization model and the genetic algorithm.

II. DEFINITION AND ANALYSIS OF PROBLEMS

The key for the problem of IoT node layout is the sampling of the monitoring area. The monitoring region can be seen as a two-dimensional plane collection which consists of many points with different importance levels in terms of monitoring. IoT node deployment is designed to choose a certain number of monitoring points, including the process with which to choose the number and the location of monitoring points. IoT node equipments are installed at those selected monitoring points. A conceptual view of IoT data acquisition is shown in Fig. 1.

(1) The monitoring region consists of monitoring nodes, each of which has different levels of importance;
(2) Homogeneous equipment is installed in each node, which means that all the IoT equipment has the same investment, maintenance, and management cost;
(3) Different node equipment has the same volume of data acquisition and data traffic;
(4) The communication costs between IoT node and data

center are not directly associated with node distribution.

This problem, which can be abstracted as a one-time sampling problem in the network, makes the sample an excellent representative one. At the same time, it can help to reach a balance among IoT node costs. The key points of the problem include the following:

(1) the evaluation design of the coverage of IoT nodes to the monitoring points;
(2) the definition and analysis of the quantity decision problem in IoT nodes and the node deployment problem;
(3) the quantity of nodes and node localization in this two-stage modeling and a solution strategy.

III. MODEL

1. Symbol Description

Table 1. Symbol Description.

Symbol	Description
$I = \{1, 2, \ldots, NI\}$	Set of monitoring points
$M_i \in (0, 1]$	The importance of monitoring points for $i \in I$, the greater the value the more important
$D_{a, b} \geq 0$	Distance between the monitoring points $a \in I, b \in I$
$R \geq 0$	Sensing radius of IoT node
$C > 0$	Unit cost of IoT node
$q_i \in \{0, 1\}$	Whether set IoT node in the point $i \in I$
$h_{si} \in \{0, 1\}$	Whether the IoT note s monitor the monitoring point i
$S (IOT)$	Set of IoT nodes
$N (IOT)$	Number of IoT nodes
$C (IOT)$	Total cost of IoT
$P (s, i)$	the representation of $s \in S (IOT)$ to $i \in I$
$IS (i)$	IoT node that on behalf of the monitoring point $i \in I$
$SI (s)$	Set of monitoring points monitored by $s \in S (IOT)$
$P (s)$	The comprehensive representative of the IoT nodes
$M (IOT)$	The total representation of IoT
$B (IOT)$	Equilibrium degree of IoT representative nodes

2. Assumptions

(1) The Euclidean distance between two monitoring points represents the geographical relationship between them;
(2) Costs of IoT node installation in any monitoring points are exactly the same;
(3) The IoT node maintenance and management costs, as well as the volume of data transferred per unit time are exactly the same.
(4) The IoT node data transfer cost is only concerned with the amount of data, and it has nothing to do with the distance between IoT node and the server.

(5) The importance of monitoring points ranges between 0 and 1; the higher the value is, the greater the relevance is.

(6) The relationship between the event and the IoT node is delegated through the set of IoT nodes.

(7) IoT node itself has a more specific sensing range (radius).

3. Sampling Evaluation

1) The Size of the IoT

The size of the IoT node is the scale of the IoT node collection. Eq. (1) denotes the set of IoT nodes. Eq. (2) shows that the scale of the IoT node can be directly identified by the variable x_i.

$$S(IOT) = \{i \in I \,|\, x_i = 1\} \tag{1}$$

$$N(IOT) = |S(IOT)| = \sum_{i \in I} x_i \tag{2}$$

2) The Total Cost of the IoT

Due to the consistency of the cost of IoT node configuration equipment, maintenance, and management, the total cost of the IoT is proportional to its scale, as shown in Eq. (3).

$$C(IOT) = C \cdot N(IOT) \tag{3}$$

3) The Equilibrium Degree of the IoT Node Representation

Define the representativeness of the IoT node ($s \in S$) to the monitoring point ($i \in N$) using Eq. (4). For different monitoring points that have the same distance as $s \in S$, the greater the importance is, the smaller its representativeness is. Accordingly, for points with the same importance, the greater their distance to $s \in S$ is, the lower their representativeness is.

$$P(s,i) = \frac{1 - M_i}{1 + D_{s,i}} \tag{4}$$

Obviously, for any monitoring point, Eq. (4) can be used to compute each representation of the IoT node. In this article, we simply take the maximum representative node as the monitoring equipment for one point, see Eq. (5).

$$IS(i) = \arg\min_{s \in S} \left(P(s,i) \right) \in S \tag{5}$$

In contrast, for any IoT node, we can get the monitoring point set represented by a node, such as shown by Eq. (6).

$$SI(s) = \{i \in I \,|\, IS(i) = s\} \subseteq I \tag{6}$$

Based on the above definition, we can see that Eq. (7) is the comprehensive representative of the IoT node.

$$P(s) = \sum_{i \in I} P(s,i) \tag{7}$$

For the entire IoT node collection, we can get the minimum of the representative using Eq. (8), while the equilibrium degree of the IoT node representation is described by the variance in Eq. (9).

$$M(IOT) = \sum_{s \in S} P(s) \tag{8}$$

$$B(IOT) = \sqrt{\frac{\sum_{s \in S} \left(P(s) - M(IOT) \right)^2}{|S|}} \tag{9}$$

4. Optimization Model

Obviously, a better sampling and IoT deployment program could balance the IoT scale, cost, and representativeness. That is, it can minimize $N(IOT)$, $C(IOT)$, and $B(IOT)$ and maximize $M(IOT)$, minimizing the objective to get Eq. (10).

$$\text{Min:} f = (z_N, z_C, z_M, z_B)$$

$$\text{Min } z_N = \sum_{i \in I} q_i$$

$$\text{Min } z_C = \sum_{i \in I} (C_i \cdot q_i)$$

$$\text{Min } z_M = 1 / \left(1 + \sum_{s \in S, i \in I} P(s,i) \right)$$

$$\text{Min } z_B = \sqrt{\frac{\sum_{s \in S} \left[\sum_{i \in I} P(s,i) - \sum_{s \in S} \sum_{i \in I} P(s,i) \right]^2}{\sum_{i \in I} q_i}} \tag{10}$$

s.t.

$$P(s,i) = (1 - M_i) / (1 + D_{si}) \tag{11}$$

$$P(s_1, i) \cdot h_{s_1, i} > P(s_2, i) \cdot h_{s_2, i}, \forall s_1, s_2 \in SI, i \in I \tag{12}$$

$$\sum_{s \in S} h_{si} = 1, \forall i \in I \tag{13}$$

$$h_{si} D_{si} \leq R \tag{14}$$

$$q_i \in \{0,1\}, h_{si} \in \{0,1\} \tag{15}$$

Eq. (11) shows us how to calculate the representation of $s \in S$ (IOT) to $i \in I$. Eq. (12) means that we take the maximum representative node as the monitoring equipment for one point. Eq. (13) indicates that the IoT node must monitor at each point. Eq. (14) is the constraint for node monitoring radius. Eq. (15) refers to the decision variables between 0-1.

The above is the model in the case of a single objective. Considering the multi-objective case, we must take into account

the difference between the objective functions; therefore, we cannot use simple addition for a single objective. A linear weighting method is applied in order to quantify the differences between the different targets. $\lambda_k, k \in K = \{1, 2, 3, 4\}$ is used to calculate the weights for Z_N, Z_C, Z_M, and Z_B, respectively. Consequently, we developed a mixed-integer nonlinear multi-objective programming model.

$$\text{Max: } F = \lambda_1 \cdot Z_N + \lambda_2 \cdot Z_C + \lambda_3 \cdot Z_M + \lambda_4 \cdot Z_B \qquad (16)$$

s.t.

$$\sum_{k \in K} \lambda_k = 1 \qquad (17)$$

$$Z_N = \frac{\max z_N - z_N}{\max z_N - \min z_N} \qquad (18)$$

$$Z_C = \frac{\max z_C - z_C}{\max z_C - \min z_C} \qquad (19)$$

$$Z_M = \frac{\max z_M - z_M}{\max z_M - \min z_M} \qquad (20)$$

$$Z_B = \frac{\max z_B - z_B}{\max z_B - \min z_B} \qquad (21)$$

Eq. (16) is the objective that has been weighted for each single target, and the sum of every weight should be 1 in Eq. (17). Eq. (18) through 21 are the unified quantification methods for each target. Because Z_N is the minimization objective of the IoT scale, the minimization objective of the IoT cost (Z_C) can be described by Z_N.

IV. ALGORITHM

1. Genetic Algorithm

The encoding pattern reflects the corresponding relationships between the possible solutions to the problem and the genetic chromosome. According to De Jong's two highly operative principles of practical encoding, we take the one-dimensional array of decision variables (x) as the encoding objects and use the binary encoding method. In Eq. (22), possible solution to the problem is the solution vector X. If we set an IoT node in $i \in I$, $x_i = 1$ while $x_i = 0$. Initialize a random chromosome population, randomly set up some IoT node in some genes for each chromosome, the other part do not perform this operation.

$$X = [x_1, x_2, \ldots, x_{NI}], x_i \in \{0,1\} \qquad (22)$$

According to the objective function, determine the fitness function using Eq. (23).

$$Fit(x_i) = F = \lambda_1 \cdot Z_N + \lambda_2 \cdot Z_c + \lambda_3 \cdot Z_M \qquad (23)$$

We adopt the roulette wheel. The size of the population is *NI*, and *Fi* is the fitness of each individual *i*. The individual probability of being selected can be calculated using Eq. (24). After obtaining the selection probability, set $pp_0 = 0$, $pp_i = \sum_{j=1}^{i} pp_j$. In order to rotate *NI* times and for each rotation, randomly generate $\xi_k \in U(0, 1)$. We choose the individual *i* when $pp_{i-1} \leq \xi_k \leq pp_i$.

$$p_i = F_i / \sum_{k=1..NI} F_k \qquad (24)$$

The proliferation of the chromosomes adopts uniform crossover and uniform mutation.

We set the maximum generation as the stopping criterion.

2. Representative Matrix Generation Algorithm

Input   *I*: set of monitoring points

       px_i, $i \in I$: the horizontal coordinate of monitoring point for $i \in I$

       py_i, $i \in I$: the vertical coordinate of monitoring point for $i \in I$

       M_i: the importance of monitoring points for $i \in I$

       λ_k: the weights of the single objective

Output P_{ab}: the representative matrix between the points $a \in I$ and $b \in I$

       $q_i = 1, \forall_i \in I$: the point to be set a IoT node

       $h_{si} = 1, s \in S, \forall_i \in I$: set of monitoring points monitored by $s \in S$

       Z_N, Z_C, Z_M, Z_B: the optimal value of the single objective

       F: the optimal value of multi-objective based on the single objective

Step 1   Set out D_{ab}: set the default value of the matrix elements to infinity and the diagonal element set to 0

       $\forall a, b, D_{ab} = G$: *G* is a sufficiently large number such as 9999

       $\forall a, D_{aa} = 0$

Step 2   Initialization :

$$\forall a, b : D_{a,b} = D_{b,a} = \sqrt{(px_a - px_b)^2 + (py_a - py_b)^2}$$

Step 3   Calculating the representative for any point $a \in I$ to $b \in I$

$$\forall a, b \in I, P_{a,b} = (1 - M_b) / (1 + D_{a,b})$$

Step 4   Taking the maximum representative node as the monitoring equipment for a point

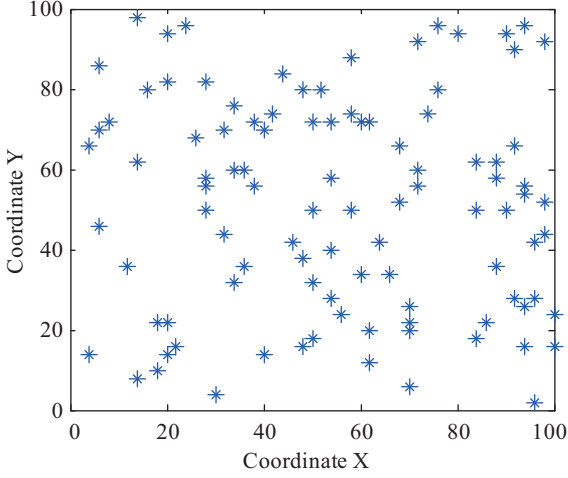$$\forall i \in I, IS(i) = \arg\min_{s \in S}(P(s, i)) \in S$$

Fig. 2. Monitor nodes position.

Step 5 Calculating the set of IoT nodes

$$S(IOT) = \{i \in I \mid q_i = 1\}$$

Calculating the monitoring point set represented by the IoT node $s \in S$

$$SI(s) = \{i \in I \mid IS(i) = s\} \subseteq I$$

Calculating the optimal value of the single objective Z_N, Z_C, Z_M, Z_B
Assigning to λ_k and calculating F

V. SIMULATION AND VERIFICATION

In order to validate the model, we generated a set of monitoring points randomly, where $NI = 100$, and the vertical and horizontal coordinates are random numbers from 0 to 100. The importance value of each monitoring point is also a random number $(0,1)$, $R = 15$, $C = 5$. The position of each monitoring point (*) is shown in Fig. 2. Based on Eq. (3) in Chapter 3.3, we can easily find that the total IoT cost is proportional to its size. Therefore, we utilized Z_N to take the place of Z_C. Therefore, we just used Z_N, Z_M, Z_B as the targets of analysis.

1. Single-Objective Analysis

1) The Size and Cost of the IoT

Obviously, if $\forall i \in I, \exists x_i = 0$, that is to say we do not set an IoT node at any point, and min $z_N = 0$, then min $z_C = 0$ if $\forall i \in I$, $\exists x_i = 1$, which is used to set the IoT node in each point, and max $z_N = 100$, then max $z_C = 500$. So $z_N \in [0, 100]$.

2) The Total Representation of IoT

The total representation of the IoT will be at the maximum when the whole points are set to the IoT node (i.e., $\forall i \in I, \exists_{xi} =$

1). In this case, max $M(IOT) = 81.8068$, and min $z_M = 0.0121$. On the contrary, the total representation will be the minimum when none of the points is used to set the IoT node, so min $M(IOT) = 0$, max $z_M = 1$, and $z_M \in [0.0121, 1]$.

3) The Equilibrium Degree of the IoT Node Representation

Regardless of whether we set only one IoT node or several equal representation IoT nodes, the variance of the equilibrium degree of the IoT node representation will be the minimum (min $z_B = 0$). If there are only two nodes in the IoT, and they are placed at $\max_{i \in I} P(i)$ and $\min_{i \in I} P(i)$, respectively, then the variance of the equilibrium degree of the IoT node representation will be the maximum. In this case, max $z_B = 0.7438$, and $z_B \in [0.07438]$.

2. Correlation Analysis of the Objective Function

In Chapter 5.1, $z_N (z_C)$, z_M, and z_B were solved as the single targets. We denote that the results corresponding to X as YN, YM, YB, and the correlation between YN, YM, and YB can be seen as the correlations between objective functions. From 5.1, we can see that YN and YM are actually two extremes; therefore $z_N (z_C)$ is completely non-correlated with z_M, z_B, which is influenced by the degree of IoT node representational difference, rather than the quantity of the IoT node. However, $z_N (z_C)$ and z_M are distinctly influenced by the number of IoT nodes. Therefore, the correlation between z_B and $z_N (z_C)$ is ambiguous, and so is the correlation between z_B and z_M.

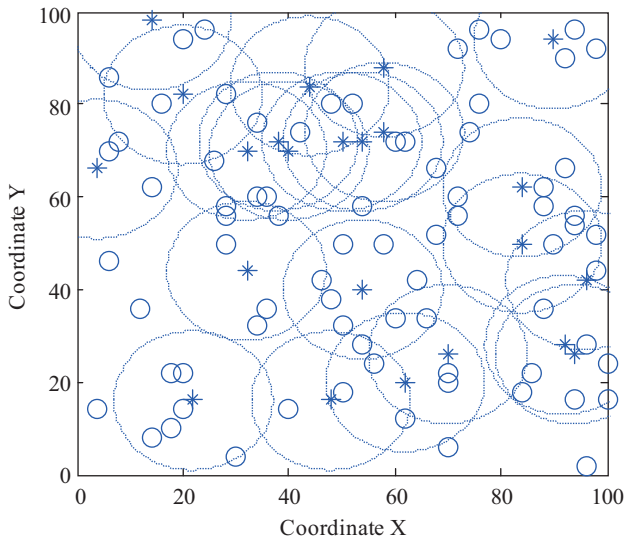### 3. Linearity Weighted Aggregation Method

As shown in Eq. (25), the maximum objective is composed of single objectives z_N, z_M, and z_B, with weights of λ_1, λ_2, λ_3, respectively. Because z_N has taken the place of z_C, the first weight should be multiplied by 2. Then $2\lambda_1 + \lambda_2 + \lambda_3 = 1$.

$$\max F = \frac{\lambda_1}{\max z_N - \min z_N} 2(\max z_N - z_N)$$

$$+ \frac{\lambda_2}{\max z_M - \min z_M}(\max z_M - z_M)$$

$$+ \frac{\lambda_3}{\max z_B - \min z_B}(\max z_B - z_B) \qquad (25)$$

Seven different weight combinations are provided in Table 2. Group1 represents equal emphasis on the four objective functions. Groups 2-4 represent individual attention to the size and cost of things, the overall representation of things, and a balanced representation of the degree of networking nodes. Groups 5 through 7 represent the importance of two of the three objectives of the function z_N, z_M, z_B. We used genetic algorithms to solve them, and used the decision variables x_i. Constitute the $1 \times NI$ binary one-dimensional array as chromosome coding using roulette wheel selection, uniform crossover, and uniform mutation. The cross rate is 0.8, the mutation rate

Table 2. The Optimization Results under Different Weight Combinations.

	λ_1	λ_2	λ_3	Z_N	Z_M	Z_B	F
1	0.25	0.25	0.25	0.77	0.9662	0.6687	0.7937
2	0.4	0.1	0.1	0.86	0.9498	0.6532	0.8483
3	0.1	0.7	0.1	0.73	0.9734	0.6577	0.8931
4	0.1	0.1	0.7	0.72	0.9720	0.7441	0.7621
5	0.3	0.3	0.1	0.84	0.9476	0.6203	0.8503
6	0.1	0.4	0.4	0.72	0.9714	0.6793	0.8043
7	0.3	0.1	0.3	0.81	0.9521	0.6695	0.7821

Fig. 3. Weight combination 1.

Fig. 4. Weight combination 2.
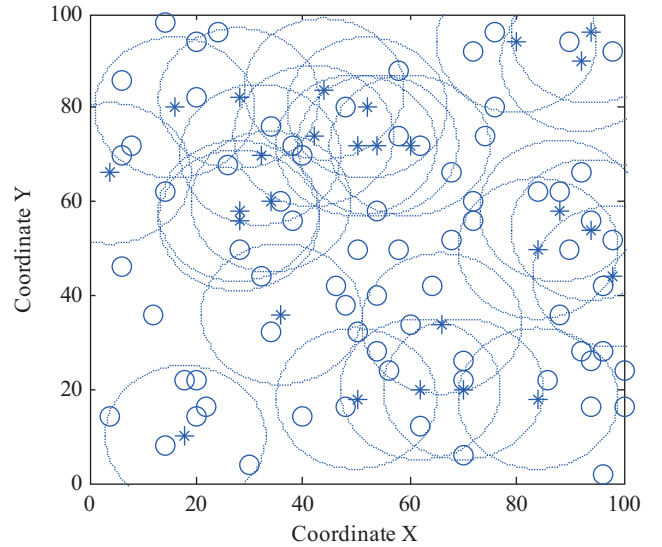

Fig. 5. Weight combination 3.

is 0.015, the population size is 20, and the number of iterations is 60. The greater the values of z_N, z_M, and z_B are, the more attention should be paid to their corresponding targets.

Based on Table 2, we can easily find that Z_N, Z_M, and Z_B are deeply influenced by the weights. For example, the weight of Z_N (Z_C) in the second combination is greater than that in any other combination, so the number of IoT nodes obviously decreased. However, the weight value of Z_N (Z_C) in the third, fourth, and sixth combination is only 0.1, which leads to a greater quantity of IoT nodes. In order to quantify the sensitivity of the objective to the weight, we set S_N in Eq.(26) to measure the weight sensitivity of Z_N (Z_C). $\lambda_{1,i}$ and $\lambda_{1,j}$ are two of the values of λ_1 in the combination of i and j, and ZN_i and ZN_j are respective values of ZN in the combination with i and j. Similarly, the sensitivities of S_M and S_B are available too. By calculating, we can know that $S_N = 8.8500$, $S_M = 1.3448$, and $S_B = 2.4981$. It is clear that Z_N (Z_C) is more sensitive than the other two targets, and the sensitivity of Z_M is the minimum.

$$S_N = \sum_{i=1}^{7} \sum_{j}^{i-1} \left| \frac{Z_{N_i} - Z_{N_j}}{\lambda_{1,i} - \lambda_{1,j}} \right| \ where \ \lambda_{1,i} \neq \lambda_{1,j} \qquad (26)$$

The deployment program on the ground of the seven different combinations is shown in Fig. 3 to Fig. 9. ○ denotes the points that have not been set in the IoT node while * denotes the points that have been set in the IoT node. The dotted line circle indicates the sensing range of each IoT node.

VI. CONCLUSION

This paper proposed a deployment solution to nodes of an internet of things for monitoring system. It mainly stresses determining the quantity of IoT nodes and layout program. By converting the problem to a sampling problem in the network topology data set, we established an evaluation model for the representation of IoT node to monitoring point and the equilibrium degree evaluation model for IoT node representation.
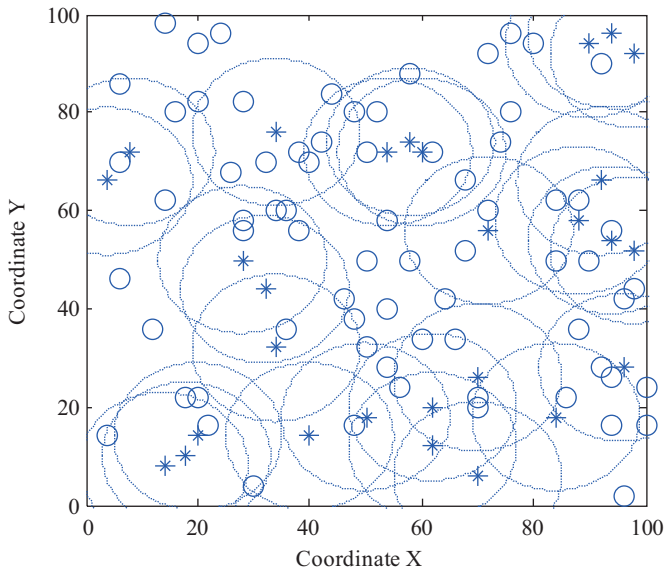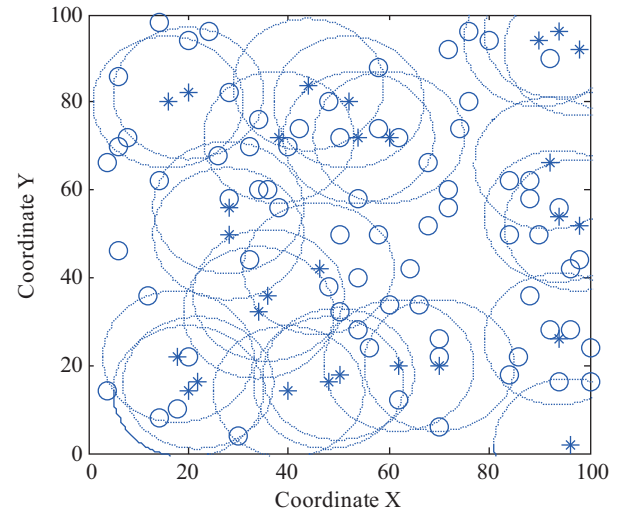
Fig. 6. Weight combination 4.

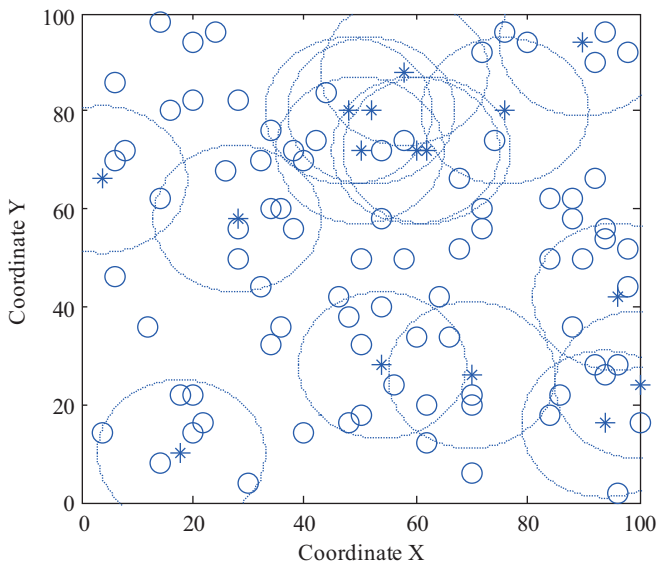**Fig. 8. Weight combination 6.**

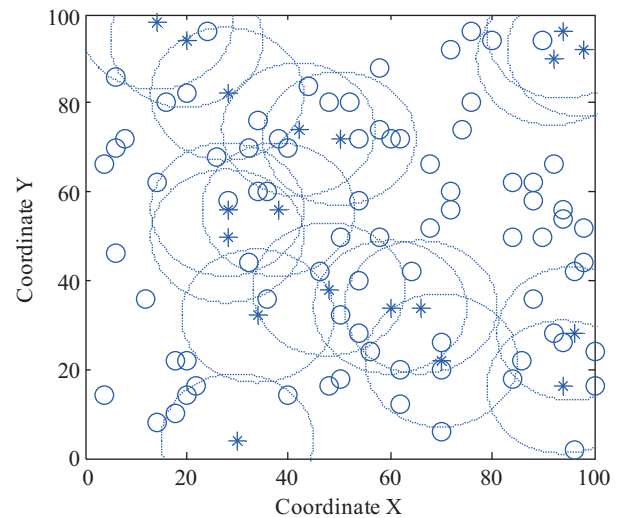**Fig. 7. Weight combination 5.**

Fig. 9. Weight combination 7.

With that, we built the IoT node selection decision-making model. In the simulation cases, the single objectives and the multiple objectives were all taken into account, and the results showed that paying different attentions to each single target would produce different solutions. Furthermore, we drew the conclusion that the size of the IoT is more sensitive to weight alteration and would exert a profound influence on the number of IoT nodes.

Based on this article, the study of heterogeneous network nodes layout, the energy consumption of IoT nodes, and the connectivity and fault tolerance problems between nodes need further exploration.

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