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Co-evolutionary Algorithm Based Energy Efficiency Regulation of Distributed Sensor Networks in Smart Buildings

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Abstract With the growing demand for environmental monitoring and energy management in smart buildings, energy efficiency optimization of distributed sensor networks has become the key to improve system performance. In this paper, a distributed sensor network energy efficiency regulation method (DCCMOEA) based on cooperative co-evolutionary algorithm is proposed. The multi-objective optimization of network energy consumption, coverage and node lifetime is achieved through the mechanism of decomposition variables and sub-population co-evolution. Compared with FA and GA, the optimized clusters of DCCMOEA algorithm are more uniformly distributed, the number of active nodes decreases the slowest at p=20%, and the number of active nodes is more than that of FA and GA. when the number of iterations is greater than 20, the coverage rate of DCCMOEA algorithm is stable at more than 95%, and the average node oscillation time is stable at less than 5ms. For the deployment of 10 wireless sensor network nodes, the data transmission packet loss rate of DCCMOEA on 10 network nodes is always below 0.6, which is lower than the comparison methods. The application of DCCMOEA algorithm provides an efficient solution for the deployment of sensor networks in smart buildings.\

Index Terms intelligent buildings, distributed sensors, cooperative co-evolutionary algorithm, multi-objective optimization, energy efficiency regulation

I. Introduction

As early as the 1980s, human society has begun to step into the information age, and at the same time, it has entered the sensor era, distributed wireless sensor network is a product of the continuous development of technology in the sensor era, which effectively solves the drawbacks of the traditional wired sensor network. In today's intelligent society, intelligent building is the inevitable product of modernization and intelligent technology [1]. By putting a building's structural system, system services and management services, etc., according to the user's requirements to carry out the optimal combination, so as to achieve the purpose of providing a more efficient, more comfortable, more convenient modern, humanized building environment [2]-[5]. Among them, the distributed wireless sensor network realizes the function of data acquisition, data processing, data transmission, and the data acquisition surface is very wide, and no wiring, small volume, low power consumption, so it occupies a great advantage in the application, and is an important part of the construction of such a modernized and humane building [6]-[9]. Distributed wireless sensor network technology also plays more important roles in the field of intelligent buildings, such as applied to its fire protection system, security access control, building automation and so on various parts [10]-[12]. In today's society, big data, intelligence is the trend and inevitable, so we should pay more attention to and vigorously develop this as one of the basic technology of information technology sensor technology [13].

Distributed wireless sensor network technology is applied in the field of intelligent buildings due to the advantages of low energy consumption of sensor nodes, small size, easy installation, etc., but the energy reserve of sensor nodes is limited [14], [15]. How to improve the network energy utilization efficiency and maximize the use of its limited energy to extend the network life cycle is an important research topic for sensor network technology to achieve a wider range of applications. Although distributed rechargeable sensor networks have appeared, their charging effect is limited by the environment and resource investment, and the study of their energy efficiency optimization algorithms is still of great significance [16], [17].

Due to the problems of limited battery power supply energy, limited communication capability and limited data processing capability of sensor nodes, and in most application scenarios, it is inconvenient to carry out secondary replenishment [18]. In order to utilize the limited energy, improve the energy utilization rate of nodes as much as possible, extend the network lifetime, and maximize the economic benefits of the network, scholars at home and abroad have researched on the energy efficiency regulation methods of distributed sensor networks. Literature [19] explores the minimum number of nodes to guarantee quality of service (QoS) routing in wireless sensor networks using distributed learning automata (DLA)-based algorithms, and also utilizes a multi-constrained optimal path model to improve the reliability and energy efficiency of a sensor network for end-to-end transmission. The study in literature [20] showed that the multi-hop communication of the cluster routing algorithm negatively affects the load balancing of the entire wireless sensor network, for this reason a non-uniformly distributed fuzzy clustering algorithm is used to calculate the probability of a sensor node to be a cluster head based on the energy parameters and other factors, so as to optimize the energy consumption of the sensor network. Literature [21] used particle swarm optimization algorithm to solve the clustering and routing optimization problem of wireless sensor networks and proposed a load balancing based energy efficient clustering algorithm for nodes, which significantly improves the performance of the sensor network in terms of life expectancy, energy consumption and data transmission. Literature [22] proposes a wireless sensor network coverage hole detection and restoration method, which helps to reduce the overall network energy consumption and extend the coverage of the sensor network by detecting the degree of overlap of the sensing area between sensor nodes and repairing the energy holes at the same time. Literature [23] examined the energy-saving coverage method for sensor networks based on genetic algorithms, which is able to achieve higher target coverage with less energy consumption in the sensor sensing area, realizing the balance between target coverage and energy consumption. Literature [24] emphasizes that clustering and aggregation in wireless sensor networks is the most effective way to save energy, for this reason, an energy efficient clustering algorithm based on particle swarm optimization technique is proposed to determine the cluster head sensor nodes, which effectively improves the life cycle of the sensor network. The above literature describes the scheduling optimization method of cluster routing technology in wireless sensor networks, which can ensure data integrity while reducing network energy consumption to extend network lifetime. However, at this stage, the research lacks targeted optimization measures for intelligent buildings, and continues to promote intelligent control algorithms that combine sensor feedback and actuator output to form a closed-loop regulation mechanism to ensure the comfort and stability of intelligent building environments.

In this paper, we first construct a ZigBee-based wireless sensor network architecture and analyze its layered protocol and node deployment characteristics. A sensor configuration model with the objective of coverage optimization is established, and the network performance is quantified by combining the exponential and binary sensing models. Based on the cooperative co-evolution mechanism, the coupling relationship between multiple objectives is solved through variable decomposition and sub-population co-optimization. Simulation experiments are conducted to verify the effectiveness of the proposed algorithm in terms of cluster head distribution, network lifetime, coverage and anti-jamming capability.

II. Optimized design of distributed sensors based on co-evolutionary algorithms in intelligent buildings

Smart buildings, as an important part of modern cities, rely on distributed sensor networks to realize environment sensing and energy management. However, the problems of limited energy of sensor nodes, uneven network coverage and communication load imbalance constrain its long-term stable operation.

II. A. Distributed system based on wireless sensor networks

II. A. 1) Wireless Sensor Networks and Zighee

A wireless sensor network WSN is a multi-hop, self-organizing network system consisting of a large number of inexpensive miniature sensor nodes deployed in a monitoring area and formed by wireless communication. The underlying protocols of WSNs (physical layer PHY and media access control layer MAC) follow IEEE 802.15.4, whose main purpose is to collaboratively sense, collect and process information about sensed objects in the network coverage area and send it to observers, and of course to exercise some control over the nodes. Wireless sensor network synthesizes high and new technologies such as sensor technology, embedded computing technology, modern network technology, wireless communication technology and distributed information processing technology, which has become a hot field of international research in recent years.

The structure of wireless sensor network is shown in Figure 1, which usually includes sensor nodes and gateway nodes. A large number of nodes (sensing nodes) are deployed inside the monitoring area, constituting a network through self-organization. The data monitored by the sensor nodes are transmitted along other sensor nodes hop by hop, routed to the gateway node after multiple hops, and finally reach the monitoring center via the Internet (IP/TCP) or other mobile networks (GPRS, CDMA). The user configures and manages the sensor network through the monitoring center, releases detection tasks and collects monitoring data.

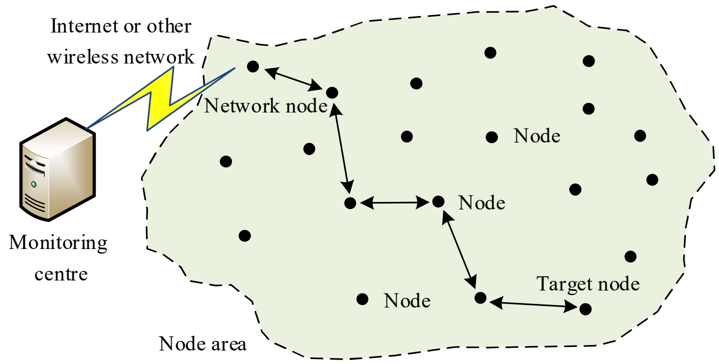


Figure 1: Wireless Sensor Network WSN

Zigbee is a technology that has been developed based on the underlying 802.15.4 protocols for applications, specific device designs, etc. Zigbee can be viewed as a specific implementation of WSNs and a set of network protocols that involve more layers. Zigbee, due to the support of the so-called zigbee consortium which includes many large companies, has become more mature in terms of technology and devices, and is well equipped to realize reliable and low-cost applications. Currently on the market, integrated circuits such as CC2420, CC2430, MC13192, etc. have implemented the zigbee protocol stack at the device level and have a better price/performance ratio.

II. A. 2) Distributed Sensor Networks in Intelligent Buildings

This section discusses the application of distributed sensor networks in intelligent buildings using a distributed wireless access control system as an example. The key to realize the distributed wireless access control system is to design the wireless network to realize the communication network function in the dotted box. Combined with zigbee technology, the overall structure of the system can be obtained as shown in Fig. 2.

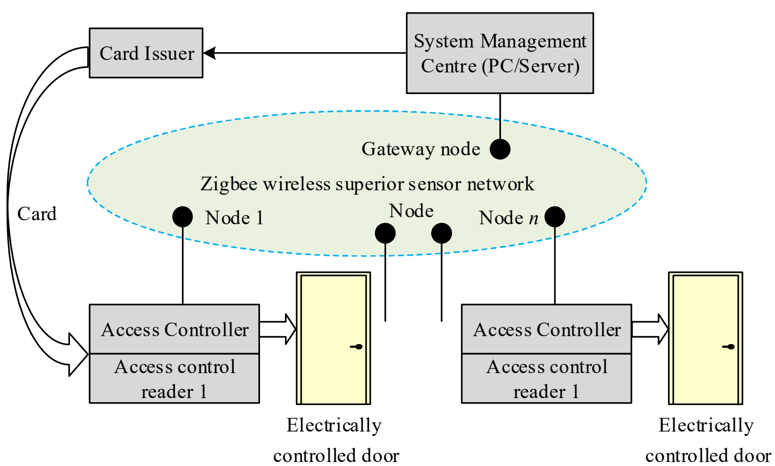


Figure 2: Structure of Zigbee's distributed access control system

The rest of the system adopts the more classic access control system scheme, including the management center, card issuer, smart card, card reader, access control unit, electronically controlled door (lock) and other components. Circuit, software module division and system physical structure design as far as possible with this logical structure. In order to increase module reusability, access control readers and controllers are assembled into a unit, the core circuit board of the card issuing unit and the card reading unit is also designed to be exactly the same, only the communication mechanism and software is different. Application of the reader to enable more than one port to realize the control of the electronically controlled door.

Smart card using the increasingly widespread use of Mifare1 radio frequency card, operating frequency of 13.56MHz, communication rate of 106kbps. note that, here between the radio frequency card and the reader is also wireless communication, through a simple electromagnetic induction to realize, do not confuse it with the system nodes as a communication network between zigbee network. Mifare1 RF card follows ISO/IEC 14443 TypeA communication protocol, and the distance is only 100mm.

Access control unit selected TI's MSP430F149 as the main control MCU, the core board integrated read (write) card circuit, electronic lock control circuit, host computer interface circuit. Read and write card circuit selection of NXP's MF RC522 chip as the core, to meet the ISO/IEC 14443 protocol.

The PC centralized control software of the system adopts the industrial control configuration software as the framework, which is convenient for real-time monitoring. The background database of the system adopts SQL Server.

II. B. Optimal Sensor Configuration Model and Configuration Criteria Based on Coverage Optimization

One of the most important issues in the research and application of sensor optimization configuration is the coverage control of the sensing network, through the measurement of network coverage can understand whether there is a communication and detection of blind zones, as well as the coverage of the sensor network in the monitored area, and then re-adjust the distribution of the sensor nodes or other measures to improve. By adjusting the density of network coverage, more sensor nodes are deployed in important areas of the monitored area to ensure the accuracy and reliability of measurement data. Therefore, the issues related to coverage control are of great significance and have a very intuitive impact on the performance of the sensing network.

The coverage of sensor nodes is largely determined by the sensing ability of sensors, which in turn affects the coverage performance of the entire network. To study the coverage problem of sensor networks, it is necessary to discuss the sensor perception model and characteristics of the sensor nodes equipped with sensors. Currently, sensing models are mainly divided into two categories: exponential sensing models and binary sensing models.

(1) Exponential sensing model

The probability that a node detects a signal from a source is inversely proportional to the distance between them to the power of $n(n \geq 2)$. Such a model is said to be called an exponential perception model. In some research occasions, especially when analyzing moving object targets, the exponential perception model is more in line with the actual situation than the binary model, and thus is more favored by researchers.

(2) Binary Perception Model Coverage

Typically, most of the node perception models are a circular area with the node as the center and the radius of its perception detection distance (determined by the node hardware characteristics). Only signal sources within this circular area can be sensed (i.e., covered) by this sensor node, otherwise they cannot be monitored and sensed. According to the general mathematical rules, the signal source in the monitoring distance by the node to monitor the node, then we recorded as “1”, beyond the monitoring distance and was not perceived by the node a recorded as “0”, so also known as such models for 0-1 coverage model. In the actual application process, the perception model not only has circular perception coverage, there are many other regular or irregular perception area coverage.

II. B. 1) Optimized Configuration Model

A model structure for the optimal configuration of the following sensor coverage is established: a square plate structure composed of isotropic material with the target monitoring structure and the location of the signal source as shown in Fig. 3.

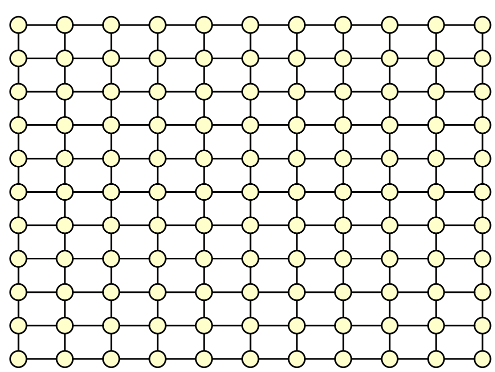


Figure 3: Target monitoring structure and signal source location

Considering the boundary effect, it is worthwhile to select a 10 × 10 grid from an infinite square plate structure, where the black nodes on the figure indicate the specific location of the signal source, and now 20 FBG sensors are to be arranged in this plate structure area, each with a coverage radius of a2 = 1.5 grid units and b2 = 1 grid unit; a1 = 3 grid units and b1 = 2 grid units. Then the next task is to discuss how to arrange these 20 sensors in a 10×10 grid so that the joint coverage of these 20 sensors is maximized.

The reason why the number of 20 sensors is chosen here in the study is because in the case of particle swarm optimization based algorithms, in order to achieve a better coverage of this number of sensors in a 10×10 grid, i.e., a certain range of cross-repeat phenomena (which best represents the universal coverage phenomenon in this case).

II. B. 2) Guidelines for optimal sensor configuration

In order to improve the target measurement probability, multiple sensor nodes need to be used to measure the target at the same time, and their joint measurement probability is as follows:

$$P(s)=\bigcup_{i=1}^{N}P_i=1-\prod_{i=1}^{N}(1-P_i) \tag{1}$$

In the formula, N represents the number of sensors, and the formula denotes the coverage of N sensors on a signal source to monitor the probability of joint measurement.

Then the coverage of N sensors on M signal sources is shown below:

$$P=\frac{\sum_{M}P(s)}{M} \tag{2}$$

To get the optimal layout of sensors, that is, to maximize the value of equation (2). This is the sensor layout optimization configuration criterion, through the sub-criteria, adjust the density of sensor coverage, deploy more sensor nodes in the important areas of the monitored area, to ensure the accuracy as well as reliability of the measurement data.

II. C. Cooperative Co-evolutionary Multi-Objective Evolutionary Algorithm

In this paper, the Distributed Cooperative Co-evolutionary Multi-Objective Evolutionary Algorithm (DCCMOEA) is proposed based on the idea of cooperative co-evolution.DCCMOEA is based on decomposition to solve multi-objective large-scale optimization problems. First, based on the improved variable analysis method, the decision variables are divided into multiple groups, and each group is optimized by a sub-population. Further, the individuals in each sub-population are further divided into multiple sets.

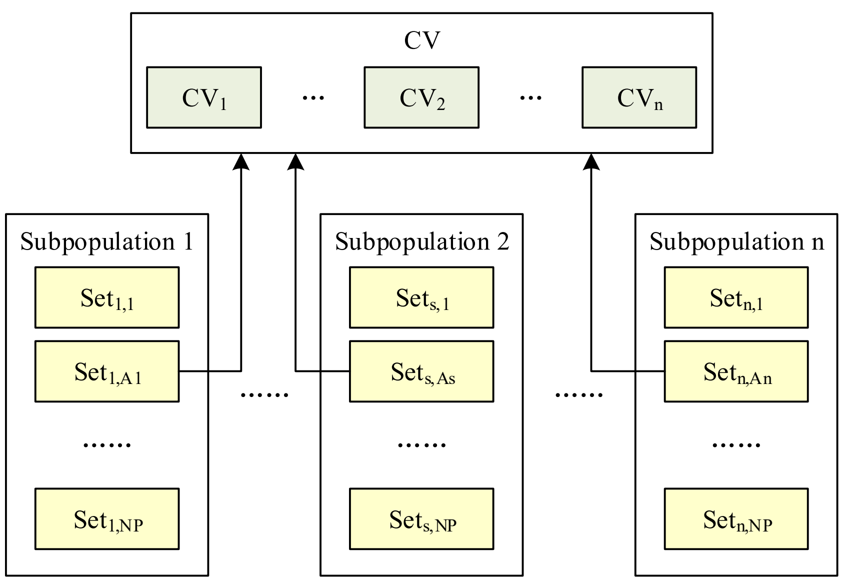


Figure 4: CC framework

II. C. 1) Cooperative Synergistic Evolution

Cooperative Coevolution (CC) is applied to Genetic Algorithms (GA), the framework of which is shown in Fig. 4. For SOPs, first, the variables are divided into multiple groups; after that, each group is optimized by a subpopulation.

The CV represents the background vector, which is updated according to the optimal individuals in each group. For adaptation value evaluation, for fully divisible problems, the adaptation values of the individuals in each group can be computed individually; however, in the real world, most of the problems are not fully divisible, and therefore, adaptation value evaluation is required based on the complete solution. The two mechanisms of adaptation value assessment produce two algorithms: cooperative co-evolutionary genetic algorithm 1 (CCGA-1) and cooperative co-evolutionary genetic algorithm 2 (CCGA-2). Compared to CCGA-1, CCGA-2 is suitable for solving problems where there are interrelationships between variables, however, for fully separable problems, CCGA-1 outperforms CCGA-2.

In large-scale optimization, there are numerous variables. Classifying the variables into multiple groups and optimizing based on the CC framework 6' can have better results. In different groups, the variables will be optimized separately and by combining them with each other to form a complete solution vector for adaptation value evaluation.

II. C. 2) Algorithmic Architecture

A variety of decomposition strategies are incorporated, including variable decomposition and subpopulation decomposition. As a result, the population is decomposed into multiple subpopulations; individuals in each subpopulation are divided into multiple concentrations. This decomposition framework is shown in Figure 5.

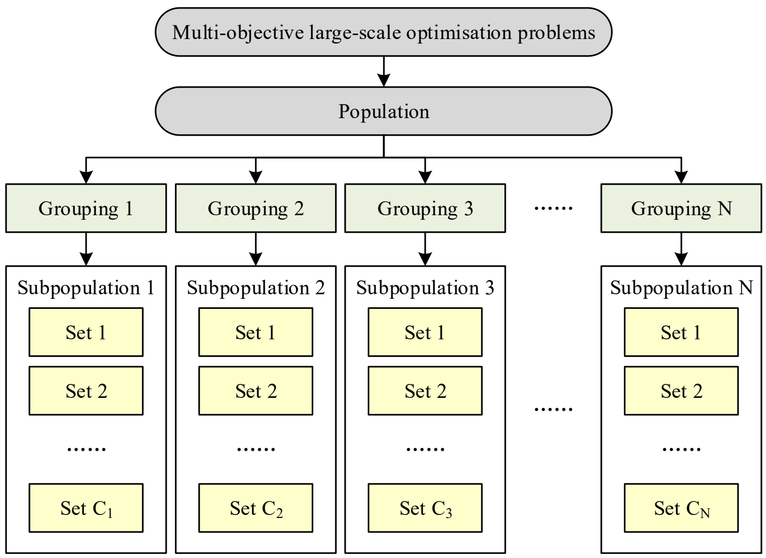


Figure 5: Algorithm Framework

II. C. 3) Population optimization process

The operator used is DE. The optimization process can be described as follows.

$$child_{i,j} = p_{i,j} + F \times (p_{a_1,j} - p_{a_2,j}) \quad if\ j \in Index \tag{3}$$

where p_i is the parent vector; i is the number of the newly generated vector $child_i$, which is selected by a binary tournament selection method; j is the number of the decision variable; a_1 and a_2 are two additional randomly selected solutions in addition to i; and $Index$ is the set of variables to be optimized in the current set of the current generation.

Each set performs a hybrid optimization of the diversity category and the assigned convergence group, with the switch between the two depending on the average improvement of the individuals. For adaptation value evaluation, the remaining variables should be combined with the newly generated children to compose a complete solution. Since the complete solution for each individual is saved in each set, the newly generated vectors will be combined with this information to obtain a complete solution.

To enhance the search of the solution space and to improve diversity, two other vectors in addition to the parent generation are used.

$$trail_{i,j} = \begin{cases} child_{i,j}, & if\ j \in Index \\ p_{i,j}, & if\ j \notin Index \wedge r_1 < 0.5 \\ p_{b_1,j}, & if\ j \notin Index \wedge r_1 > 0.5 \wedge r_2 \le 0.5 \\ p_{b_2,j}, & otherwise \end{cases} \tag{4}$$

where $trail_i$ is a vector of trials; r_1 and r_2 are uniform random numbers in the range (0, 1); and b_1 and b_2 are the solutions of two different random choices other than i. Afterwards, we perform polynomial variation on $trail_i$. After the evaluation of fitness values, the population is updated similarly to MOEA/D.

III. Simulation analysis of distributed sensor network energy efficiency regulation based on co-evolutionary algorithm

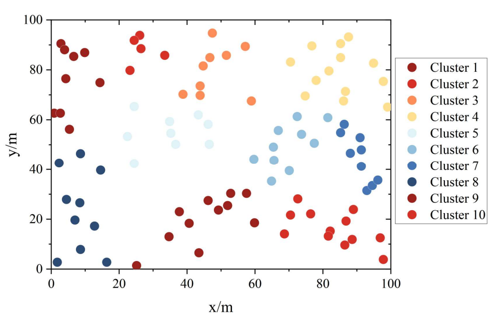
III. A. Simulation test parameter setting

In order to verify the feasibility of the DCCMOEA algorithm, simulations are performed in MATLAB simulation software. The node redeployment method based on firefly algorithm (FA), node deployment method based on genetic algorithm (GA) and DCCMOEA algorithm are used to optimize the deployment within the same monitoring-for-environment, respectively. Two hundred nodes are deployed in a 100m × 100m area with a set cluster head ratio p varying from 10% to 30%.

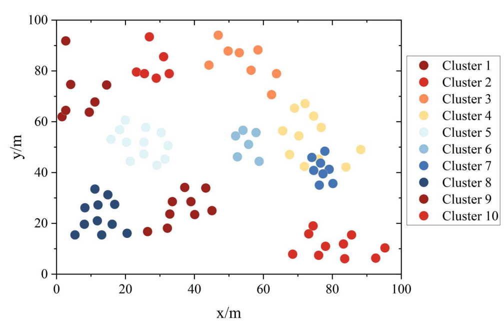
III. B. Simulation results

III. B. 1) Cluster distribution

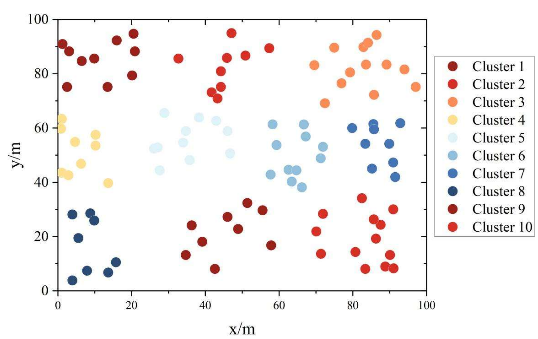
DCCMOEA corrects the value of the elected cluster head, aiming to make the cluster distribution more uniform.The cluster distribution under the optimization of FA, GA and DCCMOEA algorithms is shown in Fig. 6(a~c). Compared with FA and GA, the cluster distribution under the optimization of DCCMOEA algorithm is more uniform and the aggregation of each cluster is better. This indicates that DCCMOEA makes the nodes with large residual energy and close to sink become the cluster head by correcting the value of election head, which makes the cluster distribution more uniform.



(a) FA



(b) GA



(c) DCCMOEA

Figure 6: Cluster distribution

III. B. 2) Network life cycle

The parameter p is set to vary from 10% to 30% and sink is located at (50, 50).The results of the time comparison of the first node failure under FA, GA and DCCMOEA optimization are shown in Fig. 7. From Fig. 7, it can be seen that:

(1) Increasing p prolongs the death time of the 1st node. The reason is that in the 10% to 30% interval, the larger p is, the more clusters there are, the denser the cluster distribution is, and the smaller the average distance of the nodes from the cluster head is within the network. The decrease in the average distance of nodes transmitting data to the cluster head saves node energy and prolongs the node death time. However, when the cluster head ratio

p=1, the cluster structure fails. This is because data aggregation between cluster heads is not possible, resulting in a rapid increase in energy consumption across the network and energy optimization cannot be achieved. Therefore, the value of cluster head ratio should be kept in a reasonable range to balance the network energy consumption and improve the life cycle.

(2) Compared with FA and GA, DCCMOEA optimization effectively prolongs the death time of the 1st node due to the following reason: DCCMOEA avoids nodes with low energy from running for the cluster head by the node energy constraint random number, which makes the cluster structure more stable and thus prolongs the death time of the 1st node.

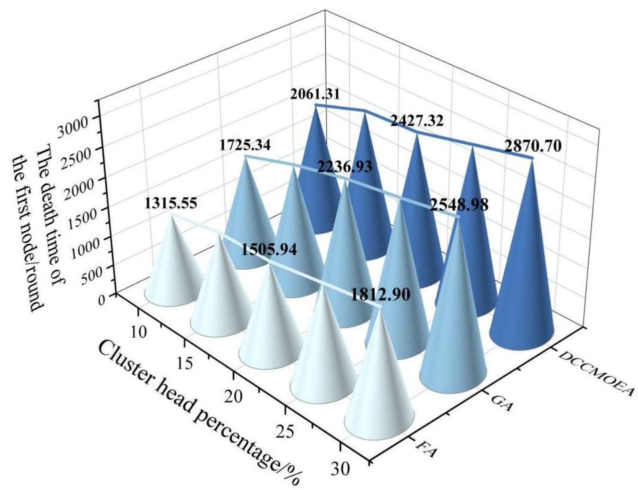


Figure 7: Comparison of the failure time of the first node

The parameter p = 20% is set and sink is located at (25, 25). The number of active nodes under FA, GA and DCCMOEA optimization is shown in Fig. 8. The number of active nodes decreases rapidly as the number of rounds increases, with the fastest decrease under the FA scheme and the slowest decrease under the DCCMOEA scheme. And the number of active nodes under DCCMOEA scheme is more than FA and GA. this is attributed to the fact that DCCMOEA corrects the threshold value using node energy and distance and stabilizes the cluster structure. Optimizing the inter-cluster data transmission path reduces the energy consumption of nodes and balances the inter-node energy consumption, which ultimately eases the node death time and increases the number of active nodes.

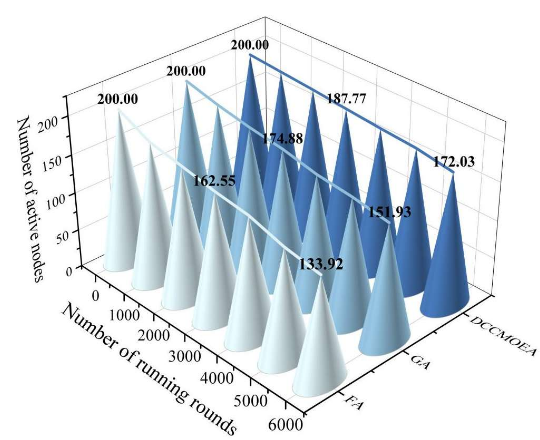


Figure 8: Comparison of active node numbers

III. B. 3) Coverage

Wireless sensor network coverage must consider several performance metrics in order to make the network coverage more reliable and efficient. The coverage of different algorithms is shown in Fig. 9. When the number of iterations is less than 20, it can be seen that the coverage of the DCCMOEA algorithm is similar to that in the FA and GA algorithms. When the number of iterations is greater than 20, the coverage of the DCCMOEA algorithm is stabilized at more than 95%, which is much better than that of the FA and GA algorithms.

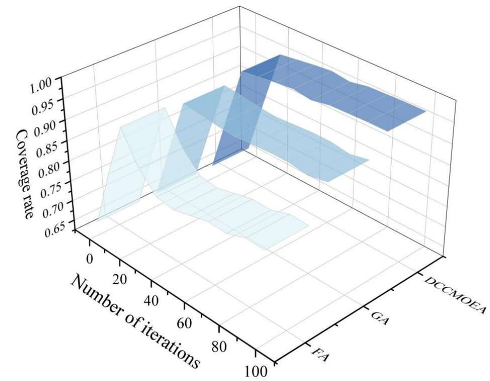


Figure 9: Coverage rate comparison

A comparison of the average oscillation times of the nodes of different algorithms is shown in Fig. 10, which shows that many nodes of the FA and GA algorithms oscillate back and forth when the number of iterations is at 20 ⩽ t ⩽ 40. The FA and GA algorithms do not analyze and deal with the problem of continuous node oscillation in detail, which leads to slow and unstable convergence of the algorithms and reduced area coverage. In contrast, the average node oscillation time of the DCCMOEA algorithm is stabilized below 5ms.

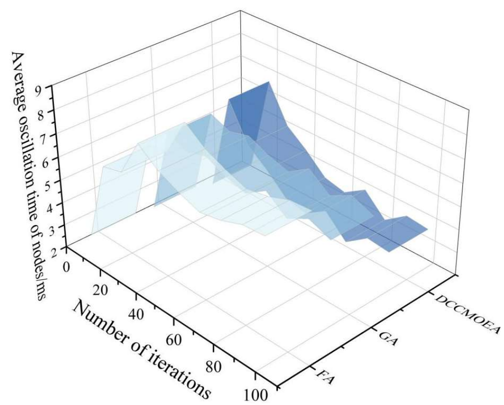


Figure 10: Comparison of the average oscillation time of nodes

III. B. 4) Packet Loss Rate

The deployment of 10 wireless sensor network nodes, set the time interval for each node to receive and send data for 25min, and the total number of nodes forwarding data packets is 1200. With this as the premise, the packet loss rate of the sensor network deployed by the three algorithms is calculated, and the results of the packet loss rate comparison are shown in Fig. 11.The packet loss rates of the three algorithms are not more than 2%, but the packet loss rate of the data transmission of the DCCMOEA in the 10 nodes of the network is always below 0.6, which is lower than that of the comparison methods.The DCCMOEA algorithm realizes the security detection of the wireless sensor nodes and excludes the malicious nodes, thus making the node deployment of the wireless network more feasible. Thus, the node deployment of wireless network has higher feasibility.

III. B. 5) Perception error values

Three methods are used to deploy nodes in a local area of 50m×50m, and the deployment performance of different algorithms is simulated by comparing the sensing error values, and the specific comparison results are shown in Fig. 12.After 15 rounds of DCCMOEA algorithm, the sensing error is reduced to less than 0.6 and the fluctuation of the error tends to be stable. This is because the DCCMOEA algorithm carries out the determination of internal and external attacks on the network nodes, realizes the traversal of all the communicable nodes in the wireless sensor network, and then completes the localization of the anchor nodes to find the anchor nodes, and avoids the occurrence of target node misdistinction, and the deployment performance is obviously better than the comparison method.

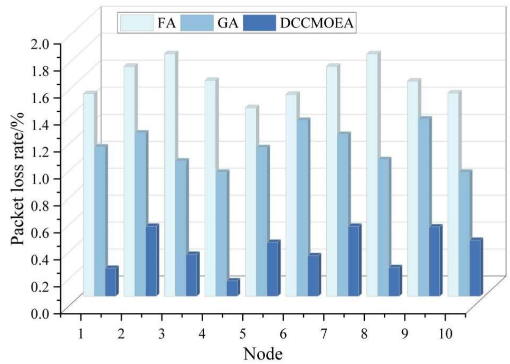


Figure 11: Comparison of packet loss rates

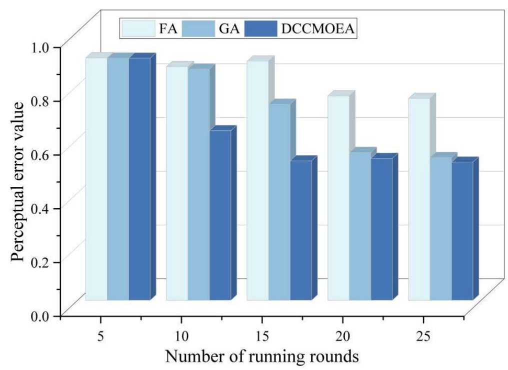


Figure 12: Comparison of perceptual error values

IV. Conclusion

Oriented to the multi-objective optimization problem of distributed sensors, this paper designs the DCCMOEA algorithm based on cooperative co-evolution, and explores its practical effect on the energy efficiency regulation of sensor networks through simulation experiments.

Compared with FA and GA, the optimized clusters of DCCMOEA algorithm are more uniformly distributed, and the aggregation effect of each cluster is better, which can effectively prolong the death time of the 1st node. At p=20%, the DCCMOEA algorithm has the slowest decline in the number of active nodes and has more active nodes than FA, GA. when the number of iterations is less than 20, it can be seen that the coverage of the DCCMOEA algorithm is similar to that in the FA, GA algorithms. When the number of iterations is greater than 20, the coverage of the DCCMOEA algorithm stabilizes at more than 95%, which is much more than that of the FA and GA algorithms. When the number of iterations is $20 \leqslant t \leqslant 40$, many nodes of FA and GA algorithms oscillate back and forth, while the average oscillation time of the nodes of the DCCMOEA algorithm stabilizes at less than 5ms.

Deployed on 10 wireless sensor network nodes, none of the three algorithms' packet loss rates exceeded 2%, but DCCMOEA's data transmission packet loss rate on 10 network nodes was consistently below 0.6, which was lower than the comparison methods. In a local area of 50m×50m, the DCCMOEA algorithm reduces the perceptual error to below 0.6 after 15 rounds of operation, and the error fluctuation tends to stabilize.

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