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CoC-SCS: Cooperative-Optimization Coverage Algorithm Based on Sensor Cloud Systems in Intelligent Computing

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ABSTRACT The coverage of traditional Wireless Sensor Networks (WSNs) is limited by node energy and data redundancy, which forces WSNs to be interrupted abnormally. Therefore, Cooperative-optimization Coverage Algorithm based on Sensor Cloud Systems in Intelligent Computing (CoC-SCS) is proposed. First, the algorithm determines the location information of the Focus Target Nodes (FTNs), and uses the Genetic Algorithm (GA) to give the node path planning. Second, the mutation parameters and the controllable threshold parameters are used in order to control the event domain nodes. Optimizing clustering makes the clustering of the nodes to be more uniform, so that it can improve the search ability of the global target nodes and even reduce the nodes energy consumption. Third, the adaptation function covers the continuity of the covered target positions and the monitoring range of the nodes. Optimization is also performed to achieve the goals of increasing network coverage and extending the network lifetime. Finally, simulation results show that the proposed CoC-SCS algorithm compared with other three algorithms in this paper has improved 11.27% and 16.35% on average in terms of network coverage, network lifetime, etc., and 13.95% in terms of network energy overhead, thereby we can further verify that CoC-SCS algorithm has strong stability and effectiveness.

INDEX TERMS Wireless sensor network, controllable threshold parameters, collaboratively optimized coverage, perceptual intelligent computing, coverage, network lifetime.

I. INTRODUCTION

Wireless sensor networks have realized the organic unification of the information world and the physical world, and also have changed the way of the human world interacts with the physical world. Wireless sensor networks can be as the large-scale networks which integrate of sensor technology, micro-electro-mechanical system technology, embedded technology, distributed information technology, cognitive computing technology, network technology and communication technology. It is widely used in many engineering fields. For example, military and defense, safety production,

medical and health, environmental monitoring, target tracking, and intelligent transportation. The organizational behavior of wireless sensor networks is mainly reflected in the following aspects. Wireless sensor networks are large-scale networks where a large number of inexpensive sensor nodes are randomly deployed in the monitoring area, and information is exchanged, and data is collected in real time through self-organization. The dynamic change of the network topology is extremely frequent. Each sensor node has a certain storage capacity, communication capacity, computing capacity, and sensing capacity, but various capabilities are also weak. The power of its work comes from its own battery, once it is exhausted, it cannot be replenished. Therefore, the quality of the coverage effect directly affects the

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wireless sensor network architecture, network protocols, target positioning and tracking, energy efficiency, and network communication. For this reason, building a reliable, real-time and efficient wireless sensor network system is a difficult and challenging task.

Early Ad-hoc networks research divided the network into mobile Ad-hoc networks and wireless sensor networks based on whether the nodes moved. In a mobile Ad-hoc network, each wireless node can move freely. Generally, a wireless Ad-hoc network is equated with a mobile Ad-hoc network. In wireless sensor networks, each wireless node is randomly distributed in a certain monitoring area. The sensor node is responsible for collecting data in the monitoring area, such as temperature, humidity, and gas concentration, and sends them to the gateway node. The gateway has more powerful processing capabilities, and can further process the information, or has a larger sending range, and can send the information to a large network so that remote users can retrieve the information. With the development of micro engine electron system technology and information technology, low-cost, flexible, movable, and powerful sensor nodes can be realized, which has more application value. Wireless sensor networks have become a major application area for the Ad-hoc network technology. Currently, the wireless sensor network is equivalent to a wireless Ad-hoc network. Ad-hoc network is a network form without any fixed facilities and centralizing wireless, mobile, and self-organizing nodes. Most of the wireless sensor networks use the architecture of wireless Ad-hoc networks. Based on the above analysis, wireless sensor networks describe the use of sensors as network nodes. Nodes can collaboratively monitor, sense, and collect information on various monitored objects in real time and process them. And then, the information is organized in a self-organized, multi-hop network. The wireless sensor network realizes the integration and penetration of the information world, material world, material world and human society. The development stage of wireless sensor networks can be summarized into three stages. The first stage is mainly devoted to the development and development of miniaturized, low power, low cost, intelligent sensor nodes. The second stage focuses on the characteristics of wireless sensor networks as communication networks. The research of this subject mainly completed the design and practice of communication protocol. The third phase focuses on the research of swarm intelligence behaviors in wireless sensor networks.

The research on the characteristics of wireless sensor networks takes network coverage as the advance condition for research. A better coverage effect on the study of characteristics achieves more results with less effort. Network deployment is the primary work for establishing a wireless sensor network and is also the basis for the normal operation of the network. Network deployment should optimize existing network resources to obtain the highest and longest network life in future applications with its network. In WSNs, nodes have both information collection and information transmission functions, network deployment must meet two aspects:

(1) under the premise of ensuring perceptual coverage, communication coverage, and connectivity coverage, the maximum monitoring area should be covered with the fewest sensor nodes (2) On the premise of ensuring the smooth transmission of information and control commands in the network, the delay should be shortened as much as possible to improve the network lifetime. In WSNs, the maximum physical space that each sensor node can sense (the sensing range) is limited. To ensure that the areas to be monitored are within the monitored range, it is necessary to arrange sensor nodes in the target area according to some method, which is the covering problem. Coverage issues are the foundation of WSNs research. It describes the networks' perception of the physical world and reflects the "perceived quality" that the network can provide. At present, the coverage problem has been combined with issues such as ensuring network connectivity, efficient use of node energy, and dynamic coverage. The connotation and extension have been greatly expanded. A comprehensive review of network coverage is helpful to understand whether there are blind spots in monitoring and communication or not, so as to readjust the distribution of sensor nodes or analyze the improvement measures that can be taken when sensor nodes are added in the future.

Firstly, the coverage problem must establish a research coverage model to improve the coverage accuracy and precision, while suppressing the rapid consumption of sensor node energy to achieve the purpose of extending the network lifetime. Secondly, for the monitoring area, in order to suppress the node's energy consumption during the coverage process, it is not necessary to cover the entire monitoring area, but effective coverage of the target node of interest is used. Thirdly, in order to effectively cover the target nodes of interest, which requires the establishment of collaborative work among the nodes, and the geographically adjacent nodes in the network are divided into connected areas to form a cluster structure. In order to further study the coverage problem, this paper takes perceptual intelligent computing and controllable threshold as the research background and proposes an optimized collaborative coverage algorithm. The main contributions of this article are reflected in the following four points:

(1) In the second chapter, this article mainly conducts the in-depth research and analysis of related papers, gives the advantages and disadvantages of related papers, and also proposes the improvement measures and implementation schemes of this paper to address the deficiencies of the above papers.

(2) In the third chapter, this paper introduces the coverage model and analyzes the model effectively, and then gives the relevant definitions and model analysis process.

(3) In the fourth chapter, the clusters of event domain nodes are optimized through the characteristics of controllable parameters and mutation parameters in genetic algorithms to improve the coverage accuracy, optimize network resources, and promote the search ability for global target nodes.

(4) In the fifth chapter, the stability and availability of the CoC-SCS algorithm which is in this paper can be verified by experiments of the simulation.

II. RELATED WORK

Coverage optimization and clustering optimization are hot topics in WSNs research. Recently, many scholars that are at home or abroad have put a lot of in-depth research work on the topics into effect. With the development of wireless sensor network applications, the types of data to be transmitted are becoming more and more diverse, and the types of sensor nodes are also becoming more and more diverse. According to the nodes, the sensor network has the sensing and detection capabilities, computing communication capabilities, configured energy and functional attributes. The differences can be divided into homogeneous networks and heterogeneous networks. Homogeneous network means that all nodes in the network have the same type and attributes, and have the same sensing ability. Heterogeneous wireless sensor network refers to a network that composes of different types of multiple sensor nodes. Heterogeneous networks include heterogeneous nodes, heterogeneous links, and heterogeneous network protocols. Correspondingly, the network coverage problem can be divided into homogeneous network coverage and heterogeneous network coverage.

Energy-efficient routing is to find the minimum energy transmission path between the source node and the destination node. Therefore, it must be some nodes at this routing intersection to perform processing and forwarding of large amounts of data, so that the energy consumption of these nodes is too fast. When the energy is exhausted, the network exits and becomes a dead node. The nodes in these areas are called "hot zone" nodes. When the "hot zone" node becomes a dead node, because of the interrelationship among the networks, the data that was originally used for data routing and forwarding in this area needs to be routed from the nodes around these nodes, which results in the nodes around the "hot zone" The load is gradually increasing, which in turn causes the problem of "hot zone" gradually expanding, which not only reduces the coverage of WSNs, but may even divide the network and cause communication and interaction among nodes. Therefore, in the design of WSNs routing, the balance of the overall energy consumption of the network should be considered to prevent nodes in a single area avoiding an excessive task load.

A. COVERAGE PROBLEM

Paper [22] pointed out that the quality of coverage not only depends on the sensor nodes' sensing ability, but also depends on the characteristics of the perceived events, such as the characteristics of the natural environment and the perceived target itself. Paper [24] proposed an intrusion target detection algorithm based on the shortest path for interference holes caused by malicious attacks in the network, which can estimate and analyze network deployment performance parameters, including the number of nodes, sensing range, number of

covered holes, hole area, and deployment area. This deployment quality measurement method is based on the shortest path strategy to estimate the behavior of intruders. In addition, many scholars have also studied the optimization of WSNs coverage in energy holes and 3D space. Paper [25] proposed a method based on algebraic topology to divide sub-regions to determine the coverage holes and perform partition repair. Coverage holes detection and repair strategies need to be selected based on the node perception model and network structure, as well as specific application requirements. Hole repair for static networks can use node attributes to adjust and add new nodes to repair coverage quality, and hole repair for mobile networks can be achieved by moving nodes.

Paper [26] proposed a virtual force coverage algorithm, which introduced the concept of repulsive force, and adjusted the sensing direction of the sensor node through the combined effect of the repulsive force of neighboring nodes and the gravitational force of unperceived areas around the sensor node. So that the nodes can avoid the sensing overlap area as soon as possible and cover the coverage blind area of the area to be monitored, thus it improves the overall coverage of the directional sensor network. Paper [27] proposed the Nodes Deployment Assignment method with Data Association Attributes (NDADA), which is a heuristic algorithm that uses the virtual force of uncovered grid points around the sensor nodes. After the large-scale initialization random deployment, the direction-adjustable characteristics of directional sensor nodes are used to adjust the sensing direction of sensor nodes in a directional sensor network through a distributed algorithm; thereby it overcomes the problem of overlapping coverage of directional sensor networks. Based on this, Paper [28] proposed a distributed coverage algorithm based on weights. Based on the distributed coverage algorithm, the algorithm weights the grid's virtual forces and introduces movable sensor nodes, which overcomes the problem that the distributed coverage algorithm which cannot dynamically adjust the coverage holes in the directed sensor network, and improves the coverage and coverage enhancement of directional sensor networks. Paper [29] proposed the Transmission with Multiple Load Balancing Schemes (TMLBSs). This algorithm divides the sensing area of each sensor node in a directed sensor network into several basic areas with different overlaps and redundancy. It optimizes the residual relationship, and iteratively selects the node with the current maximum spatiotemporal coverage to adjust the sensing direction until all nodes are scheduled; thereby it also optimizes the performance of the network scheduling task.

Paper [30] proposed a node obstacle avoidance algorithm based on virtual potential field for the area to be monitored with multiple obstacles. The algorithm uses sensor nodes to cover the overlapping area, the effective coverage area, and the obstacle blocking area of the area to be monitored. The interaction of the virtual force of the sensor continuously adjusts the sensing direction of the sensor nodes, reduces the influence of multiple obstacles in the area to be monitored on the coverage of the directional sensor network,

and enhances the communication strength between nodes, and improves the network coverage. Paper [31] aimed at the problems of coverage redundancy and large cost in the existing sensor network target coverage, and proposed an energy-efficient distributed cluster mechanism for the target coverage algorithm. The algorithm assumes that sensor nodes can be active and sleeping. A sleeping sensor node can wake up periodically and communicate with its cluster to obtain communication and perception information of neighboring nodes. This algorithm uses clusters for the first time to determine the sensing direction of directional sensor nodes to achieve maximum target coverage. Paper [32] proposed a network coverage enhancement strategy based on an improved genetic algorithm and binary ant colony algorithm. This strategy introduced a genetic operator into the binary ant colony algorithm, and used crossover and mutation to expand the search space and achieve global optimization. This algorithm can enhance the convergence speed of the algorithm, improve the efficiency of network coverage, and avoid falling into the defects of local optimization and precocity. Paper [33] proposed a Multi Working Sets Alternate Covering Scheme (MWSAC) which aimed at the problems of large communication and computational costs and high energy loss caused by the implementation of the coverage enhancement algorithm on each sensor node in the existing directional sensor network. Clustering-based directional sensor network-overlay overlaps optimization algorithm. In this coverage enhancement strategy, each cluster head first selects the active node and its sensing direction in the possible sensing area to ensure complete communication in the entire coverage area and reduce redundant sensor nodes in the network, which is helpful to achieve inter-node in the network. The balance of energy consumption greatly extends the lifetime of the network. Paper [34] aimed at the problem that it is difficult for sensor nodes to synchronize the transmission and reception of information in a directed sensor network. A cooperative neighbor discovery mechanism was proposed, and the theoretical performance of the strategy was quantified by a Markov chain analysis model. This strategy greatly reduces the discovery delay and improves the discovery rate of neighboring nodes. Paper [35] uses the improvement of non-uniform clustering, selects heads of cluster based on the probability and sets thresholds, and then selects cluster heads based on residual energy and density. The cluster radius is calculated using the cluster head density and the distance to the base station. The energy consumption of the nodes achieves the purpose of extending the network lifetime. Paper [36] combined the remaining energy of the nodes, the distance from the nodes to the cluster head, and the distance from the node to the base station as the influencing factors for selecting the cluster head. The cluster head established a minimum spanning tree based on the above factors, and used ant colony algorithm to optimizing routing effectively extends the lifetime of the network and reduce the energy consumption of nodes. Paper [37] proposed an extended ant colony-based cognitive wireless network routing algorithm,

which combined delay time with idle frequency bands and used non-uniform clustering to cluster nodes, and gave the best candidate cluster head probability solution. And then it uses the ACO algorithm to complete the path search and complete the data transmission and the delay can be reduced.

B. OPTIMIZES CLUSTERING

Paper [38] used the node energy as the research background, the unit time as the base of rotation, and the high-energy node as the cluster head node. At the same time, the greedy algorithm was put into practice to calculate path which is the shortest among adjacent nodes. Paper [39] uses a double-linked list to write the path traveled by the data transmission; when a certain path fails, the path information of the node can be obtained at the previous level from another linked list, be written into the linked list, and then the double-linked list can be updated again. Therefore, the dual path backup can be achieved. Paper [40] used graph theory tree structure to construct an undirected spanning tree, and then broadcasted the route through the central node in the cluster, and searched first to get a minimum route spanning tree, and then used the algorithm of ant colony to traverse the minimum spanning tree, and finally got the optimal route in the cluster. Paper [41] divided the monitoring area into several sub-areas, looking for the highest energy node in the sub-area as the cluster head node, and the routing link formed by the cluster head nodes in all sub-areas. The above operation was repeated after N cycles, then a new routing link can be found, and finally the maximum optimized route for data transmission can be completed. In paper [42], an annealing algorithm was used to construct a minimum spanning tree. The highest energy node in the cluster was used as the cluster head node, and the next highest energy node was used as the secondary cluster head node. The minimum delay path is calculated by the annealing algorithm and the data is sent to the base station. In the phase of data fusion, the information of the member nodes position in the cluster and the position information of neighboring nodes are used to build an energy-balanced routing tree at the upper layer to achieve the purpose of energy balance across the network. Paper [43] uses the principle of non-linear optimization to provide a method for calculating the maximum connectivity between the target node and the sensor node; and then uses a ranking algorithm to classify the energy according to the level of the energy and store the nodes in a finite linked list. In the process of covering the target nodes, the election is performed from the linked list in the order of the node energy from high to low, and finally the purpose of energy balance of the entire network is achieved. Paper [44] takes the data fusion time as the research object and gives a distributed routing algorithm based on local data fusion information. This algorithm can establish the optimal transmission path for any spanning tree, and also specify the time gap of data for any sensor node. And finally the network resources could be optimized. Paper [45] uses annealing algorithm to establish the clustering of nodes by the similarity between the remaining energy of the sensor

nodes and the data. For the data information collected by the members in the cluster, the regression data is used to obtain prediction data to determine the data transmission path. Paper [46] gives a distributed algorithm based on data behavior. This algorithm integrates static and dynamic clustering algorithms to dynamically divide members in a cluster; this cycle is kept static member nodes in the cluster. After several cycles, dynamic composition is adopted based on the relationship between sensor node energy and Euclidean distance. The cluster method divides all nodes again, and finally achieves the purpose of energy balance. Paper [47] proposed the multi-target continuous tracking algorithm by using the continuity of sensor node's sensing ability and sensor node connectivity. This algorithm also completes the tracking process of the moving target through inter-cluster communication. The cluster head node fuses the data information collected by the members in the cluster, and it is finally forwarded by the cluster head node to the base station. In paper [7], the original cluster head election threshold function was improved. A new cluster head election function was proposed based on the spacing factor, node residual energy and node position factors to effectively extend the network lifetime. However, the selection of cluster heads depends on random probability and threshold functions, so the optimality of the cluster head selection result cannot be guaranteed. Paper [48] proposed an energy-aware multi-hop multi-path layered routing protocol. This protocol establishes multiple paths from each sensor node to the cluster head and provides energy-aware heuristics to select the best path. However, the node position factor is not considered in the cluster head selection process, which may cause the cluster head nodes to be distributed unevenly. Paper [49] proposed an adaptive clustering routing protocol based on genetic algorithm. This protocol addresses the shortcomings of random selection of cluster heads in the traditional LEACH protocol, and uses genetic algorithms to select cluster head nodes, which effectively extends the network lifetime. Paper [50] used particle swarm optimization to optimize the cluster formation phase of the LEACH protocol. The proposed LEACH-PSO protocol effectively avoided the generation of uneven clusters and reduced node energy consumption. Paper [51] used the non-uniform clustering LEACH protocol to network cognitive wireless sensor networks and added the idle channel influence factor to the candidate cluster head formula. Paper [52] proposed a cluster-based spectrum-aware routing protocol, and selected cluster heads in combination with idle frequency bands and residual energy to improve energy efficiency. Paper [53] proposed a new distributed spectrum sensing clustering algorithm in the context of cognitive wireless sensor networks. Forming clusters in a self-organizing manner enables less energy consumption in the clusters; therefore, this manner derives the optimal number of clusters and improves stability.

Based on the above analysis, this paper proposes Cooperative-optimization Coverage Algorithm based on Sensor Cloud Systems in Intelligent Computing, CoC-SCS is

based on the papers [29] and [46]. The algorithm uses genetic algorithm to realize sensor nodes distributed clustering in the domain of the event, the introduction of adaptation functions and update functions can accurately select the specific location of the next-hop cluster head, and completes the distributed clustering with the event domain nodes. In order to reduce the consumption of node energy and improve the search ability for global target nodes, on the network topology, the genetic algorithm can quickly adapt to changes in the network topology and has lower search energy consumption. By updating global variables, it resists the generation of long links, achieves the purpose of equalizing node energy, prolongs the network lifetime, and optimizes network resource allocation. This algorithm can effectively fuse the data in the cluster, suppress the generation of redundant data on the entire network, improve the network coverage quality, and finally achieve the purpose of energy balance on the entire network, thereby extending the network lifetime.

III. COVERAGE MODEL ESTABLISHMENT AND ANALYSIS

A. ASSUMPTIONS AND BASIC DEFINITIONS

In WSNs, the coverage areas of sensor nodes can overlap to achieve the requirement of covering the monitored area without vulnerabilities [54]. From the perspective of saving node energy and extending the network lifetime, it is necessary to cover the monitoring area with the least number of nodes. If the coverage area is assumed to be large enough, regardless of the influence of the boundary, saving energy under the requirement of ensuring complete coverage is to maximize the coverage efficiency. In this paper, when studying the coverage problem, we need to transform the actual physical problems into abstract mathematical problems. In order to reduce the complexity of the problem without losing the generality of the problem, the following assumptions are made:

(1) The sensor nodes in WSNs are physically homogeneous, i.e., the sensing range and signal receiving capability of all sensor nodes are consistent. The nodes use omnidirectional antennas to transmit, and the transmission power is balanced.

(2) Each sensor node in the network obtains its own position information through a positioning algorithm (such as RSSI, TDOA).

(3) Each sensor node is uniquely identified, and its sensing ability is not affected by the external geographic environment.

(4) The areas where WSNs are deployed are all convex areas, i.e., the connection between any two nodes in the area completely falls within the area.

(5) At the network initial moment, every node is homogeneous and always remains disc-shaped. The sensing radius is the same, and the communication radius of all sensor nodes is also the same.

Definition 1 (Coverage Rate): the coverage rate in the wireless sensor network monitored or tracked by all sensor nodes is also called coverage degree or coverage. Coverage rate is the ratio of the size of the coverage area of all sensor

nodes with the size of the entire target area.

$$C = \frac{\bigcup_{i=1,2,\dots,N} S(A_i)}{S(A)} \quad (1)$$

Among them, C is the coverage rate; $S(A_i)$ is the size of the coverage area of the i^{th} node; N is the number of nodes; $S(A)$ is the size of the entire target area.

Definition 2 (Coverage Efficiency): Coverage efficiency is the ratio of the union of the coverage of all nodes in the monitoring area with the sum of the coverage of all nodes.

$$CE = \frac{\bigcup_{i=1,2,\dots,N} S(A_i)}{\sum_{i=1,2,\dots,N} S(A)} \quad (2)$$

The coverage efficiency reflects the degree of node redundancy. Coverage efficiency is proportional to the sensor node redundancy, the higher the coverage efficiency, the smaller the sensor node redundancy. Coverage efficiency is also the average coverage of each node.

Definition 3 (Coverage Multiple): given a plane monitoring area, if any one of its physical locations falls within the sensing range of k sensor nodes, it is called wireless sensor network k -degree coverage.

$$K_A = \sum_{i=1}^N k_i \quad (3)$$

Among them, K_A is the coverage multiple of $S(A)$ area; k_i is the i^{th} node's sensing range. In some application environments, the entire network is not covered. When the network coverage is greater than a certain threshold, i.e., $0 < K < 1$, this is called partial coverage or effective coverage.

Definition 4 (Coverage Uniformity): it is generally expressed by the standard deviation of the distance between nodes.

$$U = \frac{1}{n} \sum_{i=1}^N U_i \quad (4)$$

$$U_i = \left(\frac{1}{K_i} \sum_{j=1}^{K_i} (d_{i,j} - M_i) \right)^{\frac{1}{2}} \quad (5)$$

Among them, U is uniformity, n is the total number of nodes; K_i is the number of neighbor nodes of the i^{th} node; $d_{i,j}$ is the distance between the i^{th} node and the j^{th} node; M_i is the average of the distances between the i^{th} node with all nodes that intersect with the other sensor node's sensing range.

Definition 5 (Coverage Time): when the target node is completely covered or tracked, all working nodes required for to start from ready.

Definition 6 (Dominant Set): in the graph, where $G = (V, E)$, if a V subset is found ($S \subseteq V, S \neq \emptyset$), and for $\forall s_i \subseteq V-S, S$ is adjacent to at least one node in $V-S$, then it is called that S is the Dominating Set (DS) of graph G . The nodes in DS are called dominating set nodes, and the nodes that are not in the set are called dominated nodes, i.e., each

node in the graph belongs to a subset or is a neighbor node of at least one node in the subset.

In order to further study the problem of network coverage, this paper divides the sensor nodes into several clusters. The main purpose of clustering is to achieve the entire network energy balance and the nodes energy balance in the cluster; improve the network coverage efficiency; suppress the rapid energy consumption caused by the delay, increase the connectivity and reduce the delay; and then minimize the cluster number, therefore, it extends the network lifetime. The main task of clustering is to continuously cover the moving target nodes in real time and divide several sensor nodes into multiple clusters that can communicate with each other according to the clustering requirements, covering all clusters of sensor nodes. When the network topology changes, the cluster structure can be updated at any time to better repair and manage the cluster; the co-organization form is reflected in the division of several adjacent sensor nodes mainly with different geographical locations into clusters of different sizes through the sensing ability, so that it is convenient to complete effective coverage. The coverage of the moving target node under the clustering structure is shown in Figure 1.

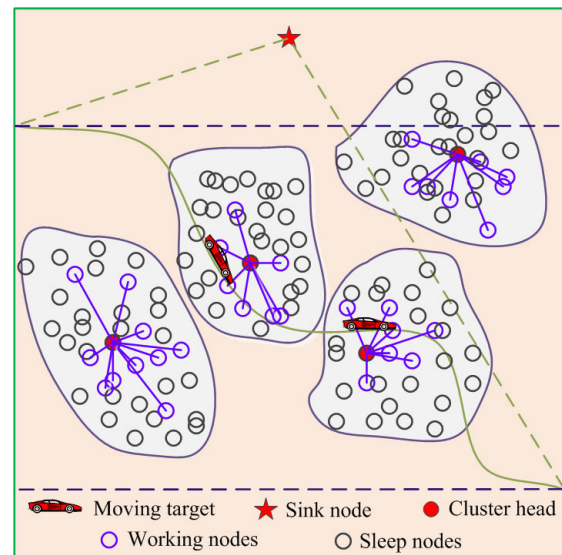


FIGURE 1. Network coverage model of moving target node under cluster structure.

Figure 1 shows the network coverage model of the moving target node under the cluster structure. As we can see from Figure 1, the sensor node is divided into four clusters in this paper. When the moving target node is in a certain cluster, the effective coverage of the moving target node can be completed. When the moving target is far away from the cluster, the cluster head node of the cluster sends a message to the adjacent cluster head node, and wakes up the adjacent cluster head node to continue to effectively cover the moving target node. During the research coverage process, we do not need to effectively cover the entire monitoring area, but only effectively cover the moving target nodes. The purpose of this

paper is to suppress node energy consumption and extend the network lifetime.

B. COVERAGE MODEL ANALYSIS

Based on the above analysis, in order to further improve the coverage efficiency, extend the lifetime of the network, and optimize the structure within the cluster, this paper introduces a genetic algorithm in the intelligent algorithm to optimize the coverage and cluster structure to achieve the best coverage effect.

The genetic operation of the genetic algorithm in the throughout evolution process uses randomness, but the characteristics displayed are not random search completely. It can use information, which is historical, to infer the set of advantages effectively that the next generation expects to improve. In this way, it continues to evolve from generation to generation, and finally converges on an individual one which is most adaptable to the environment during finding the set of the problem of the optimal solution. The reason for which the genetic algorithm has strong search ability is mainly due to its three basic characteristics, which are: Selection, Crossover, and Mutation. These three characteristics form the core of the search of genetic algorithms and are the main carriers for simulating the phenomena of reproduction, hybridization and mutation in natural selection and genetic processes.

For a given set of sensor nodes $S = \{s_1, s_2, \dots, s_N\}$, the adaptive value of the individual $s_i \in S$ is $f(s_i)$, and its selection probability is as follows:

$$p_s(s_j) = \frac{f(s_j)}{\sum_{i=1}^n f(s_i)} \tag{6}$$

Equation (6) determines the probability distribution of individuals in the sensor node set in the next cycle. Among them, the expected quantity of sensor nodes in the previous cycle is as follows:

$$P(s_j) = Np_s(s_j) \tag{7}$$

When the difference in individual fitness values in the node set is very large, the ratio of the probability that the best and worst nodes are selected will also increase exponentially. The worst node's chance of survival in the next cycle will increase significantly, while the worst node's chance of survival will be deprived. Cross operation is a unique feature of the originality of GA algorithm in intelligent evolutionary algorithms. In the dynamic clustering process, in order to increase the cluster-to-cluster reorganization, this paper uses a crossover operation. For the selected multiple clusters, multiple intersections are randomly selected to form a new intersection set.

$$\begin{cases} x_1, x_2, \dots, x_K \in \{1, 2, \dots, L - 1\} \\ x_k \leq x_{k+1} \\ k = 1, 2, \dots, K - 1 \end{cases} \tag{8}$$

The set of relevant positions for re-dividing the L-bit nodes into the new cluster is as follows.

$$\begin{cases} Q_k = \{l_k, l_{k+1}, \dots, l_{k+1} - 1\} \\ k = 1, 2, \dots, K + 1 \\ l_1 = 1, l_2 = 2, \dots, l_{K+2} = L + 1 \end{cases} \tag{9}$$

The operator form is defined as follows.

$$\begin{aligned} O(p_c, K) : a'_{1i} \\ = \begin{cases} a_{2i} & \text{if } i \in Q_k \text{ and } k \text{ is even numbers} \\ a_{1i} & \text{otherwise} \end{cases} \end{aligned} \tag{10}$$

$$\begin{aligned} O(p_c, K) : a'_{2i} \\ = \begin{cases} a_{1i} & \text{if } i \in Q_k \text{ and } k \text{ is even numbers} \\ a_{2i} & \text{otherwise} \end{cases} \end{aligned} \tag{11}$$

The performance of GA is greatly affected by using different crossover operators. Two different nodes s_i are randomly selected in different clusters, and s_j can perform crossover operations as follows.

$$\begin{cases} s'_i = \lambda s_i + (1 - \lambda) s_j \\ s'_j = (1 - \lambda) s_i + \lambda s_j \end{cases} \tag{12}$$

When the sensor nodes in WSNs are re-divided into clusters, when the time is $t_1 = T$, the nodes in a cluster are re-divided into another cluster. For this cluster, the linked list structure has changed. This node is considered to have mutated. In the genetic algorithm, the mutation operator is implemented by randomly inverting a sensor node according to the mutation probability p_m , the formula is as follows.

$$O(p_m, x) : a'_i = \begin{cases} 1 - a_i & x_i \leq p_m \\ a_i & \text{otherwise} \end{cases} \tag{13}$$

The fitness value function is a feasible solution set for evaluating the coverage quality of the members in the reconstituted cluster, and is also the number of calculations required for the evaluation of the node fitness function. Obviously, the smaller the value is, the higher the search efficiency of the corresponding GA is. The fitness function is divided into two forms: online search and offline search.

$$P_{on}(s) = \frac{1}{n(T + 1)} \sum_{t=0}^T \sum_{j=1}^n f(a_j, t) \tag{14}$$

The online performance reflects the changes of the average adaptive value of the node set after smoothing, and describes the integrity and evolutionary ability of the node set.

$$P_{off}(s) = \frac{1}{T + 1} \sum_{t=0}^T f(a^*, t) \tag{15}$$

Among them, $f(a^*, t) = \max\{f(a_1, t), f(a_2, t), \dots, f(a_n, t)\}$, i.e., the adaptive value of the best node in the current node set. This index reflects the smoothed changes of the adaptive value of the best node in the node set and describes the evolutionary ability and GA search ability of the node.

Based on the above description, GA basically does not use external information in evolutionary search, and only uses the

function of fitness value as a basis. The f function of fitness value is used to describe the adaptation degree of each node. The purpose of introducing the function of fitness value is to evaluate the nodes according to the fitness values of the nodes and calculate the pros and cons. The only requirement for the function of fitness value is that non-negative results can be calculated for the input parameters that can be compared. The function of fitness value is essentially a representation of the optimization objective function. Define the function of fitness value is as follows.

$$\text{Fit}(y) = \begin{cases} 1 - \frac{1}{2} \left(\frac{y-b}{a} \right)^\alpha \\ 1 + \left(\frac{y-b}{a} \right)^\beta \end{cases} \quad (16)$$

In formula (16), the ideal value of b is $\min y = y^*$. Since $|y-b| = a > 0$, $\text{Fit}(y) = 0.5$, so in the ideal case, it means that the distance between y and $\min y$ when the adaptive value is 0.5. α and β is the threshold parameter. Generally, the value of α is $[0.5, 1.5]$, the value of β is $[1.5, 2]$.

IV. ANALYSIS OF COVERAGE QUALITY AND CoC-SCS ALGORITHM

A. EFFECTIVE COVERAGE ANALYSIS

For a moving target, its walking trajectory and the area covered by the sensor nodes both show irregular shapes. In order to facilitate the study of the problem, this article uses a square area for illustration and calculation. Calculating the expected values of sensor nodes in an area of the square monitoring and randomly selecting k coverage expectations can rely on the theoretical knowledge of probability.

Theorem 1: The coverage rate of the sensor node is p . After N times of coverage of the moving target node, the expected coverage of the sensor node is $E(X) = [1 - (1 - p)^N]p^{-1}$.

Proof: Let X be the number of conversions when the sensor node first covers the moving target node, i.e., $X \in [1, 2, \dots, N]$. When $X = k$, it means that the sensor node does not cover the moving target node before $N-1$ times conversions when $1 \leq k \leq N-1$ exists, so the distribution density function of X is as follows.

$$P(X = k) = \begin{cases} p(1-p)^{k-1} & k = 1, 2, \dots, N-1 \\ (1-p)^{N-1} & k = N \end{cases} \quad (17)$$

Calculation formula (17) can be obtained formula (18).

$$E(X) = \sum_{k=1}^{N-1} kp(1-p)^{k-1} + N(1-p)^{N-1} \quad (18)$$

Let $q = 1-p$, $S = \sum_{k=1}^{N-1} k(1-p)^{k-1}$

$$qS = \sum_{k=1}^{N-1} kq^k \quad (19)$$

And S can be obtained.

$$S = \frac{1-q^{N-1}}{(1-q)^2} - \frac{(N-1)q^{N-1}}{1-q} \\ = \frac{1-(1-p)^{N-1}}{p^2} - \frac{(N-1)(1-p)^{N-1}}{p} \quad (20)$$

Substituting formula (20) into formula (18), we can get formula (21).

$$E(X) = p \left[\frac{1-(1-p)^{N-1}}{p^2} - \frac{(N-1)(1-p)^{N-1}}{p} \right] \\ + N(1-p)^{N-1} \\ = \frac{1-(1-p)^{N-1} + p(1-p)^{N-1}}{p} = \frac{[1-(1-p)^N]}{p} \quad (21)$$

The proof is complete.

Corollary 1: The coverage rate of the sensor node is p , and the expected value of the sensor node's first complete coverage of the moving target node is $E(X) = 1/p$; $D(X) = (1-p)/p^2$.

Proof: According to the meaning of the title, the coverage rate of any sensor node in the monitoring area is p , and the probability that it is not covered by the sensor node is $1-p$. Let $q = 1-p$, we can get the expectations value of the sensor node's first complete coverage of the moving target node.

$$E(X) = \sum_{k=1}^N kpq^{k-1} = p \left(\sum_{k=1}^N q^k \right)' \\ = p \left(\frac{q}{1-q} \right)' = \frac{1}{p} \quad (22)$$

$$E(X^2) = \sum_{k=1}^N k^2 pq^{k-1} = pq \sum_{k=1}^N k(k-1)q^{k-2} + \frac{1}{p} \\ = pq \left(\sum_{k=1}^N q^k \right)'' + \frac{1}{p} = \frac{1+p}{p^2} \quad (23)$$

$$D(X) = E(X^2) - E(X)^2 = \frac{1-p}{p^2} \quad (24)$$

The proof is complete.

The essence of the research on the coverage problem is to take into account the perception, communication, and connectivity, and use a small number of nodes when deploying the nodes in the monitoring area, i.e., the least repeatable non-blind zone coverage. In the above analysis, the physical model of node coverage should take different forms due to different physical spaces, such as physical parameters, so that the quantity of nodes which are used in the area of the monitoring could be minimized while ensuring no blind zone coverage. Therefore, this article introduces Theorem 2 and Corollary 2

Theorem 2: In a monitoring field with A area, k sensor nodes are randomly selected from the node set, and the coverage expectation satisfies $E(P) = 1 - \left[1 - \frac{\pi(R_0^2 + \sigma^2)}{S(A)} \right]^k$.

Proof: According to Definition 1, the coverage rate of any sensor node in the monitoring area is as follows.

$$P_i = \frac{\pi r_i^2}{S(A)} \quad (25)$$

Since the sensor nodes' perceptual radius obeys the normal distribution (R_0, σ^2) , R_0 represents the mean and σ^2 represents the variance. For the mobile target node, the coverage

rate is as follows.

$$P = \int_0^{2R_0} P_i \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{(r_i - R_0)^2}{2\sigma^2}\right] dr \quad (26)$$

Let $\xi = (r_i - R_0)/\sigma$,

$$P = \left(\frac{\pi}{2}\right)^{\frac{1}{2}} \frac{1}{S(A)} \int_{-\frac{R_0}{\sigma}}^{\frac{R_0}{\sigma}} (\xi\sigma + R_0)^2 \exp\left(-\frac{\xi^2}{2}\right) d\xi \quad (27)$$

Calculated formula (27),

$$P = \left(\frac{\pi}{2}\right)^{\frac{1}{2}} \frac{1}{S(A)} \times \left(\int_{-\frac{R_0}{\sigma}}^{\frac{R_0}{\sigma}} \sigma^2 \xi^2 \exp\left(-\frac{\xi^2}{2}\right) d\xi + 2 \int_{-\frac{R_0}{\sigma}}^{\frac{R_0}{\sigma}} \sigma \xi \left(-\frac{\xi^2}{2}\right) d\xi + \int_{-\frac{R_0}{\sigma}}^{\frac{R_0}{\sigma}} R_0^2 \exp\left(-\frac{\xi^2}{2}\right) d\xi \right) \quad (28)$$

Simplifying formula (28),

$$P = \left(\frac{\pi}{2}\right)^{\frac{1}{2}} \frac{1}{S(A)} \left(-\sigma^2 \xi \exp\left(-\frac{x^2}{2}\right) \Big|_{-\frac{R_0}{\sigma}}^{\frac{R_0}{\sigma}} + \left(\frac{\pi}{2}\right)^{\frac{1}{2}} (\sigma^2 + R_0^2) \right) \quad (29)$$

Simplifying formula (29),

$$P = \frac{\pi (R_0^2 + \sigma^2)}{S(A)} \quad (30)$$

Because the sensor nodes are independent of one another, the expected value of any moving target node covered by k sensor nodes in the monitoring area is as follows.

$$E(P) = 1 - \left(1 - \frac{\pi (R_0^2 + \sigma^2)}{S(A)}\right)^k \quad (31)$$

The proof is complete.

In the monitoring area, the sensor node must finish the data collection and data communication operations on the target node. In order to reduce the delay, suppress the rapid energy consumption of nodes and improve the network lifetime, it is necessary to complete the maximum area coverage with the fewest nodes during the coverage process.

Corollary 2: Complete the effective coverage of the monitoring area, the minimum number of nodes is

$$k = \ln(1 - \varepsilon) \ln\left(1 - \frac{\pi (R_0^2 + \sigma^2)}{S(A)}\right)^{-1}$$

Proof: Given a very small positive integer $\varepsilon = 10^{-5}$, the expected coverage for any sensor node is greater than available.

$$1 - \left(1 - \frac{\pi (R_0^2 + \sigma^2)}{S(A)}\right)^k \geq \varepsilon \quad (32)$$

Taking the logarithms on both sides of formula (32), we get formula (33).

$$k \ln\left(1 - \frac{\pi (R_0^2 + \sigma^2)}{S(A)}\right) \leq \ln(1 - \varepsilon) \quad (33)$$

And k can be calculated.

$$k \leq \ln(1 - \varepsilon) \ln\left(1 - \frac{\pi (R_0^2 + \sigma^2)}{S(A)}\right)^{-1} \quad (34)$$

While the monitoring area is covered effectively, the minimum quantity of sensor nodes which are used is as follows.

$$k = \ln(1 - \varepsilon) \ln\left(1 - \frac{\pi (R_0^2 + \sigma^2)}{S(A)}\right)^{-1} \quad (35)$$

The proof is complete.

B. CLUSTER ANALYSIS

The purpose of clustering is to divide all the monitoring areas into several adjacent domains. Each cluster is usually composed of a cluster head node and multiple cluster member nodes. The cluster head node of the lower-level network is a cluster member node in the higher-level network, and the highest-level cluster head node and the gateway node communicate. In the cluster topology management structure, the internal nodes of the network might be divided into cluster member nodes and cluster head nodes. The cluster head node is elected based on some algorithms or rules. It is a command center for controlling and managing cluster member nodes, coordinating various tasks in the cluster, and completes data collection and fusion in the cluster. After N cycles, the cluster head node must be re-elected according to some algorithm to make sure that the cluster head node has enough energy to complete the above operation. During the clustering process, it is inevitable that the nodes are unevenly distributed, so that redundant nodes exist. When the moving target node passes the working redundant node, a large amount of redundant data is bound to be generated, which affects the communication among the nodes in the cluster. This paper introduces Theorem 3 and Theorem 4 on the research of the dual communication mechanism of asymmetric links.

Theorem 3: The sub-image G_s connectivity remains unchanged after the asymmetric link is deleted.

Proof: According to the meaning of the title, graph G_s is a sub-image of graph G . and then $\forall s_j \in C(h_i), h_i \rightarrow s_j$; i.e., h_i and s_j are reachable to each other. Assume that $d(h_i, s_j) < R(h_i)$ and $d(h_i, s_i) > R(s_j)$, then there is a directed path $l = s_j \rightarrow s_l \rightarrow \dots \rightarrow s_k \rightarrow h_i$ between s_j and h_i .

According to the homogeneous character for member nodes in cluster, i.e., $s_i \rightarrow s_j \Rightarrow s_j \rightarrow s_i$, and then $s_k \rightarrow s_l \rightarrow \dots \rightarrow s_j$. And $R(h_i) \geq R(s_k), s_k \rightarrow h_i \Rightarrow h_i \rightarrow s_k$, we can get $h_i \rightarrow s_k \rightarrow s_l \rightarrow \dots \rightarrow s_j$. We can also get the conclusion that deleting directed edges (h_i, s_i) will not affect the bidirectional connectivity between h_i and s_j .

The proof is complete.

Theorem 4: When m moving target nodes pass a certain cluster, at least one path exists, so that the probability $P_r(\neg P_m)$ of the optimal path moved by m target nodes is greater than or equal to $1 - (1 - c^{m-1}p)S$. Among them, $p = \gamma^L \prod_{(k,l) \in w^*} \tau_{kl}$ and $C = (1 - \rho)^L$.

Proof: If and only if the finite number of routing paths is u and the set of edge sets from the source node to the destination node is (k, l) , then:

$$\gamma = \min \{ [\eta_{kl}(u)]^\beta \mid (k, l) \in w^*, u \in w^* \} > 0 \quad (36)$$

Since $\Delta \tau_{kl} \geq 0$ and $\rho > 0$, for the edge set formed from the source node to the destination node, i.e., the value of τ_{kl} is the same in the $m + 1$ period and the m period. If the constant $C > 0$, then:

$$\tau_{kl}(m + 1) = (1 - \rho) \tau_{kl}(m) + \rho \Delta \tau_{kl} \quad (37)$$

$$\Delta \tau_{kl} = \frac{1}{C} \sum_{s=1}^S \Delta \tau_{kl}^{(s)} \quad (38)$$

Calculating from formula (37) and formula (38), we can get as follows.

$$\tau_{kl}(m + 1) \geq (1 - \rho) \tau_{kl}(m) \quad (39)$$

τ_{kl} is the same in $m + 1$ period and m period, so our recursive calculation method can get formula (40).

$$\tau_{kl}(m) \geq (1 - \rho)^{m-1} \tau_{kl}(l) \quad (40)$$

Without loss of generality, it is assumed that the expected value $\eta_{kl}(u)$ can be normalized using the method $\Gamma = 1$, i.e., to optimize all routing edge sets (k, l) and the global sets, we can get as follows.

$$f(x) = \begin{cases} [\eta_{kl}(u)]^\beta \leq 1 \\ \sum \tau_{kl}(m) = 1 \end{cases} \quad (41)$$

$$\sum_{r \notin u, (k,r) \in A} \tau_{kr}(m) [\eta_{kr}(u)]^\beta \leq \sum_{r \notin u, (k,r) \in A} \tau_{kr}(m) \leq 1 \quad (42)$$

When the node $r \notin u$ is calculated by the genetic algorithm's transition probability formula, the inequality condition is satisfied.

$$p_{kl}(m, u) = \prod_{i=0}^{L-1} p_i(v_0, v_1 \cdots v_i) \geq \tau_{kl}(m) [\eta_{kl}(u)]^\beta \quad (43)$$

According to formula (36), formula (44) can be got by formula (43) and formula (44).

$$\begin{aligned} \Pr(E_m^{(s)}) &= \prod_{i=0}^{L-1} p_{v_i v_{i+1}}(m, (v_0, v_1 \cdots v_i)) \\ &\geq \gamma^L \prod_{i=0}^{L-1} (1 - \rho)^{m-1} \tau_{v_i v_{i+1}}(1) = c^{m-1} p \end{aligned} \quad (44)$$

Since the nodes are independent with each other, knowledge about probability theory can be obtained.

$$\Pr(\neg B_m) \geq 1 - (1 - c^{m-1}p)^S \quad (45)$$

The proof is complete.

C. ALGORITHM DESCRIPTION AND IMPLEMENTATION PROCESS

In this paper, the CoC-SCS algorithm is based on the collaborative coverage of sensor nodes. All sensor nodes are divided into several clusters. The nodes have higher node energy and stronger computing power. The other nodes act as member nodes. In the initial stage of network operation, since the energy of each sensor node is equal, the cluster head node generally chooses the node closer to the Sink node to act as a member; member nodes first send a "Coverage" message to the cluster head node, and then the cluster head node opens up an information space of a certain storage capacity according to the size of the storage space, builds a storage linked list, and stores the collected messages in the linked list. The "Coverage" message contains the ID information and current coverage characteristics of the sending node and the current location information and coverage expectations. After one or more rounds, after the cluster head has received the data of the cluster, all nodes in the cluster are reordered according to the rules of energy and distance priority, and the newly generated node sequence is stored in the linked list. The sensor node with the expected value and energy and the better distance is given the highest weight to act as the cluster head node; find the sensor node that meets the coverage conditions in the linked list for labeling, and send a "Notice" message to the member to schedule the coverage for the moving target node. The CoC-SCS algorithm in this paper is divided into seven steps:

Step1. The expected coverage of each sensor node is calculated to determine the clustering structure according to the cooperative characteristics of the nodes of formulas (23) and (24).

Step2. The cluster head node establishes a linked list and receives the "Coverage" message sent by the member nodes. It contains the ID and coverage characteristics of the member node as well as information such as location messages and coverage expectations.

Step3. After multiple rounds of cycles, the cluster head node sorts the nodes stored in the linked list according to the coverage expectation value and energy size according to formulas (29) and (31), and it sets the high weight to the sensor nodes with better expectation value, energy and distant.

Step4. The cluster head node searches the linked list for sensor nodes that meet the coverage conditions of the next cycle, and marks them, at the same time; the formula (43) is used to elect the cluster head node for the next round.

Step5. After the cluster head completes the above operations, it sends a "Notice" message to the node that meets the coverage conditions. After receiving the "Notice" message, the node starts the sensing module to complete the coverage of the moving target node.

Step6. When the moving target node is covered by k nodes, the cluster head node traverses the linked list again, finds the nodes that meet the coverage conditions, and returns to Step5.

Step7. When the moving target node leaves the cluster, the cluster head node sends a message to the cluster head node of the adjacent cluster, restarts the next cycle of coverage, and returns to Step 1 until the moving target node is completely covered by the sensor node.

In this paper, the CoC-SCS algorithm uses genetic algorithm optimization strategies to optimize sensor node coverage and expected values, sends and receives different information to complete the coverage of moving target nodes, and determines the cluster head selection for the next cycle by looking up the linked list. To obtain the best node to act as the cluster head node to complete subsequent coverage of the moving target node. If the CoC-SCS algorithm completes the coverage of the mobile target node in one cycle or less than one cycle, the complexity of the CoC-SCS algorithm in this paper is $O(n)$, if it completes the mobile in more than one cycle or less than the maximum network survival. The coverage of the target node, the complexity of the CoC-SCS algorithm in this paper is $O(n^2)$.

V. SYSTEM EVALUATION AND ANALYSIS

In order to further verify the stability and effectiveness of the CoC-SCS algorithm in this paper, the simulation tools Matlab7.0 is used to do comparison experiments with paper [27] and paper [29], and paper [33] in terms of coverage of the network, network lifetime, and network energy overhead. The simulation parameters are shown in Table 1.

TABLE 1. Parameter list.

Parameter description	Value
Monitoring area A	100 100 , 300 300
Initial energy E	5J
Number of nodes	1200
Sensing radius r	5m
Node emission energy consumption	50nJ/bit
Energy consumption in free space	10pJ/(bit m ₂)
length of data packet	200bit
Network running time	1500s

Figures 2 to Figure 4 show the clustering structures of cluster heads and cluster members at non-same times. We can see from the figure that the clusters formed by cluster heads and cluster members are different at different times. This paper uses dynamic parameters $\alpha = 0.5$, $\beta = 1.5$, $\lambda = 1.2$. At the same time, considering the distance relationship between the cluster head and cluster member nodes and the distance relationship between the cluster head node and the base station, the selected node is more likely to be away from the base station. Closer nodes and higher node energy are used as cluster head nodes, which can effectively reduce the energy consumption of cluster member nodes when transmitting data. In this paper, the CoC-SCS algorithm randomly selects multiple nodes as cluster head nodes based on the order of nodes in the linked list and the weight value.

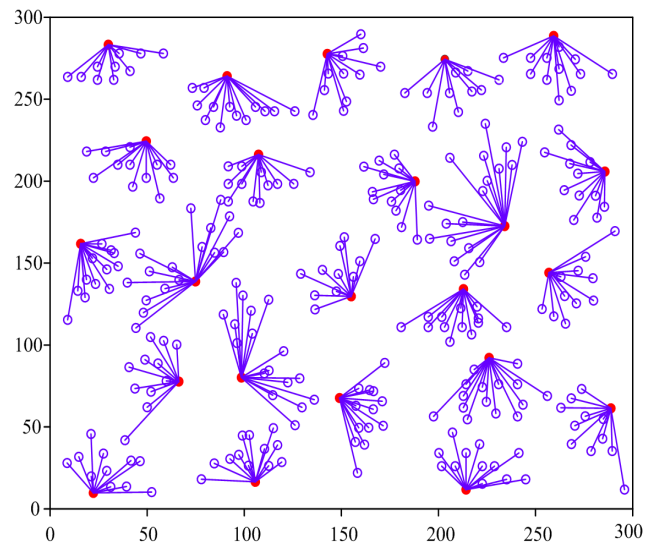


FIGURE 2. $t = 300ss$, clustering structure of cluster head and member nodes.

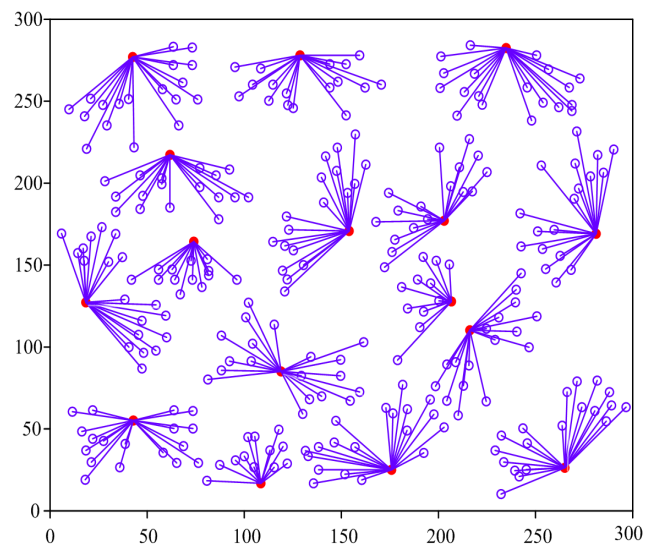


FIGURE 3. $t = 500s$, clustering structure of cluster head and member nodes.

The number of member nodes in the cluster also shows randomness, which can ensure that the coverage of the cluster is more balanced and balanced. The paper [27] uses the master-slave dual cluster head management method. When competing for cluster heads, due to the complexity of clustering reasons, the NDADA algorithm uses the primary cluster head located at the center of the cluster to collect data quickly. And the secondary cluster head is located closer to the base station to facilitate the rapid transmission of data from the cluster head which is primary to the base station. Nevertheless, the paper [27] did not consider the energy balance of the nodes in the cluster, which caused the energy consumption of the nodes in the cluster to be too fast.

Figure 5, Figure 6, Figure 9 and Figure 10 show the comparison of the number of sensor nodes and the network

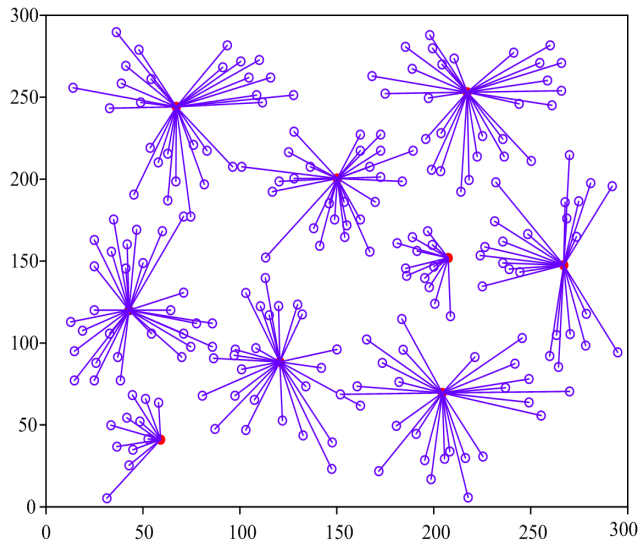


FIGURE 4. $t = 800s$, clustering structure of cluster head and member nodes.

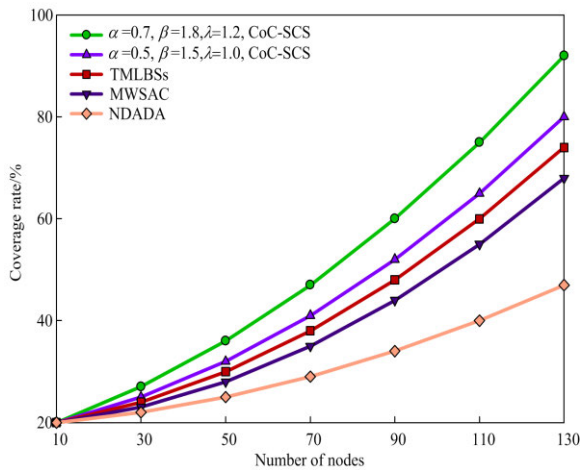


FIGURE 5. $300 \times 300m^2$, Comparison of network running time and coverage of four algorithms. ($\alpha = 0.7, \beta = 1.8, \lambda = 1.2$), ($\alpha = 0.5, \beta = 1.5, \lambda = 1.0$).

coverage under different parameters in the $300 \times 300m^2$ and $600 \times 600m^2$ monitoring area. The four different parameters selected in this paper are ($\alpha = 0.7, \beta = 1.8, \lambda = 1.2$), ($\alpha = 0.5, \beta = 1.5, \lambda = 1.0$), ($\alpha = 0.9, \beta = 2.0, \lambda = 1.5$) and ($\alpha = 0.6, \beta = 1.6, \lambda = 1.3$). It can be seen from the above four graphs that the network coverage increases with the increase of the number of sensor nodes, but the CoC-SCS algorithm network coverage which is in the paper is higher than the other three algorithms. In the Figure 5, while the quantity of sensor nodes is 90, the CoC-SCS algorithm network coverage in this paper reaches both 60% and 52%. However, the network coverage of the other three algorithms is respectively 48%, 44%, and 34%. While the quantity of sensor nodes is 130, the CoC-SCS algorithm network coverage in this paper is 92%, 80%, and the network coverage of the other three algorithms is 74%, 68%,

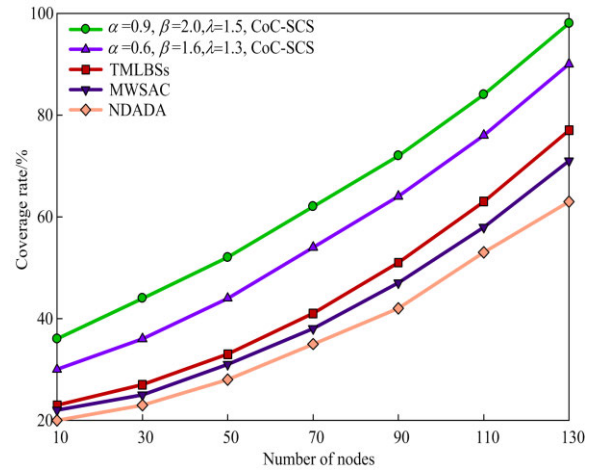


FIGURE 6. $300 \times 300m^2$, Comparison of network running time and coverage of four algorithms. ($\alpha = 0.9, \beta = 2.0, \lambda = 1.5$), ($\alpha = 0.6, \beta = 1.6, \lambda = 1.3$).

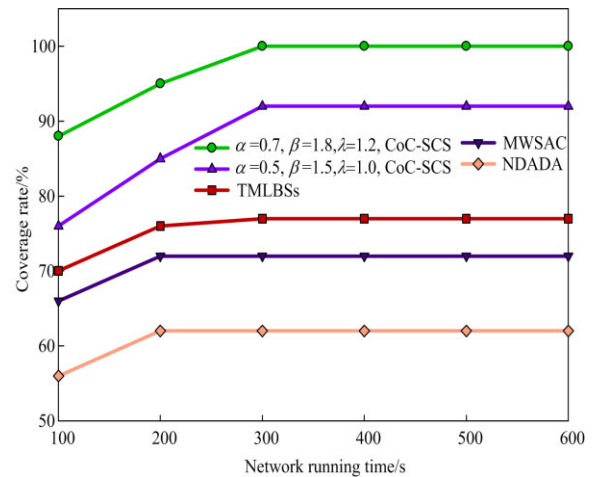


FIGURE 7. $300 \times 300m^2$, Comparison of network running time and coverage of four algorithms. ($\alpha = 0.7, \beta = 1.8, \lambda = 1.2$), ($\alpha = 0.5, \beta = 1.5, \lambda = 1.0$).

and 47%. The average network coverage of the CoC-SCS algorithm in this paper is 86%, which is 12% higher than TMLBSs algorithm, 18% than MWSAC algorithm, and 39% than NDADA algorithm. In Figure 6, while the number of sensor nodes is 90, the CoC-SCS algorithm network coverage which is in this paper reaches 72% and 64%, but the network coverage of the other three algorithms is 51%, 47%, and 42%; When the number of sensor nodes is 130, the CoC-SCS algorithm network coverage in this paper is 98%, 90%, and the network coverage of the other three algorithms is 79%, 76%, and 67%. The average network coverage of the CoC-SCS algorithm in this paper is 94%, which is 15% higher than TMLBSs algorithm, 18% than MWSAC algorithm, and 27% than NDADA algorithm. Based on the above analysis, when the parameters are ($\alpha = 0.7, \beta = 1.8, \lambda = 1.2$) and ($\alpha = 0.5, \beta = 1.5, \lambda = 1.0$), the network coverage of the CoC-SCS algorithm which is in this paper is 23%

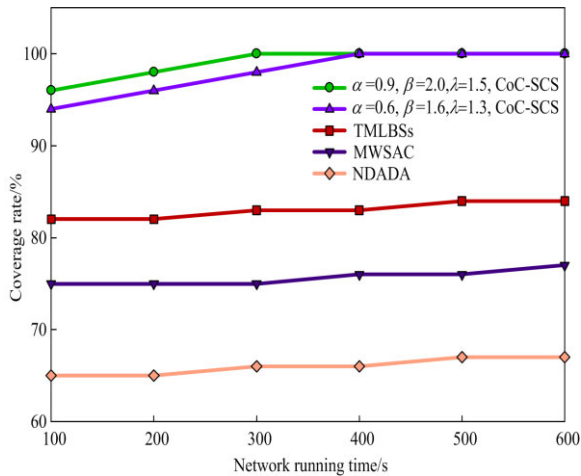


FIGURE 8. 300 × 300m², Comparison of network running time and coverage of four algorithms. ($\alpha = 0.9, \beta = 2.0, \lambda = 1.5$), ($\alpha = 0.6, \beta = 1.6, \lambda = 1.3$).

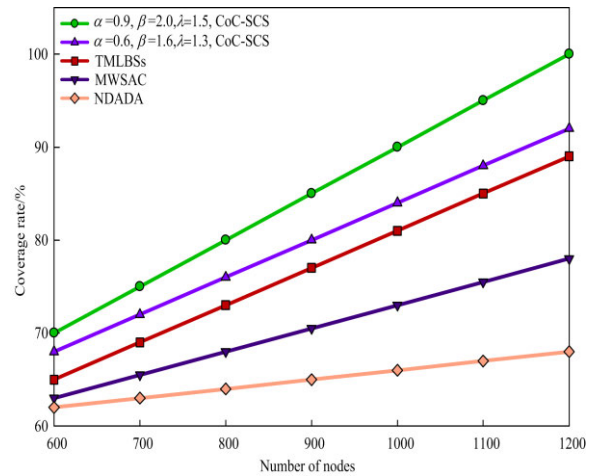


FIGURE 10. 600 × 600m², Comparison of network running time and coverage of four algorithms. ($\alpha = 0.9, \beta = 2.0, \lambda = 1.5$), ($\alpha = 0.6, \beta = 1.6, \lambda = 1.3$).

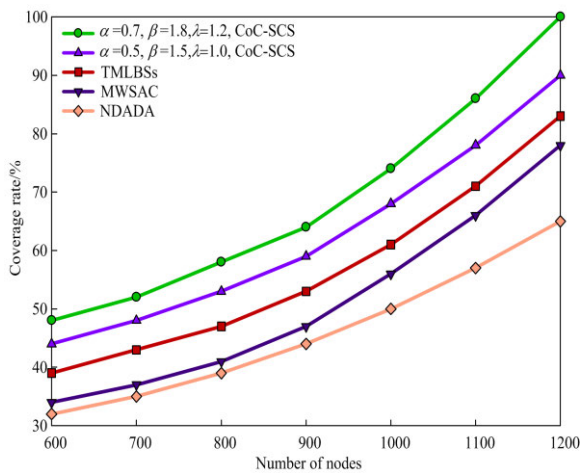


FIGURE 9. 600 × 600m², Comparison of network running time and coverage of four algorithms. ($\alpha = 0.7, \beta = 1.8, \lambda = 1.2$), ($\alpha = 0.5, \beta = 1.5, \lambda = 1.0$).

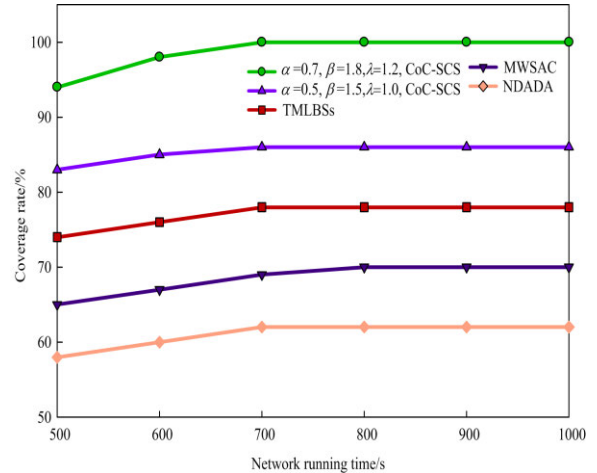


FIGURE 11. 600 × 600m², Comparison of network running time and coverage of four algorithms. ($\alpha = 0.7, \beta = 1.8, \lambda = 1.2$), ($\alpha = 0.5, \beta = 1.5, \lambda = 1.0$).

higher than that of the other three algorithms averagely. While the parameters are ($\alpha = 0.6, \beta = 1.6, \lambda = 1.3$) and ($\alpha = 0.9, \beta = 2.0, \lambda = 1.5$), the CoC-SCS algorithm network coverage which is in this paper is 20% higher than that of the other three algorithms averagely. Figure 7 and Figure 8 and Figure 11 and Figure 12 show comparison diagrams of network running time and network coverage under different parameters of the 300 × 300m² and 600 × 600m² monitoring area. The four different parameters selected in this paper are ($\alpha = 0.7, \beta = 1.8, \lambda = 1.2$), ($\alpha = 0.5, \beta = 1.5, \lambda = 1.0$), ($\alpha = 0.9, \beta = 2.0, \lambda = 1.5$) and ($\alpha = 0.6, \beta = 1.6, \lambda = 1.3$). We can see from Figure 7 and Figure 11 that while the network running time increases, the network coverage rate also increases. And when the network running time reaches 300s and 700s, the network coverage of the four algorithms reaches a balanced state, but the network coverage of the CoC-SCS algorithm which is in this paper

is higher than the other three algorithms. In Figure 7, when the network running time is 300s, the network coverage of the CoC-SCS algorithm in this paper reaches 99% and 92%, while the network coverage of the other three algorithms are 77%, 72%, and 62%, when the network running time is 300, the average network coverage of the CoC-SCS algorithm in this paper is 95.5%, which is higher than the other three algorithms 18.5%, 23.5%, and 33.5%. In Figure 11, when the network is running time is 700s, the network coverage of the CoC-SCS algorithm in this paper reaches 99% and 86%, while the network coverage of the other three algorithms are 78%, 70%, and 65%. The average network coverage of the CoC-SCS algorithm is 92.5%, which is higher than the other three algorithms 14.5%, 22.5%, and 27.5%. Figure 8 and Figure 12 show the network operating time and network coverage comparison under different parameters in monitoring area 600 × 600m². The parameters used in Figure 8 and

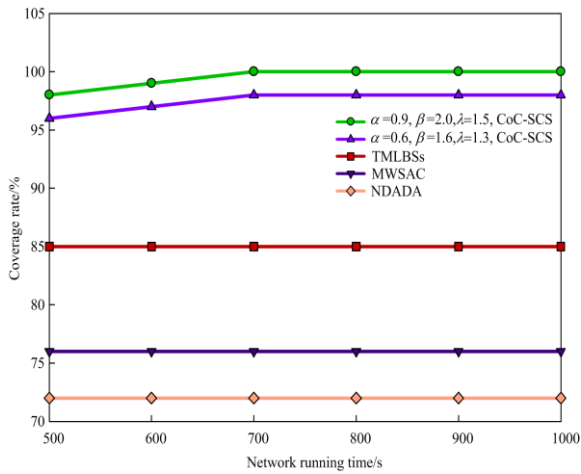


FIGURE 12. 600 × 600m², Comparison of network running time and coverage of four algorithms. ($\alpha = 0.9, \beta = 2.0, \lambda = 1.5$), ($\alpha = 0.6, \beta = 1.6, \lambda = 1.3$).

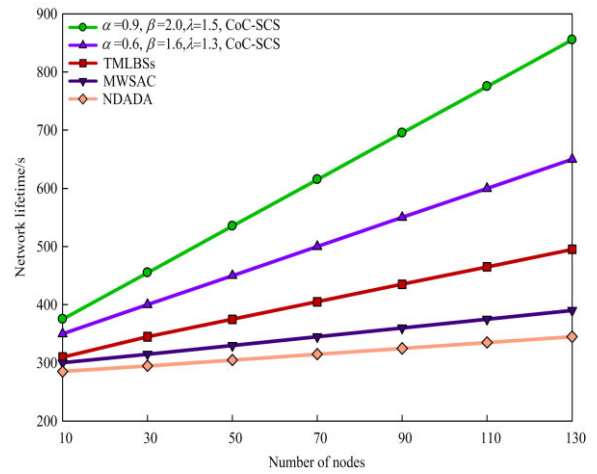


FIGURE 14. 300 × 300m², Comparison of the number of sensor nodes and the network lifetime under different parameters. ($\alpha = 0.9, \beta = 2.0, \lambda = 1.5$), ($\alpha = 0.6, \beta = 1.6, \lambda = 1.3$).

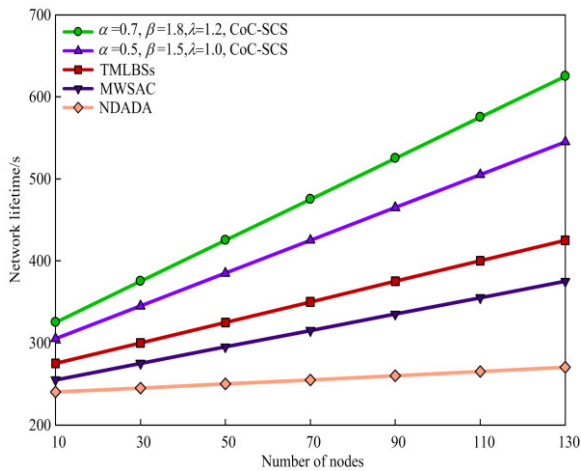


FIGURE 13. 300 × 300m², Comparison of the number of sensor nodes and the network lifetime under different parameters. ($\alpha = 0.7, \beta = 1.8, \lambda = 1.2$), ($\alpha = 0.5, \beta = 1.5, \lambda = 1.0$).

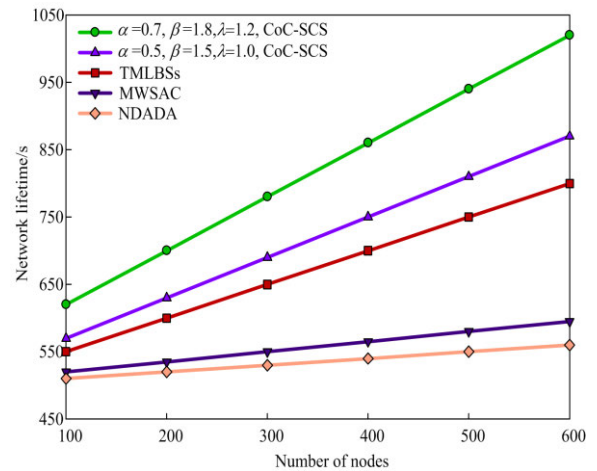


FIGURE 15. 600 × 600m², Comparison of the number of sensor nodes and the network lifetime under different parameters. ($\alpha = 0.7, \beta = 1.8, \lambda = 1.2$), ($\alpha = 0.5, \beta = 1.5, \lambda = 1.0$).

Figure 12 are ($\alpha = 0.9, \beta = 2.0, \lambda = 1.5$), ($\alpha = 0.6, \beta = 1.6, \lambda = 1.3$). It can be seen from the figure that the network coverage of the four algorithms over time are stable as the running of network time, but the CoC-SCS algorithm network in this paper is higher than the other three algorithms. In Figure 8, when the network running time is 400s, the parameters of the two groups in this paper have reached 100%, while the other three algorithms are lower than this value, which are 83%, 76%, and 68%, respectively. The average value is 17%, 24% and 32% which is higher than the other three algorithms. In Figure 12, when the network running time is 800s, the CoC-SCS algorithm in this paper is 13%, 22%, and 27% higher than the other three algorithms, respectively. The average value is 13%, 22% and 27% which is higher than the other three algorithms. Based on the above analysis results, it may be seen that the CoC-SCS algorithm in this paper is higher than the other three algorithms in the

comparison experiments of the number of sensor nodes and network coverage, and the network running time and network coverage, thereby further illustrating the CoC-SCS algorithm in this paper has strong stability and effectiveness.

Figures 13 to Figure 16 show the comparison of the number of sensor nodes and the network lifetime under different parameters in the 300 × 300m² and 600 × 600m² monitoring areas. Taking Figures 13 and Figure 14 as examples, it can be seen that as the number of sensor nodes increases, the network lifetime also increases. From the increase, it can be seen that the increase rate of the CoC-SCS algorithm in this paper is significantly higher than the other three algorithms. In Figure 13, when the number of sensor nodes is 90, the network lifetimes of the CoC-SCS algorithm in this paper are 525s, 465s, while the network lifetime of the other three algorithms is 375s, 335s, and 260s, respectively. The increasing value of average lifetime CoC-SCS algorithm is

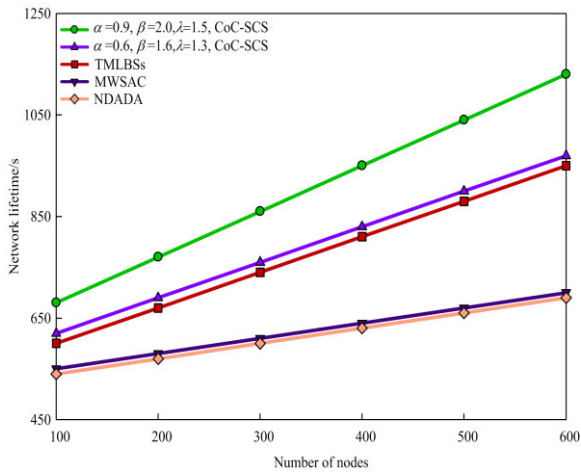


FIGURE 16. 600 × 600m², Comparison of the number of sensor nodes and the network lifetime under different parameters. ($\alpha = 0.9, \beta = 2.0, \lambda = 1.5$), ($\alpha = 0.6, \beta = 1.6, \lambda = 1.3$).

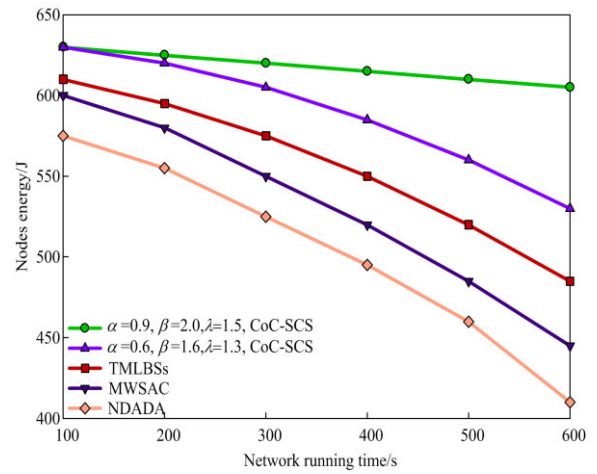


FIGURE 18. 300 × 300m², Comparison of the network running time and energy under different parameters. ($\alpha = 0.9, \beta = 2.0, \lambda = 1.5$), ($\alpha = 0.6, \beta = 1.6, \lambda = 1.3$).

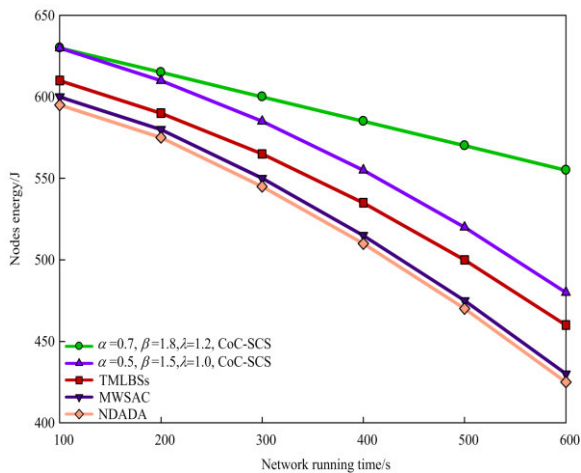


FIGURE 17. 300 × 300m², Comparison of the network running time and energy under different parameters. ($\alpha = 0.7, \beta = 1.8, \lambda = 1.2$), ($\alpha = 0.5, \beta = 1.5, \lambda = 1.0$).

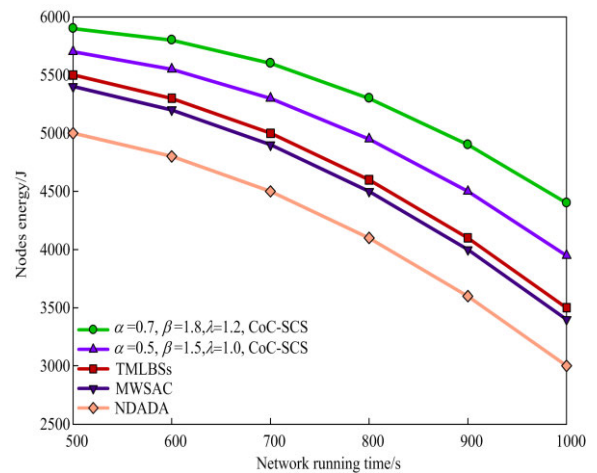


FIGURE 19. 600 × 600m², Comparison of the network running time and energy under different parameters. ($\alpha = 0.7, \beta = 1.8, \lambda = 1.2$), ($\alpha = 0.5, \beta = 1.5, \lambda = 1.0$).

120s, 160s, and 235s higher than the other three algorithms. In Figure 14, when the number of sensor nodes is 70, the network lifetime of the CoC-SCS algorithm in this paper is 615s and 500s. The network lifetimes are 405s, 345s, and 315s, respectively. The increasing value of average lifetime CoC-SCS algorithm is 152.5s, 212.5s and 242.5s higher than the other three algorithms. The main reason is that the CoC-SCS algorithm in this paper uses a local continuous coverage method for moving target nodes. During the coverage process, the controllability of the dynamic parameters of the genetic algorithm is used to optimize the network lifetime and network coverage to achieve network resources with the optimal matching result. The TMLBSs algorithm and MWSAC algorithm use the continuous coverage method of the mobile target node to complete the coverage control of the mobile target node, without considering the working state of the cluster when the mobile target node is far away

from a cluster. NDADA algorithm uses a continuous global coverage method to continuously cover the moving target node, which is equivalent to the full coverage of the entire monitoring area, and does not consider the issue of network energy consumption. Figure 15 and Figure 16 work similarly to with Figure 13 and Figure 14. Figure 17 to Figure 20 show comparison diagrams of network operating time and network energy consumption under different parameters in the 300 × 300m² and 600 × 600m² monitoring areas. It can be seen that with the increase of the network running time, the network energy consumption of the four algorithms has decreased, but the CoC-SCS algorithm network energy consumption declines less, and the NDADA algorithm network energy consumption decreases significantly. Figure 17 is an example for analysis. When the network running time is 400s, the remaining energy of the CoC-SCS algorithm in this paper is 585J and 553J, and the remaining energy of the other three

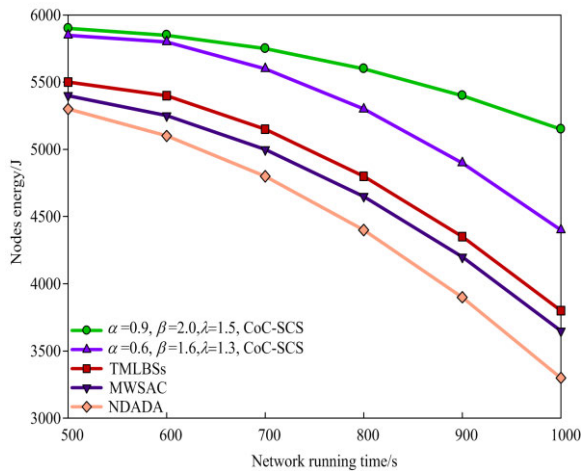


FIGURE 20. $600 \times 600m^2$, Comparison of the network running time and energy under different parameters. ($\alpha = 0.9, \beta = 2.0, \lambda = 1.5$), ($\alpha = 0.6, \beta = 1.6, \lambda = 1.3$).

algorithms is 535J, 515J, and 510J. The average value of the remaining energy of the CoC-SCS algorithm which is in this paper is higher than the other three algorithms, 35J, 55J, and 60J, respectively. In Figure 18, when the network running time is 500s, the remaining energy of the CoC-SCS algorithm in this paper is 610J and 560J, and the remaining energy of the other three algorithms is 560J, 520J and 485J. The remaining energy of the CoC-SCS algorithm is higher than the other three algorithms, 25J, 65J, and 100J, respectively, in this paper. Based on the above analysis results, the network lifetime and network energy consumption of the CoC-SCS algorithm in this paper are significantly higher than which of the other three algorithms. The adaptability and effectiveness of the CoC-SCS algorithm which is in this paper has been validated.

VI. CONCLUSION

Based on the impact of node energy problems and data redundancy on the communication link during the coverage process of wireless sensor networks, this paper proposes Cooperative-optimization Coverage Algorithm based on Sensor Cloud Systems in Intelligent Computing (CoC-SCS). In this paper, the CoC-SCS algorithm firstly analyzes the moving target node by using the coverage model and gives the specific analysis method of the coverage model. Secondly, this paper analyzes and calculates the coverage expectation value. After completing N times of coverage of the moving target node, the calculation method of the expected value of the sensor node coverage, the calculation process of the minimum number of sensor nodes required to cover the moving target node, and the probability calculation method of optimal path selection are given. Thirdly, this paper gives the description process and implementation method of the CoC-SCS algorithm and the related description of the complexity of the CoC-SCS algorithm. Finally, this paper uses simulation software to perform related experiments on the network cluster structure, network coverage, network

lifetime, and network energy consumption, and gives the simulation experiment comparison steps and methods. And then the conclusion that the algorithm has high efficiency and stability has been further explained.

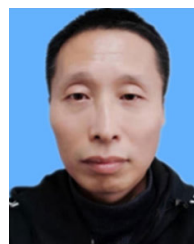
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