IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 21 January 2024, accepted 26 January 2024, date of publication 13 February 2024, date of current version 26 February 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3365511

RESEARCH ARTICLE

Wireless Sensor Network (WSN) Model Targeting Energy Efficient Wireless Sensor Networks Node Coverage

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This work was supported in part by the National Natural Science Foundation of China through the Research on Emergent Mechanism and Swarm Intelligence Algorithm of Swarm Intelligence Based on Physical Principles under Grant 61403271.

ABSTRACT With the rise of the Internet of Things, the application fields of wireless sensor networks (WSN) continue to expand. From agriculture to urban infrastructure monitoring, application requirements in various fields are increasing. The research focuses on designing and improving energy-efficient coverage methods for wireless sensor network nodes, with the goal of improving energy efficiency and data transmission reliability. Through detailed research and analysis of hierarchical and flat routing protocols, the article explores how to ensure that each monitoring point is covered by at least one sensor node by designing an energy-saving sensor network node coverage model. At the same time, the study explores an energy-efficient coverage method based on the improved gray wolf algorithm, aiming to optimize the deployment of sensor nodes and enhance the effectiveness of node coverage. Research results show that the algorithm performs significantly in network coverage optimization and achieves 100% coverage of monitoring target points. Under the 30-dimensional condition, the improved gray wolf algorithm shows excellent average performance and the smallest standard deviation. When the number of nodes is 40, compared with other algorithms, the improved gray wolf algorithm improves the coverage rate by 5.08% and achieves 100% coverage performance in a more energy-saving manner. Research on the exploration of energy-saving wireless sensor network models will help to better meet the needs of future intelligent monitoring and control, improve resource utilization efficiency, reduce maintenance costs, and promote the sustainable development of wireless sensor networks.

INDEX TERMS Wireless sensor network, node coverage, grey wolf algorithm, routing protocol, monitoring area.

I. INTRODUCTION

Research on the WSN model for energy-saving wireless sensor network node coverage proposes innovative solutions to the key challenges faced by current wireless sensor networks (WSN) - optimization of energy efficiency and node coverage [1]. Wireless sensor networks play an increasingly important role in environmental monitoring, smart city construction, disaster early warning and other fields. However, these networks are usually limited by the energy consumption and coverage of sensor nodes [2]. Traditional WSN design focuses on improving network coverage and transmission efficiency, but often ignores energy efficiency issues, which results in limited sustainable operation time of the network, especially in resource-constrained or difficult-to-reach environments. Existing research mostly focuses on improving a single aspect of performance, such as only focusing on energy saving or only improving coverage efficiency, and lacks consideration of the balance between the two [3]. In addition, many traditional methods fail to fully consider the synergy

The associate editor coordinating the review of this manuscript and approving it for publication was Maurizio Casoni.

between nodes, which often leads to inefficiency of energy utilization and the generation of coverage blind spots in practical applications. This study focuses on developing a comprehensive model that aims to simultaneously optimize energy efficiency and node coverage, coordinate the working modes and communication strategies between nodes through intelligent algorithms, and significantly improve the overall performance of the network. The innovation of the research lies in the adoption of an advanced optimization algorithm, which not only effectively manages the energy consumption of nodes, but also ensures full coverage of the monitoring area. This model comprehensively considers the deployment location, working status and data transmission path of nodes, allowing the network to achieve significant reductions in energy consumption while maintaining high coverage. Through this method, the research not only responds to the dual needs of energy saving and efficient coverage, but also provides new ideas for the sustainable development of wireless sensor networks.

The study consists of four parts. The first part is a summary of the research on WSN coverage. The second part is the design and improvement of energy-saving node coverage methods in WSNs. The third part is the verification of coverage optimization research for WSNs based on IGW. The fourth part is a summary of the entire text.

The research proposes innovative solutions in the fields of energy efficiency and node coverage of WSN, and its main academic contribution lies in the comprehensive optimization of energy efficiency and node coverage. Compared with traditional WSN design, this method pays special attention to energy efficiency issues while improving network coverage and transmission efficiency, thus solving the problem of limited sustainable operation time of the network in resource-constrained or difficult-to-reach environments. Research and apply advanced optimization algorithms that not only effectively manage the energy consumption of nodes but also ensure complete coverage of the monitoring area. In addition, the model proposed in the study comprehensively considers the deployment location, working status and data transmission path of nodes, achieving a significant reduction in energy consumption while maintaining high coverage.

II. RELATED WORKS

WSN node coverage has always been a hot research field and has made many important progress. Sharma A and other scholars proposed a node scheduling algorithm using Nash Q learning. Through the Nash Q learning method, each node made independent decisions on its behavior without the need for a pre modeled environment, minimizing the active nodes in each scheduling round while maintaining coverage and network connectivity [4]. Liu et al. used Integer Linear Programming (ILP) for sensor nodes calculation. The results showed that EENP can effectively meet the demand for monitoring the WSNs sensor nodes in practical applications, while reducing energy consumption [5]. To effectively evaluate the monitoring coverage performance of sensor nodes on network fields, scholars such as Riham et al. proposed a coverage protocols classification method, divided into coverage aware deployment, flat network sleep scheduling, and cluster based sleep scheduling [6]. To ensure the network energy efficiency, lifespan, and reliability, Suparna et al. proposed a quantitative measurement method called Area Coverage Reliability (ACR) of WSNs, which was used to comprehensively evaluate the performance of WSNs. Using Monte Carlo simulation methods, the energy matrix was used to evaluate the impact of energy depleted nodes and energy oriented data transmission capabilities on ACR [7]. A. M. A. Jameel conducted a comprehensive scientific review of the application of evolutionary intelligence in sensor networks, focusing on improving the performance and effectiveness of communication systems, robots, and automation systems through evolutionary intelligence. The review was divided into three aspects: principles, algorithms, and applications, and delved into the theoretical, mathematical foundations, and practical applications of evolutionary computing [8].

The WSN model is an important research direction in computer science and communication, and many experts have studied it. S. Govindaraj and other scholars proposed a capsule neural network architecture model to address the issue of how to improve the performance of IoT sensor nodes in WSN through network energy optimization. The aim was to optimize the network energy cost of IoT sensor nodes and transmit information to the cloud IoT through diverse communication methods in WSN, and clustering process was used to improve network quality [9]. Ahmed et al. proposed a new energy-efficient scalable routing algorithm (EESRA) to address the performance degradation of the protocol, aiming to extend network lifespan and improve network performance [10]. Kuruva et al. introduced a new scheme to address challenging issues in assisting WSN design in the Internet of Things, which mainly included IAOAC clustering technology and TLBO-MHR multi-hop routing technology [11]. Abdullah et al. established an accurate security framework to detect and prevent data integrity attacks in WSNs in microgrids. They proposed an intelligent anomaly detection method based on predictive interval (PI) to detect and prevent data integrity attacks. The combination concept of PI was used to solve the instability problem generated by neural networks for the accuracy and detection stability [12]. J. Wang proposed an adaptive clustering method using affinity propagation(APSA) to improve the performance of WSNs, which combined traditional K-medoids algorithm to improve clustering performance. The APSA method was used to search for the optimal initial clustering center for K-medoids. By utilizing the modified K-medoids algorithm to iteratively form a network topology, the weaknesses of traditional K-medoids were effectively avoided, especially in terms of homogeneous clustering and convergence speed [13].

In summary, many experts have conducted research on WSN models and coverage issues, but have overlooked the persistence of coverage, which may decrease due to node energy depletion or other factors. The research proposes a

WSN model for energy-efficient WSN node coverage, aiming to solve the long-term maintenance and maintenance of coverage while improving coverage.

III. DESIGN AND IMPROVEMENT OF ENERGY EFFICIENT NODE COVERAGE METHOD IN WSNS

Chapter 2 mainly discusses the design and improvement of energy-saving node coverage methods in WSNs. The first section discusses the advantages and disadvantages of layered routing protocols and planar routing protocols, as well as their applications and roles in networks. The second section studied an energy-saving node coverage method using the IGW, and how to improve the efficiency and performance of node coverage through this method. The third section studies the energy-saving node coverage method using the IGW, the design process and practical application of this method, and how to improve the efficiency and performance of node coverage through this method.

A. LAYERED AND PLANAR ROUTING PROTOCOLS IN WSNS

In the research on WSN models for energy-saving wireless sensor network node coverage, it is crucial to classify WSN routing protocols and demonstrate the combination with energy-saving goals. First, the core goal of the energy-saving WSN model is to reduce node energy csonsumption and extend network life while maintaining effective network coverage. This requires routing protocols to minimize node energy consumption while effectively managing data transmission. WSN routing protocols are usually divided into location-based, hierarchical, and data-driven types, with each type targeting different network requirements and optimization goals. Location-based routing protocols use node geographical location information to reduce unnecessary communication and data transmission, while hierarchical routing protocols effectively manage energy and reduce overall energy consumption by establishing node hierarchical relationships. Furthermore, data-driven routing protocols reduce energy consumption through on-demand data transmission as it only activates nodes when certain conditions or thresholds are reached. The classification of these protocols not only complies with energy-saving principles but also adapts to the specific needs of WSNs, such as coverage and network lifetime. When exploring energy-efficient WSN models, research should not only consider reasonable classifications of routing protocols, but also combine these classifications with different types of WSN coverage problems. This comprehensive consideration ensures that while achieving energy saving goals, it can also meet the specific requirements of different coverage needs, thereby achieving comprehensive optimization and effective deployment of WSN.The WSN coverage issue is an important research field that involves nodes deployment to ensure appropriate coverage of the monitoring area. According to different deployment methods and monitoring area requirements, coverage issues can usually be divided into three main types: point coverage, fence coverage, and area coverage. The classification of WSN coverage issues is shown in Figure 1.

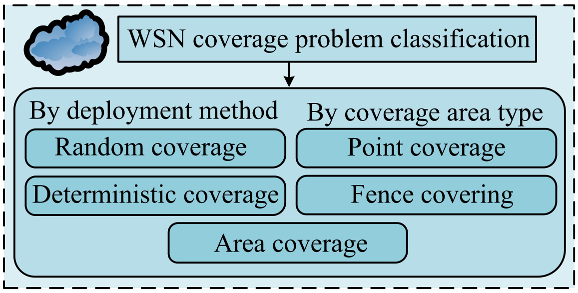


FIGURE 1. Classification of WSN coverage issues.

As shown in Figure 1, coverage control of WSN is a key issue, and its core lies in deploying sensor nodes in a random or deterministic manner based on the geographical and environmental characteristics of the monitoring area to meet user specific coverage needs [14]. Effective management of coverage quality is crucial for the performance of WSN, as only when sensor nodes are reasonably distributed can the network successfully collect environmental data information and complete its monitoring tasks. The research on coverage issues also includes how to achieve continuous monitoring of the monitoring area through efficient algorithm design, which not only involves the spatial distribution of nodes, but also includes communication and collaboration between sensor nodes to ensure high-quality acquisition and real-time transmission of information. The three types of WSN coverage are shown below.

Figure 2 shows three types of WSN coverage, where point coverage involves randomly or deterministically deploying

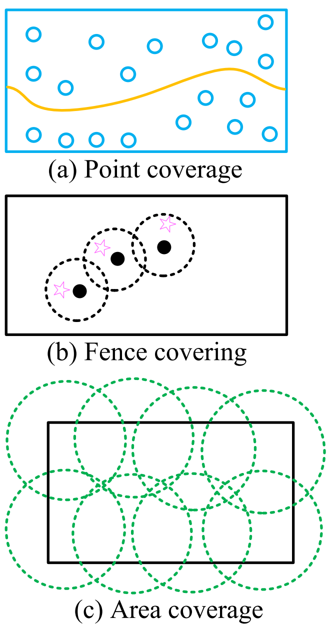


FIGURE 2. Three WSN coverage types.

sensor nodes within the monitoring area to ensure that at least one sensor node within each discrete point or area can monitor events or targets. In the problem of point coverage, the focus is on selecting the location of sensor nodes to minimize coverage voids, that is, areas within the monitoring area that are not covered. The fence coverage problem involves deploying sensor nodes into a continuous, closed coverage fence to ensure that targets are not allowed to cross the fence without being detected [15]. This type of coverage issue is particularly useful in security and boundary monitoring applications, such as monitoring intrusions into national borders, parks, or military facilities. In the fence coverage problem, the position and connectivity of sensor nodes are key considerations to ensure defect free coverage of the fence. The area coverage issue focuses on how to deploy sensor nodes to ensure that every point within the entire monitoring area can be monitored by at least one sensor node [16]. In WSNs, routing protocols are usually divided into the following types based on their design and operational objectives. First, quality of service. This classification focuses on those routing protocols that optimize network performance parameters to provide better quality of service; second, Intelligent basic routing, this type of routing protocol uses intelligent algorithms to optimize the routing decision-making process and improve network performance and efficiency; third, dedicated application routing, this classification involves routing protocols designed specifically for specific application fields, such as for specific projects. and technology domain-customized protocols [17]. The classification design of protocols is based on different network requirements and scenarios. Hierarchical routing protocols are suitable for large networks that require efficient data management and energy optimization, while flat routing protocols are suitable for scenarios with simple structures and evenly distributed nodes. Therefore, the protocol classification of the study design is shown in Figure 3. This type of coverage problem is commonly seen in environmental monitoring, agricultural fields, and disaster response applications. The area coverage problem usually requires considering the coverage overlap between sensor nodes to ensure high-quality monitoring data and timely target detection. Whether it is point coverage, fence coverage, or area coverage, the deployment of sensor nodes can be random or deterministic, depending on application requirements and resource constraints.

In Figure 3, the layered routing protocol introduces a hierarchical structure in WSN to improve energy efficiency and data transmission reliability. This protocol divides nodes into different levels, typically including sensor nodes, intermediate layer nodes, and base station nodes, each with different tasks and responsibilities in the network. Layered routing protocols can more effectively process data, reduce redundant transmission, and thus reduce energy waste. Sensor nodes are usually responsible for data collection and preliminary processing, intermediate layer nodes are responsible for data aggregation and relay, and base station nodes are the final collection points of data. This hierarchical structure enables data to be transmitted in a more efficient manner across the network, reducing unnecessary data redundancy and multiple transmissions. Flat routing protocol is a routing protocol used in WSN, characterized by the same status of each node in the network and no hierarchical structure division [18]. Each node has the same tasks and responsibilities, no specific node is responsible for data aggregation or transmission. The flat routing protocol is opposite to the hierarchical routing protocol. No intermediate layer nodes or base station nodes are introduced, and each sensor node can communicate directly with other nodes. Through the layered structure, data transmission can be effectively managed, thereby reducing energy consumption. Higher-layer nodes can process and aggregate the data, reducing the amount of data that needs to be sent to the base station. In large networks, the hierarchical structure provides better scalability and facilitates the management of large numbers of nodes. Although such a routing structure is relatively simple, it also has some limitations, so an energy-saving sensor network node coverage model is proposed for optimization.

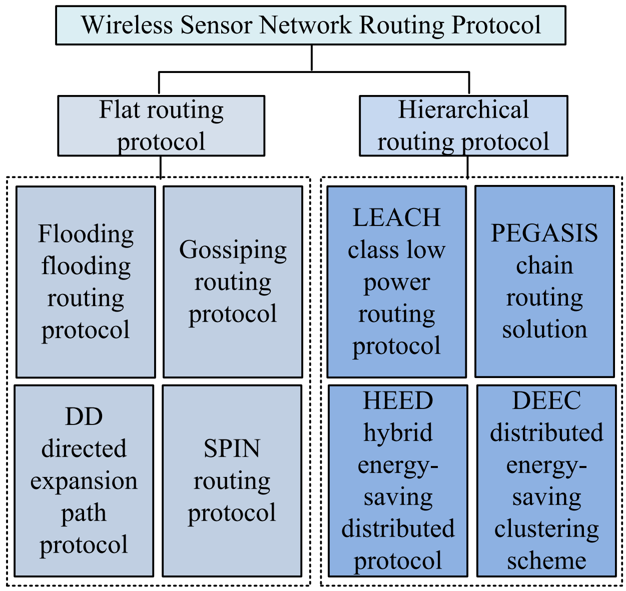


FIGURE 3. WSN routing protocol classification.

B. DESIGN OF NODE COVERAGE MODEL FOR ENERGY EFFICIENT SENSOR NETWORKS

The study sets up a two-dimensional planar monitoring area A, where N sensor nodes are randomly distributed and have specific perceived radius R_s and communication radius R_c. The position of each sensor node s_j is represented by (x_j, y_j), $1 \leq j \leq N$, while the collection points of monitoring target points are $S = \{s_1, s_2, \ldots, s_N\}$, and the position of each point p is determined by $\left\{x'_k, y'_k\right\}$. It should be emphasized that the Sink node has the location information of all sensor nodes, which is used for monitoring and data collection. The network is considered static and follows the principle of N far greater than M to ensure sufficient coverage of all monitoring target points. To ensure reliable transmission of all collected data to sink nodes, complete network connectivity is a necessary prerequisite. In addition, the study assumes that all wireless channels are ideal, that is, the communication channels between sensor nodes and aggregation nodes are reliable, without transmission errors or the need for retransmission. Therefore, the network can fully connect under full coverage conditions when $R_c \geq 2R_s$, as shown in equation (1).

$$G_{j,k} = \begin{cases} 1, & if \sqrt{(x_j - x_k)^2 + (y_j - y_k)^2} < R_s \\ 0, & otherwisp \end{cases} \tag{1}$$

In equation (1), $\sqrt{(x_j - x_k')^2 + (y_j - y_k')^2}$ can be used to represent the distance between the sensor node s_j and the monitoring target point p_k. If the distance between the two is less than R_s, $G_{j,k} = 1$ indicates that the sensor s_j can cover the target point p_k. In the case of randomly distributed sensors, more than one sensor node v can monitor or detect this target point p_k, and it may be multiple sensor nodes covering or detecting this target point together, as shown in equation (2).

$$G_{1,k} + G_{2,k} + \ldots + G_{v,k} = v \tag{2}$$

In equation (2), if the target point p_k is covered, the conditions of equation (3) need to be met.

$$\sum_{j=1}^{N} G_{j,k} \geq 1 \tag{3}$$

The key goal of sensor coverage monitoring of target points is to ensure the coverage quality of the network, in order to effectively collect data from the target points and transmit it to the aggregation node when needed to meet monitoring needs. In sensor networks, initial energy is crucial for the long-term operation of nodes, assuming that the initial energy of all is the same, represented by E-nodes. The main energy consumption occurs during the communication process. The choice of communication distance determines the adoption of different channel models, namely the Free Space (FS) model and the Multipath Fading Channel (MP) model [19]. Specifically, if the communication distance is less than a specific threshold d_0, FS will be used for communication. Conversely, if the distance exceeds d_0, the MP model will be used, as shown in equation (4).

$$E_T(l, d) = \begin{cases} l \cdot E_{elec} + l \cdot \varepsilon_{fs} \cdot d^2, & d < d_0 \\ l \cdot E_{elec} + l \cdot \varepsilon_{mp} \cdot d^4, & d \cdot d_0 \end{cases} \tag{4}$$

In equation (4), E_{elec} represents the transmission or reception energy consumption per unit bit, d represents the transmission distance between the transmitting and receiving nodes, ε_{fs} and ε_{mp} are used to determine which communication model should be used. In addition, and represent the energy consumption factor per bit in FS and MP, and d_0 represent the distance threshold, as shown in equation (5).

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \tag{5}$$

$E_R(l)$ represents the energy required to receive l bit messages, as expressed in equation (6).

$$E_R(l) = l \cdot E_{elec} \tag{6}$$

The total amount of energy required to receive bit messages is shown in equation (7).

$$\begin{aligned} E_{od}(l, d) &= E_T(l, d) + E_R(l) \\ &= \begin{cases} 2l \cdot E_{elec} + l \cdot \varepsilon_{fs} \cdot d^2, & d < d_0 \\ 2l \cdot E_{elec} + l \cdot \varepsilon_{mp} \cdot d^4, & d \cdot d_0 \end{cases} \end{aligned} \tag{7}$$

Cluster head nodes (CH) play an important role in sensor networks, responsible for receiving and processing information, and sending it to base stations (BS). The received energy consumption E_{CH_R} is used to receive data transmitted from ordinary nodes within the cluster, while the fused energy consumption E_{CH_F} is used to process and fuse the received data to generate summary information. Transmission energy consumption E_{CH_T} is used to transmit processed data to BS. The energy consumption received is shown in equation (8).

$$E_{CH\_R} = l \cdot w \cdot E_{elec} \tag{8}$$

In equation (8), w represents the number of ordinary nodes, and the fusion energy consumption is shown in equation (9).

$$E_{CH\_F} = (w + 1) \cdot l \cdot E_{DA} \tag{9}$$

In equation (9), E_{DA} represents the energy required for CH to process data. CH itself can perceive environmental information, so the information is represented as $l \cdot w$, plus the information it perceives, there is a total of $(w + 1) \cdot l$ information that needs to be processed. Therefore, the emission energy consumption is shown in equation (10).

$$E_{CH\_T} = l \cdot E_{elec} + \begin{cases} l \cdot \varepsilon_{fs} \cdot d_{toBS}^2, & d_{toBS} < d_0 \\ l \cdot \varepsilon_{mp} \cdot d_{toBS}^4, & d_{toBS} \cdot d_0 \end{cases} \tag{10}$$

In equation (10), d_{toBS} represents the distance between CH and BS, and the energy consumed by CH can be obtained as shown in equation (11).

$$\begin{aligned} E_{CH} &= E_{CH\_R} + E_{CH\_F} + E_{CH\_T} \\ &= l \cdot (w + 1) \cdot (E_{elec} + E_{DA}) \\ &\quad + \begin{cases} l \cdot \varepsilon_{fs} \cdot d_{toBS}^2, & d_{toBS} < d_0 \\ l \cdot \varepsilon_{mp} \cdot d_{toBS}^4, & d_{toBS} \cdot d_0 \end{cases} \end{aligned} \tag{11}$$

In WSNs, the physical information perception of monitoring target points (MTP) is a high energy consuming task, as it leads to sensor nodes consuming their limited electrical resources. The lifespanof a network is a key factor. If any MTP is not fully covered, network operations will be interrupted, and the total working time will be limited by the π value [20]. In addition, when multiple sensor nodes simultaneously monitor the same MTP, redundant coverage may occur. If these nodes are active at the same time, it will lead to rapid power consumption. In order to effectively extend the network lifespan, one strategy finds the minimum sensor nodes for all MTPs coverage, and adopt a rotating coverage method to extend the working time. The schematic diagram of redundant coverage strategy is shown below.

As shown in Figure 4, when multiple sensor nodes monitor the same monitoring target point (MTP) at the same time, redundant coverage will occur. In this case, if all nodes work in parallel, it will not only cause energy to be exhausted quickly, but also generate a large amount of redundant data. In the process of being sent to the base station, these redundant data further consume the limited energy resources of the node. In order to effectively deal with this challenge, a strategy can be adopted to use only a single node to cover each MTP in the initial stage, and when the node energy is exhausted, the neighboring nodes in the dormant state are activated for replacement. This method not only reduces energy consumption, but also reduces the redundancy of data transmission, thereby significantly extending the overall operating time of the network. When the distribution density of sensor nodes is high, redundant coverage may occur. This means that if sensor nodes are all active, it will result in a large amount of energy waste and excess data generation. In addition, when transmitting the collected data information to BS, these redundant data will also deplete the limited energy resources [21]. Therefore, the problem of maximizing network lifespan can be divided into sensor node scheduling and routing protocol optimization. Firstly, the sensor node scheduling problem is a set coverage problem, with the core problem being using the minimum sensor nodes to cover all monitoring target points, thereby more effectively managing and utilizing energy resources. Secondly, in order to optimize routing protocols and save more communication energy, the study proposes and describes the problem of maximizing energy savings. This issue focuses on how to optimize routing protocols to further extend the network's lifespan given the minimum coverage set. By considering these two sub problems simultaneously, it is possible to better describe and solve the problem of maximizing network lifespan, in order to achieve more effective energy management and extend network lifespan.

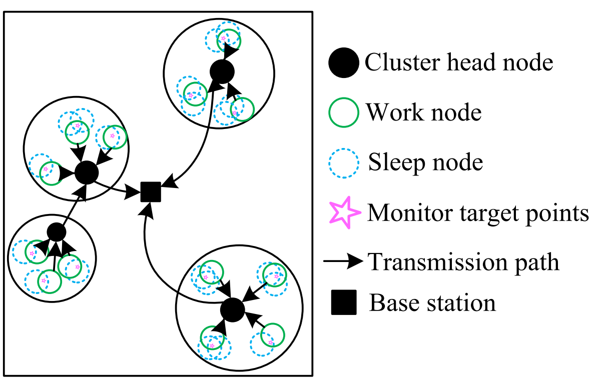


FIGURE 4. Schematic diagram of redundant coverage strategy.

C. ENERGY EFFICIENT NODE COVERAGE METHOD USING IGW

In the research of energy-saving node coverage methods using IGW, initializing the Grey Wolf population is crucial as it directly affects the quality and efficiency of solving node coverage problems [22]. It aims to achieve efficient coverage within interest region while minimizing energy consumption by optimizing the sensor nodes selection. Firstly, they are represented in binary encoding, with 1 indicating selected and 0 indicating not selected. Next, the size of the population is determined and an appropriate size is selected based on the problem size and computational resource constraints. Then, gray wolf individuals are randomly generated to ensure that they meet the constraints of the problem, such as not exceeding the sensor nodes quantity and the coverage requirements of the region of interest [23]. Each individual's fitness is calculated, considering both coverage and energy consumption. The best individuals are retained as the current 'leaders'. Through this initialization process, it ensures the legality and diversity of the population, subsequently improving the Grey Wolf algorithm to optimize node selection and achieve energy-saving node coverage. Figure 5 shows the social hierarchy diagram of the grey wolf.

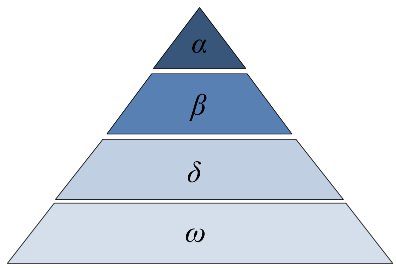


FIGURE 5. Gray wolf social hierarchy chart.

In Figure 5, α represents the gray wolf leader, who is the highest level in the population. In the node coverage problem, the leader represents the currently known best node selection scheme. The task of a leader is to guide and guide other gray wolves towards a more optimized node selection direction. β represents the deputy leader, the deputy leader is a sub level gray wolf, usually an individual with the second highest adaptability [24]. Vice leaders have a certain level of leadership ability, and when the leader is not available, they can temporarily replace the role of the leader. The deputy leader assists the leader in guiding the group to find better node choices. δ refers to a mid level member of a wolf pack, with a fitness level between the leader and deputy leader. Middle level gray wolves typically play a supportive role, helping leaders and deputy leaders identify potential node selection solutions and participate in collaborative processes. ω is the lowest level gray wolf at the grassroots level, and its adaptability is relatively low. Although the influence of grassroots gray wolves is limited, they provide diversity in the search space, helping to maintain the exploratory nature of the population. Grassroots gray wolves can provide new ideas and possible solutions [25]. The process of updating the wolf pack location is shown in Figure 6.

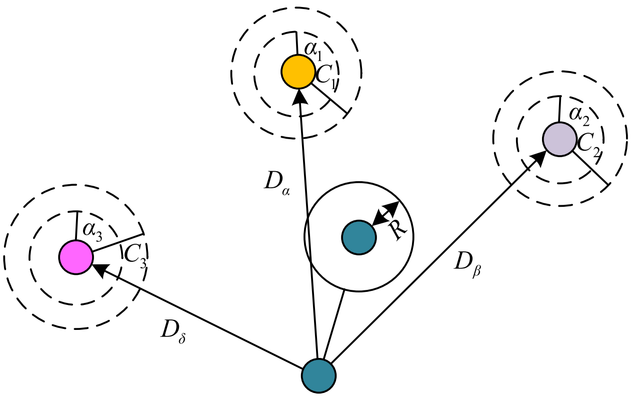


FIGURE 6. Wolf pack location update.

In the research of node coverage problem using the grey wolf algorithm, updating the wolf pack position is a core step. Firstly, each wolf's fitness value is calculated to evaluate its performance [26], [27]. Then, the leader and deputy leader are determined by their fitness values, representing the highest and second highest fitness, respectively. The leader wolf leads the group towards a more favorable solution space, and other wolves will be attracted by it and gradually approach the leader wolf's position. The deputy leader wolf has a similar effect, but has less influence and is used to explore more solution space [28]. The location update process typically includes random searches and approaching leaders or deputy leaders to maintain diversity and exploration. These steps are repeated in multiple iterations until the stop condition is met. Reassessment of fitness values ensures whether location updates are beneficial for problem-solving. The Grey Wolf Optimization (GWO) algorithm usually uses a randomness based approach to initialize the population. However, this randomness may cause the early grey wolf population to be too concentrated in a small area, leading to premature problems and having a negative impact on the performance. To overcome this challenge, the study introduces a strategy called the best point set method, which aims to improve the grey wolf population initialization and make its distribution more balanced. Through this method, the early aggregation problem is alleviated, improving the algorithm performance and efficiency, ensuring better exploration of the solution space, and thus obtaining better optimization results. The comparison between random initialization and optimal point set initialization is shown in Figure 7.

As shown in Figure 7, the key idea of initializing a set of good points is to establish a suitable starting point for individuals so that they can effectively work together for the best solution to the problem. At the beginning, individuals are randomly distributed, simulating the initial positions of biological individuals in nature. In the m-dimensional space, there is a unit cube G_m, which can be taken as $r_q = 2\cos(2\pi q/p)$ and has a value of $1 \leq q \leq m$.

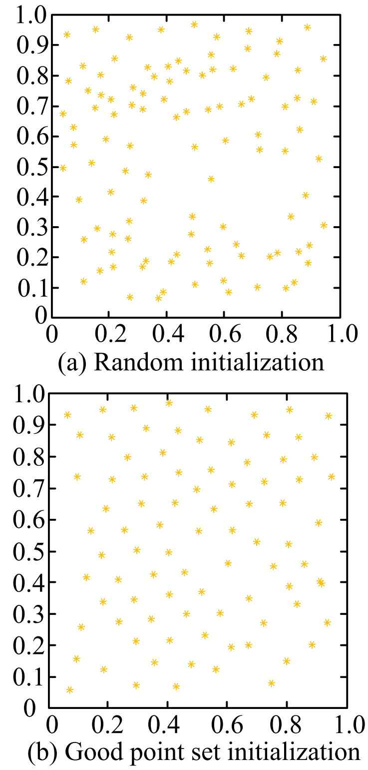


FIGURE 7. Comparison between random initialization and best point set initialization.

If $1 \leq q \leq m$, and p is the minimum prime number that satisfies the condition $(p-3)/2 \geq m$, then r is defined as the best point. The best point method outperforms other methods while keeping the number of points unchanged. By projecting the best points into the solution space, a more uniform initial distribution of the original population can be achieved. Compared with traditional random methods, this method has a more balanced initial allocation, better traversal performance, and greater assistance in optimizing results.

In GWO, search behavior is controlled based on the value of parameter A, where the value range of A is between [0,2], which affects the breadth or locality of the search. When A >1, the search distance increases, which helps with wide area search. When A<1, the search distance decreases, making it more suitable for local search. The magnitude of this A value is determined by the variation of parameter a over time t. It is worth noting that the GWO algorithm itself is a nonlinear search mechanism, so adjusting parameter a in a linear manner cannot effectively meet the needs of GWO search. A method for improving the convergence factor is proposed as shown in equation (12).

$$\alpha = 2 \times ((1 - \frac{t}{T})^{\frac{1}{4}}) \tag{12}$$

In the GWO algorithm, high-level wolves have the same leadership as low-level wolves, but the higher the wolf's level, the closer its attack distance is, and the greater the likelihood of launching an attack. $f_\alpha, f_\beta, f_\delta$ correspond to the reciprocal

TABLE 1. Standard function test set.

Function	Ranges	The optimal value	Dimension
$F_1=\sum_{i=1}^{n} x_i^2$	[-100,100]	0	30
$F_2=\sum_{i=1}^{D-1}[100(x_{i+1}-x_i^2)+(x_i-1)^2]$	[-30,30]	0	30
$F_3=\frac{1}{4000}\sum_{i=1}^{n} x_i^2-\prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{2}})+1$	[-600,600]	0	30
$F_4=-20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right)-\exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos 2\pi x_i\right)+20+e$	[-32,32]	0	30

fitness values of the first three levels of wolves, as shown in equation (13).

$$\begin{cases} w_1 = |f_\alpha| / \left(|f_\alpha| + |f_\beta| + |f_\delta|\right) \\ w_2 = |f_\beta| / \left(|f_\alpha| + |f_\beta| + |f_\delta|\right) \\ w_3 = |f_\delta| / \left(|f_\alpha| + |f_\beta| + |f_\delta|\right) \end{cases} \tag{13}$$

By using different leadership factors w_1, w_2, w_3 to represent the leadership of the first three levels of wolves over lower level wolves, the position update equation of ω-level wolves can be adjusted, as shown in equation (14).

$$X(t+1) = w_1 \times X_1 + w_2 \times X_2 + w_3 \times X_3 \tag{14}$$

Mutation operations areperformed on the optimal wolf position using an adaptive t-distribution strategy, as shown in equation (15).

$$X_{i+1} = X_{best} + X_{best} \times t\,(iter) \tag{15}$$

In equation (15), X_{i+1} represents the optimal gray wolf position after t distribution variation, X_{best} represents the position before variation, but $t\,(iter)$ is a parameter that depends on the number of iterations used to adjust the shape of the t distribution. The design of this equation fully considers the current population information and the number of iterations, resulting in smaller t values in early iterations and enhanced global search ability, while larger t values in later iterations improve local search ability.

$$X_i(t) = \begin{cases} X_i'(t), & fit\left(X_i'(t)\right) > fit\left(X_i(t)\right) \\ X_i(t), & fit\left(X_i'(t)\right) < fit\left(X_i(t)\right) \end{cases} \tag{16}$$

As shown in equation (16), although introducing a t distribution mutation strategy can change the position of the optimal solution, it cannot guarantee that the new solution has better adaptability. Therefore, a greedy mechanism is adopted to preserve the optimal solution.

IV. WSN COVERAGE OPTIMIZATION VERIFICATION BASED ON IGW

The third chapter mainly discussed the application of IGW in WSN to optimize the coverage effect of nodes. The first section elaborated on the specific application steps and validation methods of IGW in WSN coverage optimization. The second section conducted in-depth analysis and evaluation of the coverage effect of IGW in WSN.

A. IMPROVED GREY WOLF ALGORITHM VERIFICATION APPLIED TO THE COVERAGE OPTIMIZATION STEPS OF WSNS

Two key simulation experiments were conducted for the different optimization algorithms performance evaluation in depth. Firstly, Experiment 1 used four widely used test functions to systematically compare the performance of the multi-objective flower pollination algorithm (FPA) in [29], the genetic algorithm (GA) in [30], and the improved Grey Wolf Optimizer (IGWO). The standard test function set is shown in Table 1.

Research focused on their convergence speed and search accuracy to gain a deeper understanding of the performance in different optimization problems. Secondly, Experiment 2 applied IGWO to WSN, specifically covering optimization problems. This experiment aimed to verify IGWO's feasibility and performance.

According to the trend observation in Figure 8, as iteration increased, IGWO showed significant improvement in search accuracy and convergence performance on the four test functions. It was particularly noteworthy that even in the later iteration stage, the IGWO algorithm still maintained continuous performance improvement, indicating its excellent global search ability. In addition, the IGWO algorithm also exhibited relatively fast convergence speed, which helped to effectively avoid falling into local optima. These results emphasized the potential of IGWO algorithm in complex optimization problems, especially in solving diversity and complexity problems. Therefore, the IGWO algorithm provided a powerful tool for practical application problems, not only improving search accuracy, but also maintaining a fast convergence speed. A 1m $\times$1m flat area was used to verify the optimization effect of network coverage.

Figure 9 shows the significant effect of IGWO in network coverage optimization. First, Figure 9(a) presents the random deployment of nodes, at which time the coverage is 88.9%.

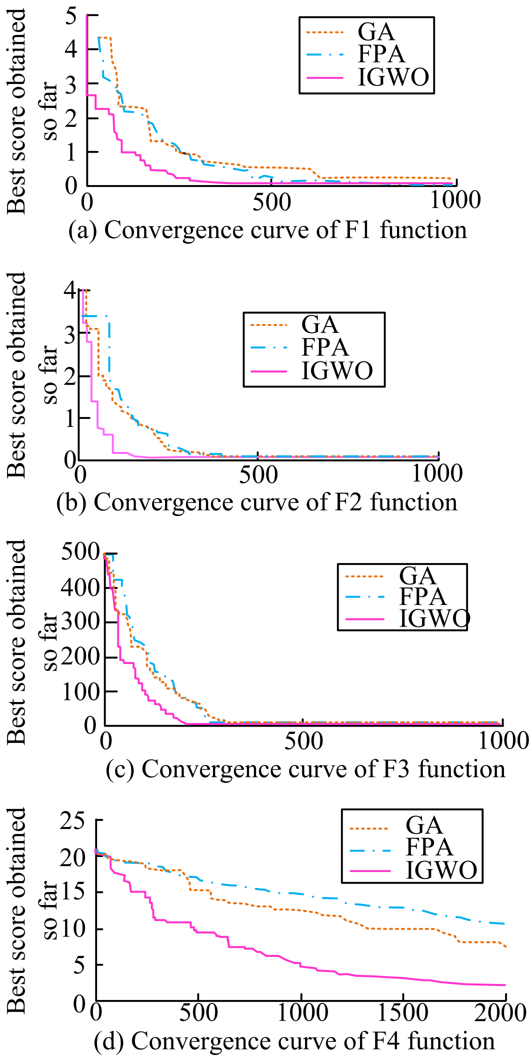


FIGURE 8. Function convergence curve.

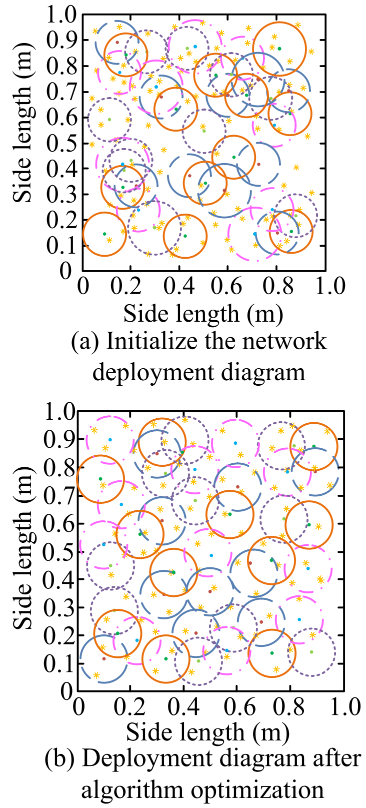


FIGURE 9. Comparison before and after optimization of network deployment diagram.

The main problem with this deployment is the uneven distribution of nodes, which leads to two significant problems. Firstly, there are multiple uncovered paths in the network, that is, there are monitoring blind spots, which affects the overall coverage efficiency of the network; secondly, it is observed that the distance between some nodes exceeds twice the radius of their communication range, which causes Due to network connectivity problems, even if some areas are covered, data cannot be effectively transmitted between nodes. Then, by applying the IGWO algorithm for optimization, Figure 9(b) presents a significant improvement in the node coverage effect. In this case, all paths are effectively covered, and the coverage rate reaches 100%. Because the IGWO algorithm adjusts the position of nodes, ensuring uniformity of coverage and eliminating blind spots; at the same time, the algorithm also considers the communication range between nodes and optimizes their relative positions, thereby enhancing network connectivity. Such optimization not only improves coverage, but also ensures efficient operation of the network, as each node can now communicate effectively with neighboring nodes, thereby increasing the reliability of data transmission.

In Figure 10, the performance of FPA, IGWO, and GA was compared on the coverage of monitoring target points under different sensor node numbers. When nodes were 50, IGWO and CCFPA achieved 100% coverage of monitoring target points, while FPA required 65 nodes to achieve complete coverage. It was particularly noteworthy that the IGWO algorithm only required 20 iterations to fully cover the monitoring target points, while GA required 50 iterations to achieve the same results. This series of results clearly indicated that the IGWO algorithm exhibited faster convergence speed and higher coverage in network coverage optimization, thus having the best performance in these aspects.

B. WSN COVERAGE OPTIMIZATION ANALYSIS USING IMPROVED GREY WOLF ALGORITHM

To comprehensively evaluate the IGWO performance, comparative experiments were conducted to compare it with the standard GWO in [31], MGWO in [32], and EGWO in [33]. The selection of these comparative algorithms helped to analyze the optimization potential and better understand the improved IGWO algorithm performance compared to other algorithms. The experiment reintroduced four standard

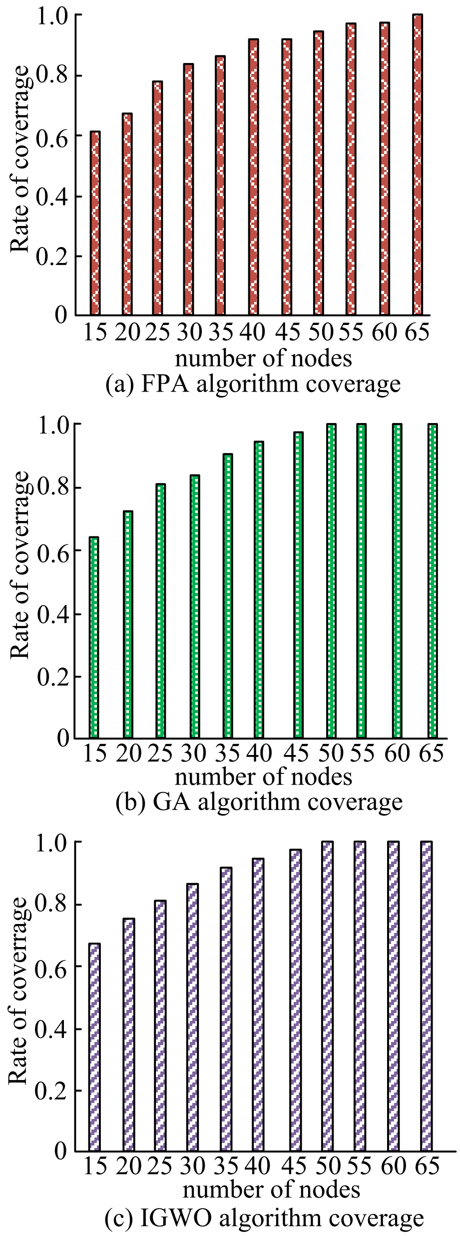


FIGURE 10. **Comparison of coverage rates.**

classical test functions, which had wide applications in the evaluation of optimization problems, as shown in Table 2.

In the experiment, the hardware environment used AMD Ryzen 5 2500 processor, 8GB of running memory, and Windows 10 64-bit, while the software environment used MATLAB 2018b. In order to ensure the unbiased and reasonable simulation results, the study set the population size to 30, the dimension to 30, and the overall iteration number to 500. All algorithm experiments were independently run 40 times in the same environment, with mean and standard deviation as indicators to evaluate algorithm performance. The Standard class test function is shown in Table 3.

The data comparison in Figure 11 shows that for the unimodal function F1-F5, the improved strategy significantly improved the solution accuracy of the solution, increasing by an order of magnitude compared to GWO, MGWO, and EGWO, respectively. In the multimodal function F6-F8, the improved algorithm showed good optimization performance on F6 and F8, finding the theoretical optimal value. However, although the optimization accuracy on F7 was comparable to EGWO, its convergence speed was faster, indicating that the improved algorithm had stronger wide-area search ability. In the 30 dimensional range, IGWO exhibited better mean performance compared to other algorithms. In addition, the standard deviation of IGWO in 7 out of 8 test functions was the smallest, which highlighted the robustness of the improved algorithm.

The study compared the performance of four algorithms in the case of dimension 30, covering 8 different test functions. Each algorithm independently ran for 40 times under each test function and the mean results were recorded. From Table 3, it was evident that the IGWO algorithm showed significant advantages in testing functions F1-F4 and F6-F8. In testing function F1, the IGWO algorithm decreased by 6 orders of magnitude, while the other three algorithms decreased by 15, 22, and 27 orders of magnitude, respectively. On the F6 and F8 test sets, the IGWO algorithm not only found the theoretical optimal value, but also had a faster convergence speed. In the test function F6 under 30 dimensions, the IGWO algorithm achieved convergence in the 51st generation, reducing the number of iterations by 35.29% compared to other algorithms. This indicated that the IGWO algorithm effectively avoided falling into local optima and had excellent high-dimensional problem-solving ability.

From Figure 12, the improved Grey Wolf algorithm can significantly improve coverage performance in WSN node deployment, reduce node count requirements, save energy, and improve network sustainability. Specifically, when nodes reached 40, the difference in coverage between the improved algorithm and the pre-improved algorithm was the highest, reaching 5.08%. Compared with MGWO and EGWO algorithms, the improved Grey Wolf algorithm increased coverage by 2.68% and 3.8%, respectively. It was particularly noteworthy that when the number of nodes reached 60, the improved Grey Wolf algorithm achieved 100% coverage performance for the first time, while the other three algorithms, although also close to 100% coverage when the number of nodes was 70, used more nodes. These observations clearly indicated that even with a limited number of nodes, excellent 100% coverage performance can be achieved. This was particularly important for resource constrained environments and application scenarios, as reducing the number of nodes not only reduced costs but also prolonged network lifespan. Facing a large number of nodes, the improved algorithm also exhibited excellent performance, further emphasizing its efficiency in WSN coverage.

In order to verify the effectiveness of the proposed WSN node deployment strategy in improving coverage

TABLE 2. Standard classic test function.

Function	Ranges	The optimal value	Dimension
$F_1=\sum_{i=1}^{n} x_i^2$	[-100,100]	0	30
$F_2=\sum_{i=1}^{D-1}[100(x_{i+1}-x_i^2)+(x_i-1)^2]$	[-30,30]	0	30
$F_3=\frac{1}{4000}\sum_{i=1}^{n} x_i^2-\prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{2}})+1$	[-600,600]	0	30
$F_4=-20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right)-\exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos 2\pi x_i\right)+20+e$	[-32,32]	0	30
$F_5=\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert$	[-10,10]	0	30
$F_6=\sum_{i=1}^{n}\left(\sum_{j=1}^{i} x_j\right)^2$	[-100,100]	0	30
$F_7=\max_i\{\lvert x_i\rvert,1\le i\le n\}$	[-100,100]	0	30
$F_8=\sum_{i=1}^{n}\left[x_i^2-10\cos(2\pi x_i)\right]+10$	[-5.12,5.12]	0	30

TABLE 3. Standard classic test function.

Function	Dimensions	GWO	IGWO	MGWO	EGWO
F1	30	2.14E-27	8.20E-181	1.60E-44	6.69E-50
F2	30	2.70E+01	2.73E+01	2.72E+01	2.74E+01
F3	30	2.75E-03	0.00E+00	0.00E+00	0.00E+00
F4	30	1.03E-13	8.88E-16	1.47E-14	1.72E-15
F5	30	9.72E-17	5.36E-89	5.37E-27	7.02E-30
F6	30	2.72E-05	2.21E-181	5.82E-10	1.01E-11
F7	30	648E-07	1.07E-87	1.25E-12	1.60E-13
F8	30	2.62E+00	0.00E+00	7.85E-02	0.00E+00

in monitoring areas of different sizes, the study selected three monitoring areas of different sizes, namely 60m×60m, 120m×120m and 210m×210m. Within each area, sensor nodes are first randomly deployed, and then the proposed optimization strategy is applied to redeploy these nodes. After each deployment, the study collected data on node coverage. These data show the coverage under different deployment strategies, see Table 4 for details.

In the smaller monitoring area of 60m×60m, when using 10 sensor nodes, the initial coverage rate is 0.354, and the coverage rate of the method proposed in the study is increased to 0.445. As the number of sensors increases, the coverage increases steadily. Especially when the number of sensors reaches more than 30, the method proposed in the study improves the coverage rate to nearly complete coverage, and a similar improvement trend is observed in the larger 120m×120m monitoring area. In the largest monitoring area of 210m × 210m, although the initial coverage rate is relatively low, the method proposed in the study significantly improves the coverage rate, reaching 0.681, and as the number of sensors increases, the coverage rate continues to increase, reaching a maximum of 0.981. Therefore, the method proposed in the study effectively improves the coverage of wireless sensor networks in monitoring areas of different sizes. Through these methodological verification steps, this study not only demonstrated the effect of the proposed method in improving wireless sensor network coverage in monitoring areas of different scales in theoretical simulations, but also further confirmed the validity and effectiveness of these results through actual testing and data analysis. reliability. Therefore, it can be concluded that the method proposed in this study effectively improves the coverage performance of wireless sensor networks in monitoring areas of different sizes.

In order to test the optimization effect of the IGWO algorithm on WSN network coverage, the SSA and TEPP algorithms were selected for comparison in three different test environments, and the same algorithm parameters were set in the experiments [34], [35]. In order to make the experimental results more credible, the two algorithms independently calculated the coverage 40 times and recorded the average value, and finally compared them. The test is a comparison of the coverage performance of square areas to be tested with side lengths of 60, 120 and 210 meters.

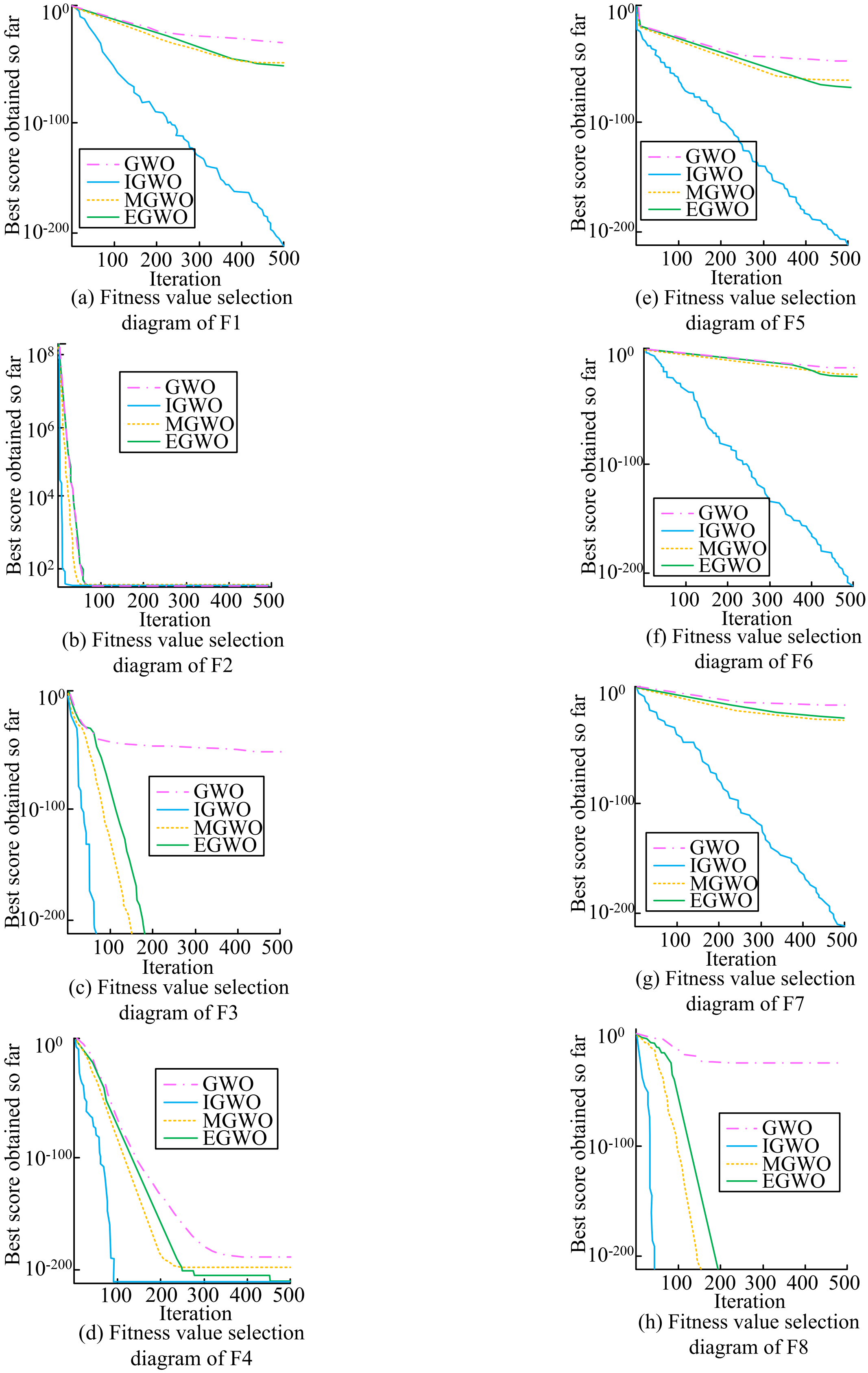
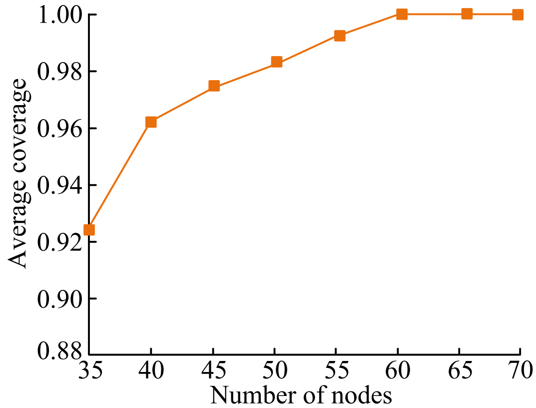
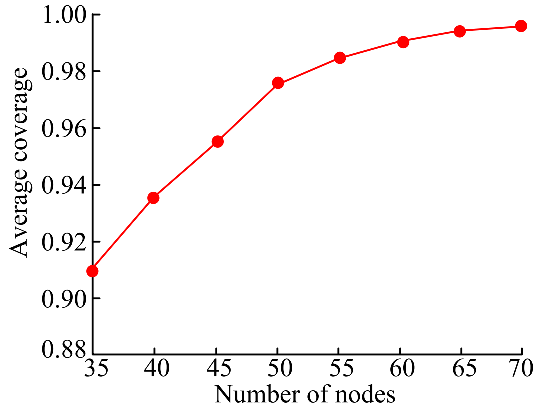


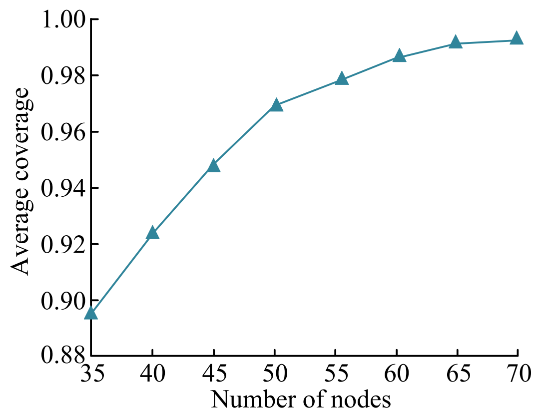
FIGURE 11. **Fitness value selection diagram of four algorithms under different standard tests in 30 dimensions.**



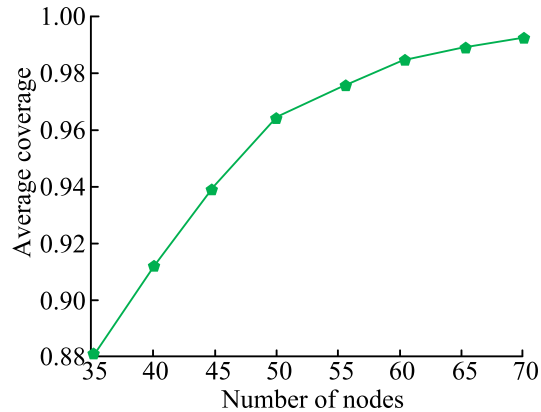
(a) The relationship between the number of nodes and coverage rate of IGWO



(b) The relationship between the number of nodes and coverage rate of MGWO



(c) The relationship between the number of nodes and coverage rate of EGWO



(d) The relationship between the number of nodes and coverage rate of GWO

FIGURE 12. Relationship between number of nodes and coverage rate.

TABLE 4. Coverage effects of different area sizes and different number of nodes.

Monitoring area size	Number of sensors	Initial coverage	Proposed method
	10	0.354	0.445
	20	0.567	0.852
60m×60m	30	0.720	0.991
	40	0.754	0.988
	50	0.865	0.989
	60	0.517	0.632
	90	0.639	0.852
120m×120m	120	0.711	0.958
	150	0.806	0.983
	180	0.877	0.985
	200	0.512	0.681
	270	0.622	0.864
210m×210m	340	0.700	0.952
	410	0.766	0.973
	480	0.821	0.981

As shown in Table 5, the algorithm proposed in the study compared the SSA algorithm and the TEPP algorithm, and the coverage rate in the 60m×60m environment was 96.83%, which increased by 5.9% compared to SSA and 4.29% compared to TEPP. Similarly, in the environments of 120m×120m and 210m×210m, the improvements were

TABLE 5. Comparison of coverage rates of different algorithms in different environments.

/	SSA	TEPP	IGWO
60m×60m/Average coverage (40 times)	90.93%	92.54%	96.83%
120m×120m/ Average coverage (40 times)	89.03%	91.47%	94.28%
210m×210m/ Average coverage (40 times)	93.26%	95.19%	97.01%

5.25%, 2.81%, 3.75%, and 1.82% respectively, which all reflect the significant advantages and practicality of the algorithm proposed in the study. Therefore, in practical applications, the proposed algorithms can effectively improve coverage, which is crucial for actual wireless sensor network applications.

V. CONCLUSION

WSN consists of many distributed wireless sensor nodes, aimed at monitoring various parameters in the environment, such as temperature, humidity, pressure, lighting, etc. The research adopts multiple methods aimed at improving energy-saving node coverage in WSNs, thereby improving the efficiency and performance of the network. The research methods mainly include analyzing routing protocols, designing coverage models, and using improved grey wolf algorithms to improve node deployment, thereby improving network performance and efficiency. The research results showed that IGWO had a significant effect on network coverage optimization. The random deployment of nodes showed a coverage rate of 88.9%, and after optimization using the IGWO algorithm, IGWO was able to achieve 100% coverage of monitoring target points. In the 30 dimensional range, IGWO exhibited better mean performance compared to other algorithms, and 7 out of 8 test functions had the smallest standard deviation. When the nodes reached 40, the coverage difference between the improved algorithm and the pre improved algorithm was the highest, reaching 5.08%. Compared with MGWO and EGWO algorithms, the improved Grey Wolf algorithm increased coverage by 2.68% and 3.8%, and the improved Grey Wolf algorithm still achieved 100% coverage performance. However, the other three algorithms, although approaching 100% coverage when the number of nodes was 70, used more nodes and consumed more energy. The research may be limited by the experimental scale and fail to cover all potential scenarios of large-scale networks.

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