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Research Article

A Method of Selecting Optimal Control Nodes for WSNs Based on C-Means Clustering Algorithm

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The wireless sensor networks (WSNs) require an optimal selection of control nodes for improving the operational performance of the overall network. The data are increasing day by day, and it is difficult to a handle huge amount of data. For speedy transmission of data, it is mandatory to deploy sophisticated methods for improving the operations of WSNs. There are many methods proposed by the researchers to improve the operations of WSNs, but the data are increasing and more methods are needed to be explored to handle the operations of WSNs to smoothly handle a huge amount of data. To cater to this need, this research is proposing a method of selecting optimal control nodes for WSNs based on the C-means clustering algorithm (CCA). The CCA is improved by the weighting mechanism in the cluster, and the remaining energy of the node is taken into account. If the node energy is more as compared to the average energy in the cluster in each round, it will have the chance to serve as the cluster head node (CHN) and the adaptive assignment of CHN is made according to the generated cluster size by WSN. Every node possesses the probability of becoming a CHN to save the energy utilization of the node and to obtain the optimal control for node selection in WSN. The experimental results reveal that the coverage rate of WSN is improved after applying the proposed method. The network energy utilization is optimized, which effectively prolongs the lifetime of WSN and improves the overall network output including throughput, energy consumption rate, and data transmission rate.

1. Introduction

The WSN is the group of distributed and exclusively allocated sensors for keeping the record and examining the conditions around. The data that have been gathered are arranged and stored at the central repository. The WSN is a comprehensive intelligent information system, which is integrating information collection, information transmission, and information processing [1]. It has broad application prospects including organization and management of the network [2]. It is a new field in information network technology and an area of research for many aligned applications [3]. Data collection and quantification, processing, and transmission applications can be used in diverse fields like military reconnaissance for strategic planning, environmental observation, medical examination, space research, traffic control in the cities, and warehouse management [4–7]. The WSNs generally have the specific characteristics of encompassing large-scale networks, self-organization of data, random deployment, and spanning complex environment. The WSN also has challenges when it comes to the number of sensor node resources and frequently changing network nodes [8, 9]. Inappropriate selection of control node in WSNs leads to the problems such as (a) more power consumption during transmission or communication of data, (b) lifespan of the network will get compromised as a result of limited node energy, and (c) the wireless signal of each node in the network will cover a large number of other nodes, which will aggravate signal interference between nodes and affect communication quality, which will eventually reduce the network throughput [10–13]. There will be a large number of redundant edges in the generated network nodes, resulting in a huge amount of repetitive information in the network nodes. It will enhance complex routing calculations and exhaust valuable computing resources [14, 15].

In [13], authors address the issue of distributed scheduling of MSNs. It enhances the region span and reduces the coverage holes with minimum energy loss. They also have stated various algorithms for multiple MSNs with their performance comparison. In [14], authors have focused on the control and optimization of WSNs' nodes. The problems with the design and management of WSNs have also been discussed. It also emphasizes on the importance of energy consumption consideration in the protocol design of each layer of the network. The establishment of node control mechanism for effective energy consumption has been proposed to optimize the energy utilization and the network lifespan. In [15], authors have proposed the QACS method for programmed mining of the encoded information in blockchain communications.

In [16], authors have proposed an optimal relay node (RN) selection method. The suggested methodology picks RN depending on the combined optimization of delay in data transmission and reliability of the network link. The Pareto frontier of this optimization is used to describe the balance between the two abovementioned parameters. The proposed node selection method identifies all possible RNs. It addresses the joint optimization problem; in each hop, the weight of the biobjective problem is updated and the best RN is selected among all possible RNs. This method has good operational reliability but poor efficiency. In [17], authors have proposed a combined selection of relay along with link rate assignment based on OHD selection. It saves energy, which analyzes the influence of the minimal hop distance in WSNs on the network life while considering the link service quality needs. The OHD measures the distance between the optimal relay position of a node and its next hop to the target node, and ORP finds the output of the energy-saving relay. For the given node pair, the minimum energy path can be obtained if the OHD comes out to be equal to that of the characteristic distance of the path. This method has better operating efficiency but poor reliability.

In [18], authors have proposed a two-phase solution. In phase I, the distributed algorithm is used to enhance the probability perception algorithm, and it is based on the probability model. In phase II, phase I is expanded to 3D space. The heuristic algorithm (greedy) is used. The simulation shows better performance of the algorithm as compared to the existing methods. In [19], authors have proposed a technique for node deployment. It uses the grey wolf-based technique for optimization. The study explores the wolf representation scheme and a new multiobjective fitness function. The efficiency of the proposed technique is proven with the help of simulation and statistical techniques. In [20], authors have proposed a novel approach for the simultaneous selection of control node in the complex network. The method focuses on an open-loop optimal control problem. An adaptive search method is used as a solution for the resulting mixed-integer optimization.

In the selection of optimal control nodes in WSN, four major performance factors need to be considered: (a) coverage, (b) energy consumption, (c) mobile node rate, and (d) lifetime. The existing work in the selection of optimal control nodes in WSN compromises one or more above factors. In this study, our aim is to have fair efficiency toward all the four factors.

The major highlights of the study are as follows.

This study offers a method for selecting optimal control nodes for WSNs based on CCA. The weight-based rough C-means algorithm is proposed to optimize and enhance the network performance by calculating the degree to which the node object deviates from the cluster center where each node object is assigned a different weight value. Different weights are dynamically assigned to each node object, which improves the performance of node clustering and makes the position of nodes evenly distributed. Based on this, the optimal control node selection model for WSNs is obtained and the CCA achieves the target of enhancing the performance of the network.

(i) This study is proposing a method of selecting optimal control nodes for WSNs based on weight-based rough CCA.
(ii) The CCA is improved by the weighting mechanism within the cluster, and the remaining energy of the node is taken into account.
(iii) If the node is greater than the average energy in the cluster in each round, it will have the opportunity to serve as the CHN and adaptive assignment of CHN is made according to the generated cluster size by WSN.
(iv) Each node has the probability of becoming a cluster CHN to save the energy consumption of the node and to obtain the optimal control for node selection in WSN.
(v) The experimental results reveal that the coverage rate of WSN is improved after applying the proposed method. The network energy consumption is optimized, which effectively prolongs the lifetime of WSN and improves the network parameters including throughput, energy consumption rate, and data transmission rate.

The next section elaborates on the proposed work in detail.

2. CCA Based on Intracluster Weighting

In WSNs, clustering is the process of dividing the nodes in the network into multiple clusters to extend the life cycle of the network. However, the nodes in the WSN are densely distributed in the monitoring area. How to use the clustering method to select the optimal control node and improve the scalability of the network is the current key research problem. The partition-based clustering algorithm divides the nodes in the network into multiple regions, and each region can independently perform tasks such as data perception. The typical partition-based clustering algorithms such as the C-means algorithm can be used to enhance the output of the nodes. This study first summarizes the rough CCA and improves the shortcomings of the algorithm by weighting within the cluster.

2.1. CCA. The basic idea of the C-means algorithm is to set the initial parameters before updating the algorithm of each iteration, that is, given the input parameter X and the specified number of clusters C, we first select C sample points as the initial cluster centers; then calculate other samples that point the distance to the initial cluster center and assign the sample objects to the clusters closest to it; then update the cluster center formula to calculate C new cluster centers; and loop execution until a certain termination condition is met and the algorithm ends. In general, the *C*-means algorithm uses Euclidean distance as a similarity measurement method, and through iterative steps, the updated objective function is minimized, thereby obtaining the optimal clustering effect [17]. Rough CCA uses C-means clustering to partition a group of objects into the sets, which are nonoverlapping. Rough sets are more accommodating for real-time representation than classical sets. It uses fuzzy sets with hard partitioning along with subjective member function on the dataset. The proposed rough CCA encompasses the advantages of the abovementioned methods. There are limitations of the mean iterative function when the same weights have been assigned to all the data. The proposed hybrid model proves to be more suitable for real-life applications like selecting optimal control nodes for WSN [18]. In [21], authors consider various performance parameters to determine variations and similarities by using *C*-means. The proposed clustering function for validity proves to be more effective for clustering on different datasets. The results have been proven with the help of simulation.

This makes *C*-means algorithm the perfect choice for developing a method of selecting optimal control nodes for WSN.

The rough set is introduced into the *C*-means algorithm. The sample points are arbitrarily allocated to the nearest cluster, and the distance between the point and the center of the cluster is determined. If it is less than a certain threshold, the sample point belongs to the upper set of the cluster; otherwise, it is the next approximation set [18]. Finally, it is judged whether the objective function is less than a predetermined value, and the algorithm ends.

The step-by-step approach of the rough C-means is as follows.

A rough set $X \in U$, $\overline{a}U$ $\underline{a}U$ is its upper approximation and lower approximation, respectively, and its attributes are as follows:

(1) Some object x_k, if $x_k \in \underline{a}U_i$, then $x_k \notin \underline{a}U_j$, and $i \neq j$.

(2) If the object is $x_k \notin \underline{a}U_i$, then $x_k \in \overline{a}U_i$.

(3) If the object is $x_k \in ab_i$, then $x_k \in \overline{a}U_i, \underline{a}U_i \ldots, i \neq j$.

The rough *C*-means algorithm iteratively divides the sample points into *C* clusters, which minimizes the objective function considering the remaining energy of the nodes. The cluster center update formula of each cluster is shown in equation (1).

$$\overrightarrow{m_k} = \left\{ w_l \sum_{\overrightarrow{x_n} \in C_k} \frac{\overrightarrow{x_n}}{C_k} \right. \tag{1}$$

The objective function formula is shown in equation (2).

$$J = \sum_{c=1}^{c} \left(\left| x_i - m_k \right|^2 \right). \tag{2}$$

The basic algorithm flow is shown below as follows:

Step 1: We initialize the parameters, set the number of clusters C, and arbitrarily select C sample center $C_i = (i = 1, 2, \ldots, c)$, distance threshold ε, and weight values w_l and w_u.

Step 2: We calculate the Euclidean distance d_{ik} from each object x_k to the cluster center $C_i = (i = 1, 2, \ldots, c)$, and d_{jk} is the Euclidean distance from x_k to the cluster center c_i, c_j.

Step 3: We choose d_{ik} as the minimum value and d_{jk} as the second minimum value.

If $d_{jk} - d_{ik} < \varepsilon$, then x_k cannot belong to the lower approximation of any cluster; otherwise, d_{ik} is the smallest value among C clusters.

Step 4: We update the cluster center formula m_k.

Step 5: We repeat steps 2 to 4 until the objective function J is the smallest.

2.2. Rough CCA Based on Intracluster Weighting. The rough C-means algorithm mentioned above uses a uniform weight value for the upper and lower approximations when calculating cluster centers, ignoring the differences within the sample objects. According to the difference in the degree of contribution of sample objects to their clusters, differentiated metrics should be used to measure the contribution of sample objects; otherwise, it will lead to the misclassification of certain points. Although some scholars are aware of the differences in the objects in the cluster, they mainly change the weight of the objects in the cluster by adding complex weight formulas, which increases the execution time of the algorithm during the operation of the algorithm [19].

2.2.1. Weighted Metrics within Clusters. By calculating the degree to which the sample objects in the cluster deviate from the cluster center, each object is assigned a different weight value. The closer the sample object to the cluster center is, the heaviest contribution to the cluster is, and the more weight should be assigned [20].

When the formula is iterated, the intracluster weight value of each sample object is set as shown in equation (3).

$$A_{ij} = \frac{1}{\sigma_{ij}^2 \sum_{j=1}^{m_i} \left(1/\sigma_{ij}^2 \right)}. \tag{3}$$

The constraints are as follows: $\sum_{j=1}^{m_i} A_{ij}$, where σ_{ij} is the standard deviation from the sample object to the cluster center, and m_i is the number of samples in i categories. It can be seen from the above formula that the closer the object within the class is to the cluster center, the smaller the value of σ_{ij}, which indicates that the greater its contribution to the class, the greater the weight value assigned. Conversely, if the offset is greater, the distance from the σ_{ij} sample object to the cluster center is farther, the contribution to its class is lower, and the weight value obtained by the corresponding sample object is lower.

The values of w_l and w_u are as follows. This section no longer uses the default parameter values, but refers to the number of upper and lower approximation objects in the sample. w_l and w_u are the number of approximation objects under (upper) sample compared to the number of samples as shown in equations (4) and (5).

$$w_l = \frac{\sum_{x_j \in \underline{a}U} 1}{\sum_{x_j \in \underline{a}U} 1 + \sum_{x_j \in \overline{a}U} 1}, \tag{4}$$

$$w_u = \frac{\sum_{x_j \in \overline{a}U} 1}{\sum_{x_j \in \underline{a}U} 1 + \sum_{x_j \in \overline{a}U} 1}. \tag{5}$$

2.2.2. In-Cluster Weighted Improved CCA Algorithm. The rough CCA based on intracluster weighting is improved on the basis of formula (1), where the weight of the sample object in the cluster is the reciprocal of the total number of all samples; ignoring the difference in the contribution of individual samples to the class, this study will introduce formula (2) into the cluster center iteration formula. At the same time, w_l and w_u in formula (1) are greatly affected by the initial parameters. Considering the number of objects of the upper and lower approximate samples, the specific process of the improved algorithm is as follows:

Step 1: We initialize the parameters, set the number of clusters C, and arbitrarily select C sample center $C_i = (i = 1, 2, \ldots, c)$ and distance threshold [13].

Step 2: We calculate the weight values w_l, w_u, and the Euclidean distance from each object x_k to the center of the sample $C_i = (i = 1, 2, \ldots, c)$. d_{ik} and d_{jk} are the Euclidean distance from x_k to the center of mass c_i, c_j.

Step 3: We choose d_{ik} as the minimum value and d_{jk} as the second minimum value.

Step 4: We update the cluster center formula shown in equation (6).

$$V_i = \begin{cases} w_l \sum\limits_{xj \in \underline{a}U_i} A_l s_j + w_u, \\ \sum\limits_{xj \in \underline{a}U_i} A_l s_j + \underline{a}U_i, \\ \sum\limits_{xj \in \overline{a}U_i - \underline{a}U_i} A_l s_j - \underline{a}U_i. \end{cases} \tag{6}$$

Step 5: We repeat steps 2 to 4 in a loop until the objective function value is less than the set threshold. In step 4, the weight values of the lower approximation and the boundary area are no longer fixed values in the traditional sense. In each iteration, the corrected cluster center is close to the center of the cluster and tends to be stable.

3. Selection Method of Optimal Control Node for WSN

In WSNs, energy constraints are strong, reducing energy consumption and promoting load balancing, which play a pivotal role in extending the life of WSNs. The WSNs have certain complexity. Due to different application scenarios, the requirements for network coverage will be different. Network coverage control optimization is to control network nodes and optimize the coverage structure in order to reduce node energy consumption and increase A network resource optimization method used for network coverage quality. However, in the network, often because of the difference in the task amount of each node, some nodes are exhausted due to the excessive task amount, while other nodes are rarely used [14, 15].

In order to improve the survival time of WSNs and balance the network load consumption, the intracluster weighted improved CCA is used to balance the network load; the node optimal control optimization selection algorithm is proposed; and the optimal control node selection method is studied to reduce the network medium energy consumption, optimize the configuration of node resources in the network, and extend the network lifetime.

3.1. Construction of WSN Cluster. The CHN is randomly selected with equal probability periodically, and the adjacent ordinary nodes dynamically join the CHN. The ordinary node only communicates with the CHN of the cluster, and the CHN integrates the data information of the cluster, which is processed by it. The data are forwarded to the base station in a single-hop or multihop fashion. Since the CHN needs to fuse and process the information of ordinary nodes, and transmit the result to the base station, the CHN consumes more energy in the communication process. A rotation system is adopted to balance the energy consumption of the network to each node so that the CHN in each round will not lose its working ability due to the exhaustion of battery energy.

The stage of cluster construction includes cluster head selection and cluster formation. The CHNs are randomly generated with equal probability during the cluster head selection stage. Whether each node becomes a CHN is related to the optimal number of cluster heads expected in the network and whether it has served as a CHN until this round. Whether it becomes the expected percentage of CHNs in the current round depends on the total number of nodes in the network, which is generally a given fixed value. The flowchart of the LEACH protocol in the cluster construction phase is shown in Figure 1.

In the initial state, each node randomly assigns a random number of [0, 1]. If the random number is less than the

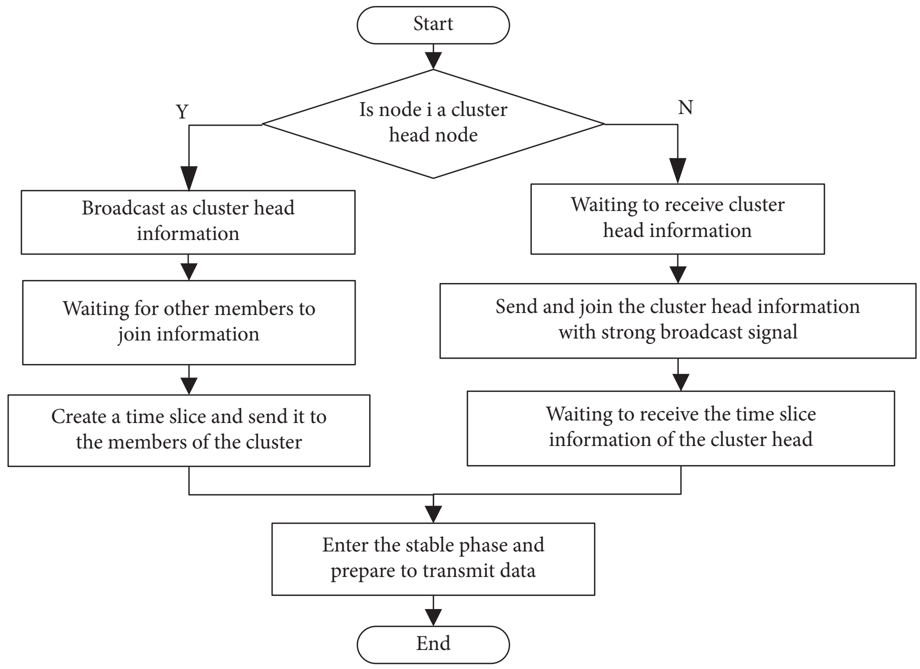

Figure 1: The construction phase of the LEACH protocol cluster.

threshold value $T(n)$ set in this round, then this node is determined as the CHN in this round of selection; otherwise, it becomes a normal node. The formula for threshold $T(n)$ is as shown in equation (7).

$$T(n) = \begin{cases} \dfrac{p}{1 - p * (r \bmod (1/p))}, & n \in G, \\ 0, & \text{other}. \end{cases} \tag{7}$$

In formula (7), p represents the expected percentage of nodes becoming CHNs in a certain round, generally the ratio of the number of CHNs in the network to the number of all nodes; r represents the current number of rounds of cluster head selection; n represents each node in the WSN, and each has a unique ID; and G represents a collection of ordinary nodes that have not served as CHNs in the last $(1/p)$ rounds.

Once a node confirms that it has become a CHN, it immediately broadcasts the information that it has become a CHN to other nodes in the network and informs other ordinary nodes that a CHN has been generated, and other ordinary nodes rely on the CHN's received broadcast signal strength, join this CHN based on the principle of proximity, and notify the corresponding cluster head, so that all nodes in the network form numerous virtual clusters. When an ordinary node joins the CHN, the CHN will set a TDMA transmission time slice for each ordinary node to avoid cluster members sending information to the cluster head at the same time to cause network congestion and allow non-CHNs not to be in their working time slice, in a dormant state, thereby reducing node energy consumption. After the members of the cluster obtain the TDMA time slice designated by the CHN, the establishment of the cluster is completed and the stable data transmission phase is entered.

In the stable phase, cluster member nodes automatically adjust their own transmission power according to the broadcast signal strength of the received cluster head information to ensure that there is enough energy to transmit data to the CHN. At the same time, according to the time slot allocated in the TDMA table, the monitored data are time-shared and sent to the cluster head, and it stays in the dormant state at other times to save energy. The cluster head receives the data collected by all cluster members, first performs fusion processing on these data to reduce redundant data and noise interference, and then forwards the processed data to the base station. The round ends. Because the CHN has been processing the working state and needs to fuse data in the cluster, it needs to consume a lot of energy. In order to reduce the additional processing overhead, the general stabilization phase lasts longer than the construction phase. After the stabilization phase lasted for a while, the entire network began to enter a new cycle, re-entering the cluster construction phase, making each node take turns to serve as the CHN, balancing the energy consumption in the network to each node, and improving WSN node energy utilization.

3.2. Optimal Control CHN Selection Based on CCA. The rough C-means algorithm based on intracluster weighting is used to improve the optimal control CHN selection method. Through node positioning technology, the geographical coordinates of randomly deployed sensor nodes are obtained. According to their coordinate values, all nodes are divided into C subsets according to the distance from themselves to the cluster center by using the WCRCM algorithm. C represents the number of optimal clusters, namely, dividing the sensor nodes of the entire monitoring area into C virtual subarea nodes, so as to ensure the even distribution of nodes in the geographical position. According to the nature of the rough set, the nodes in each area are classified into the upper approximation set or the lower approximation set of the area. The nodes in the lower approximation set must belong to the area, and the residual energy factor of the node is added to the objective function. Through the optimized objective function, the attribution of the sensor node is determined to achieve the purpose of automatic classification.

The proposed work has been compartmentalized into three phases as follows:

(a) Identifying the range of CHN;
(b) Calculating the probability of the node to become CHN;
(c) Selecting optimal control node for WSN using CCA.

3.2.1. The Range of CHN Selection. The WCRCM algorithm names the node as the upper node or the lower node. Since the upper node belongs to multiple areas, it may perceive information from multiple adjacent areas, and the upper node is generally at the boundary of the area, so the data fusion, processing, and transmission process will consume more energy, but the lower A node only exists in one area, and only the information in the area is monitored. Therefore, when selecting the CHN in this study, only the lower nodes in each area are considered.

3.2.2. Probability of Becoming a CHN. The calculation formula for the number of cluster heads is as follows:

$$k = \frac{\sqrt{N}}{\sqrt{2\pi}} * \frac{M}{d}. \tag{8}$$

In formula (8), the monitoring area is divided into k subareas. If each area has a CHN, then the probability that all nodes defined by the LEACH protocol become CHNs p is the reciprocal of the number of all nodes in each newly divided area. We add the remaining energy of the node and the average energy of the area where the node is located into the probability formula of becoming a CHN as shown in equation (9).

$$p = \frac{k}{C}. \tag{9}$$

3.2.3. Selection Method of Optimal Control Node for WSN. In the WSN coverage algorithm, it is necessary to consider optimizing the network energy consumption as much as possible while increasing the network coverage. At the same time, a balance between a single node and the total energy consumption of the network should also be considered. If the energy in the network is low, and if the node still performs the same task as other nodes, then the node will "die" early, affecting the transmission performance and reliability of the entire network. This study proposes a method for selecting optimal control nodes for WSNs based on CCA, analyzes the factors that affect the life cycle of WSN nodes, and establishes the dependency between the life cycles of WSN nodes and the quality of target tracking. The CCA and the CHN probability formula are introduced into the optimal control node selection method to obtain the optimal control node selection method.

If the error data probability of the abnormal dynamic node o in the high-dimensional data flow in the network is set to FA, $h(FA_o)$ represents the possibility of the false alarm rate of target tracking data of the abnormal node FA_o, when the optimal control node o is selected, the energy loss formula is as shown in equation (10).

$$C_{\mathrm{o}}^{c} = \begin{cases} h(\mathrm{FA}_o)\cdot\left(C_{\mathrm{o}}^{s} + C_{\mathrm{o}}^{a}\right), D_o = \varnothing, \\ h(\mathrm{FA}_o)\cdot\left(C_{\mathrm{o}}^{s} + C_{\mathrm{o}}^{a} + c^{*}C_{\mathrm{o}}^{r}\right), \left|D_o\right| = c. \end{cases} \tag{10}$$

In equation (10), when C_{o}^{r}, C_{o}^{a}, and C_{o}^{s} are sampling the target key sequence data, the energy consumed by dynamic nodes are r, a, and o in the whole cycle, s describes the number of target tracking nodes of dynamic node o, and D_o describes variables.

To set the optimal control node set $\ddot{N} = \left\{n_1, \ldots n_{|\ddot{N}|}\right\}$ of the WSN, it is necessary to obtain the element vector $(y_1, \ldots y_{|\ddot{N}|})$ of $|\ddot{N}|$ and the middle $y_o \in \{0, 1\}$. The following conditions must be met.

(1) Maximize the value of $\min_{o\in\ddot{N}} y_o l_o$.
(2) $\sum_{o\in\ddot{N}} y_o A_o \leq \mathrm{FA}_T$.
(3) $\sum_{o\in\ddot{N}} y_o \geq k$.

Among them, the value of FA_T is set according to the actual target tracking requirements, and k is the minimum value of the target tracking node. According to the CCA, it is used to balance the network load and reduce the energy consumption in the network. The optimal control node selection model of the WSN is obtained through the selection range of the CHN as shown in equation (11).

$$x_\iota^{\kappa+1} = x_\iota^{(\kappa)} + \delta(P + V_i). \tag{11}$$

4. Experimental Analysis

In order to verify the effectiveness of the proposed method for selecting optimal control nodes for WSNs based on the CCA, the literature [3] method and the literature [4] method are used as experimental comparison methods. Through simulation experiments, the network coverage, analysis of network energy consumption, and network connectivity are determined.

4.1. Experimental Environment and Parameter Settings. The experiment was carried out in the MATLAB simulation software. The scene was set as follows: static sensor nodes and mobile nodes were set in the monitoring area $100 * 100\,\mathrm{m}^2$. The node sensing radius range was 5–20 m, and the simulation parameters are shown in Table 1.

During the research, the network is set to an ideal state without considering the phenomenon of interference

Table 1: Experimental environment simulation parameters.

Parameter	Value
Network size	100 ∗ 100
Node number *a*	200
Node number *a*	300
Sensing range	5–20
Min energy(J/battery)	0.01

Table 2: Simulation parameters of WSN model.

Parameter	Value	Unit
Number of nodes	100	A
Data packet length	4000	Bit
Control message length	32	bit

between nodes and packet loss in transmission. The network model of the wireless sensor assumed in this study has parameters as shown in Table 2.

The nodes used in this study are 100 nodes randomly generated by MATLAB2012, which are randomly distributed in a 100 ∗ 100 square row area, and the distribution is shown in Figure 2.

In the above experimental environment, the effectiveness of the proposed method is verified, and the experimental results are analyzed.

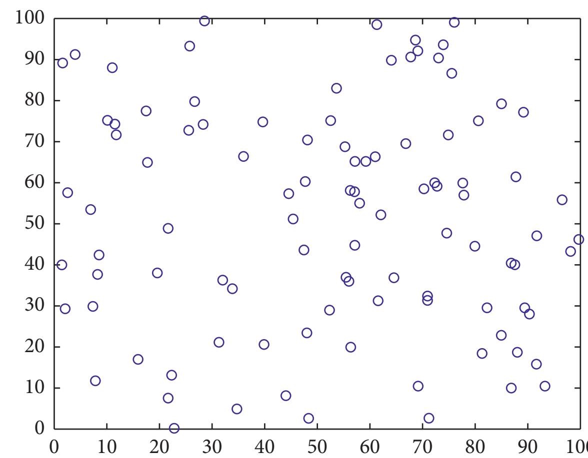

Figure 2: Distribution of 100 nodes.

4.2. Analysis of Experimental Results

4.2.1. WSN Coverage Experiment. Network coverage can reflect the effective coverage of the entire network and is one of the effective indicators to measure the quality of network coverage. For most application scenarios, as long as the network coverage is controlled within a certain reasonable range, the network effectiveness will not be affected. Comparing the WSN coverage under the control of the three methods, the comparison result is shown in Figure 3.

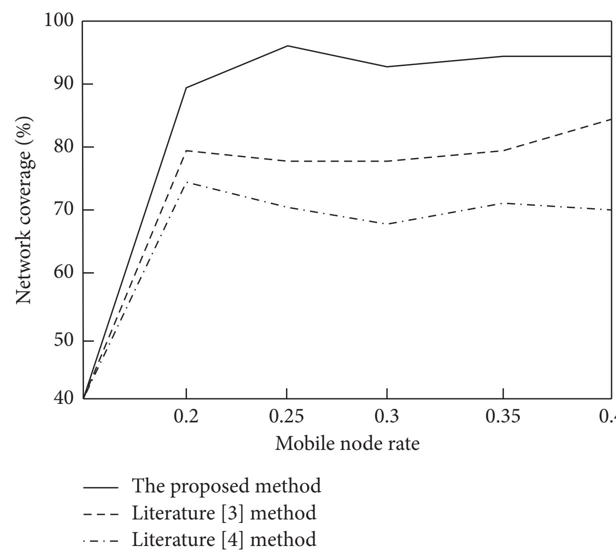

Figure 3: Comparison of results of network coverage.

The number and location of static node equipment in the network are the same. In the initial stage of network operation, the network coverage changes are not very different, but with the introduction of mobile nodes, the network coverage of the proposed method is beginning to be higher than that of the literature comparison method, and especially over time, this advantage becomes more apparent.

4.2.2. Energy Consumption of WSN. The limited energy of WSNs determines that network energy consumption is one of the key factors affecting the performance of the entire network. Nodes in the network perceive each other. Due to the difference in the amount of tasks each node undertakes, as the network time runs, the remaining energy and perception range of the nodes have a certain difference. Comparing the three methods of WSN energy consumption, the comparison result is shown in Figure 4.

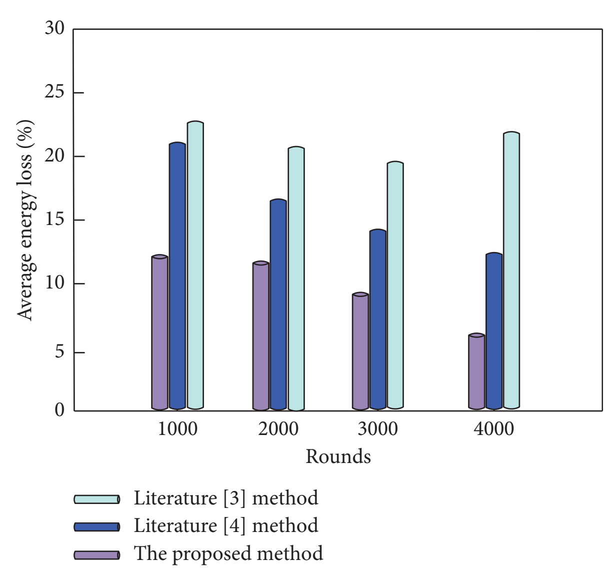

Figure 4: Comparison results of network energy consumption.

It can be seen from the results in Figure 4 that the proposed method takes into account the remaining energy of the surrounding nodes when calculating the specific location of the mobile node to repair the network blind zone, effectively reducing the number of dead nodes in the

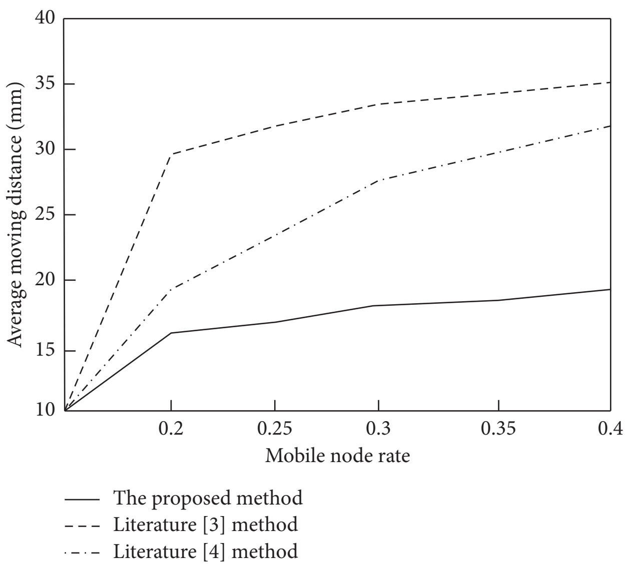

Figure 5: Comparison results of average mobile node distance.

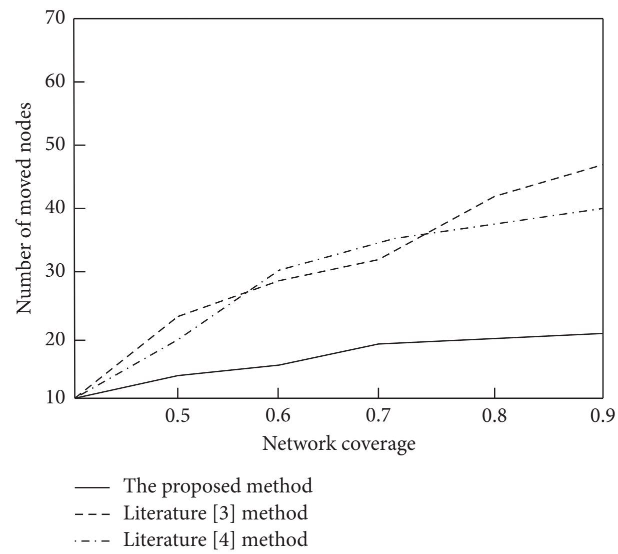

Figure 6: Comparison results of average mobile node distance.

network and reducing the number of new networks due to dead nodes. In terms of energy consumption of the entire network, the three algorithms show an upward trend, but the energy consumption of the proposed algorithm is lower.

4.2.3. Mobile Node Rate of WSN. The mobile node rate is the ratio of the number of mobile nodes working in the network to the total number of all working nodes in the network. In the case of the same network mobile node rate, the algorithm compares the average moving distance of the mobile node during the coverage area repair process. If the average moving distance is relatively short, it means that the mobile node has a shorter moving distance during the area repair process, which reduces the mobile nodes. For the energy consumption caused by mobility, the average mobile node distance of the three methods is shown in Figure 5.

Analyzing Figure 5, we can see that the average moving distance of the proposed method is relatively short, and it can be found that the average moving distance of the algorithm smoothly changes, indicating that the algorithm is superior to the literature comparison method in planning the moving path of mobile nodes.

Using mobile nodes to repair the network coverage area can improve the network coverage quality, but during the repair process, it is necessary to move as few nodes as possible, reduce the energy consumption of mobile nodes during the movement, and complete the network area coverage repair task. It can be seen from Figure 6 that after coverage restoration, the network coverage rate is constant. When the proposed method uses mobile nodes for coverage restoration, the number of mobile nodes used is relatively small, and the network restoration rate is better.

4.2.4. Lifetime of WSN. The network lifetime is a relatively intuitive performance indicator that reflects the operating conditions of network nodes. It can effectively measure the

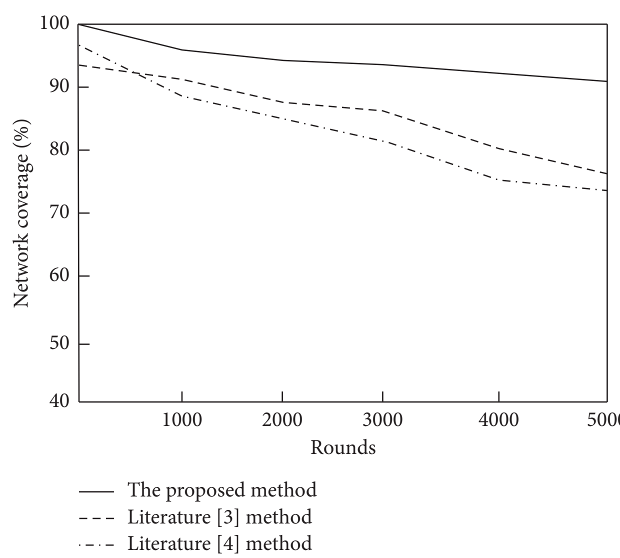

Figure 7: Comparison results of network lifetime.

length of the network's service life. When the network coverage reaches a certain critical value, the network performance will be reduced and the quality of service will be reduced. The specific network monitoring task means the end of the network lifetime at this time. Figure 7 shows the coverage changes.

It can be seen from the figure that the actual network service quality of the proposed method is slightly higher than the expected value, which is closer to the network coverage requirement than the literature comparison method, and makes the distribution of resources within the network more balanced. The proposed method determines the optimal location of mobile nodes, controls the number of network nodes based on the network coverage, repairs the network coverage area, improves network coverage and connectivity, and extends the network lifetime.

5. Conclusions

Due to the limited energy of the nodes in the WSNs, there is generally no power to supplement the equipment. At the same time, the nodes in the WSN are large in scale and randomly distributed where the communication radius of the nodes is limited. It makes the architecture of the new WSN more complex. The method and communication protocol are different from traditional networks. The main task of the traditional wireless network routing algorithm is to find the optimal path from the source node to the destination node by avoiding the network congestion and by improving the quality of service of the network. However, problems such as balancing network traffic and network energy consumption are beyond the scope of its design. In this study, a method for selecting optimal control nodes for WSNs based on CCA is proposed, and a rough C-means clustering based on intracluster weighting is proposed. By calculating the degree of deviation of the node object from the cluster center, it is determined for each node object. The closer the node to the cluster center, the greater the weight of the cluster where it is located, which indicates that the object contributes the most to the cluster where it is located. The sensor nodes in the entire wireless network area are divided into multiple subareas, and the number and location of the nodes in each area are roughly the same, thereby ensuring the uniformity of the CHNs in the geographic location. A rough C-means clustering is used to construct the optimal control node selection model for WSNs. The experimental results of the proposed work have been compared with the state-of-the-art methods for the parameters like network coverage, energy consumption, mobile node rate, and network lifetime. The simulation experiment on the proposed work shows outstanding performance in all the above-mentioned parameters. In the future, more performance parameters will be considered and more algorithms will be introduced to achieve better efficiency in the process of selecting optimal control nodes for WSNs.

Data Availability

The data are available on valid request.

Conflicts of Interest

The authors have no conflicts of interest to declare.

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References

[1] P. Bhavathankar, S. Chatterjee, and S. Misra, "Link-quality aware path selection in the presence of proactive jamming in fallible wireless sensor networks," *IEEE Transactions on Communications*, vol. 66, no. 4, pp. 1689–1704, 2018.

[2] M. Kaur, "FastPGA based scheduling of dependent tasks in grid computing to provide QoS to grid users," in *Proceedings of the 2016 International Conference on Internet of Things and Applications (IOTA)*, pp. 418–423, Pune, India, September 2016.

[3] S. Redhu, M. Anupam, and R. M. Hegde, "Optimal relay node selection for robust data forwarding over time-varying IoT networks," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 9, pp. 9178–9190, 2019.

[4] Z. Ding, S. Xing, and F. Yan, L. Shen, Impact of optimal hop distance on the network lifetime for wireless sensor networks with QoS requirements," *IEEE Communications Letters*, vol. 23, no. 3, pp. 534–537, 2019.

[5] S. Redhu and R. M. Hegde, "Optimal relay node selection in time-varying IoT networks using network contact pattern information"," *IEEE Transactions on Vehicular Technology*, vol. 98, Article ID 102065, 2020.

[6] M. Kaur and S. Kadam, "Bio-Inspired workflow scheduling on HPC platforms," *Tehnički Glasnik*, vol. 15, no. 1, pp. 60–68, 2021.

[7] K. Patil, K. De Turck, and D. Fiems, "A two-queue model for optimizing the value of information in energy-harvesting sensor networks," *Performance Evaluation*, vol. 119, no. 03, pp. 27–42, 2018.

[8] P. Rajpoot and P. Dwivedi, "Optimized and load balanced clustering for WSNs to increase the lifetime of WSN using MADM approaches," *Wireless Networks*, vol. 26, no. 1, pp. 215–251, 2020.

[9] G. Yogarajan and T. Revathi, "Nature inspired discrete firefly algorithm for optimal mobile data gathering in WSNs," *Wireless Networks*, vol. 24, no. 4, pp. 2993–3007, 2018.

[10] S. Basak and T. Acharya, "Spectrum-aware outage minimizing cooperative routing in cognitive radio sensor networks," *Wireless Networks*, vol. 26, no. 1, pp. 1069–1084, 2020.

[11] M. Kaur, S. Kadam, and N. Hannoon, "Multi-level parallel scheduling of dependent-tasks using graph-partitioning and hybrid approaches over edge-cloud," *Soft Computing*, vol. 26, no. 4, https://doi.org/10.1007/s00500-022-07048-1, 2022.

[12] A. Gumusalan, R. Simon, and H. A. Aydin, "Dynamic modulation scaling enabled multi-hop topology control for time critical WSNs," *Wireless Networks*, vol. 26, no. 3, pp. 35–49, 2020.

[13] A. Jadhav, M. Kaur, and F. Akter, "Evolution of software development effort and cost estimation techniques: five decades study using automated text mining approach," *Mathematical Problems in Engineering*, vol. 202211 pages, 2022, https://doi.org/10.1155/2022/5782587, Article ID 5782587.

[14] M. Kaur, A. Jadhav, and F. Akter, "Resource Selection from Edge-Cloud for IIoT and Blockchain-Based Applications in Industry 4.0/5.0," *Security and Communication Networks*, vol. 2022, Article ID 9314052, 13 pages, 2022, https://doi.org/10.1155/2022/9314052.

[15] W. Zhang and M. Kaur, "A novel QACS automatic extraction algorithm for extracting information in blockchain-based systems," *IETE Journal of Research*, 2022.

[16] R. Kumar and T. Amgoth, "Adaptive cluster-based relay-node placement for disjoint WSNs," *Wireless Networks*, vol. 26, pp. 651–666, 2020.

[17] J. Xu and C. Song, Y. D. Zhang, S. H. Wang, and S. Liu, Design and improvement of optimal control model for WSN nodes," in *Multimedia Technology and Enhanced Learning. ICMTEL 2020. Lect. Notes of the Inst. For Comp. Sci, Social Info. and*

*Telecom. Engineering*vol. 327, Berlin, Germany, Springer, 2020.

[18] K. Jaiswal and V. Anand, “A QoS aware optimal node deployment in WSN using Grey wolf optimization approach for IoT applications,” *Telecommunication Systems*, vol. 78, no. 4, pp. 559–576, 2021.

[19] A. Haber, S. A. Nugroho, P. Torres, and A. F. Taha, “Control node selection algorithm for nonlinear dynamic networks,” *IEEE Control Sys Letters*, vol. 5, no. 4, pp. 1195–1200, 2021.

[20] T. Zhang, L. Chen, and F. Ma, “A modified rough CCA based on hybrid imbalanced measure of distance and density,” *International Journal of Approximate Reasoning*, vol. 55, no. 8, 2014.

[21] G. Wang, J. S. Wang, and H. Y. Wang, “Fuzzy C-mens clustering validity function based on multiple clustering performance evaluation components,” *International Journal of Fuzzy Systems*, vol. 24, 2022, https://doi.org/10.1007/s40815-021-01243-2.