Received March 7, 2018, accepted April 1, 2018, date of publication April 6, 2018, date of current version May 2, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2824245

Polar Coordinate-Based Energy-Efficient-Chain Routing in Wireless Sensor Networks Using Random Projection

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This work was supported in part by the Natural Science Foundation Project of Shanxi Province, China, under Grant 2013011019-1.

ABSTRACT Random projection based on compressed sensing can reduce the amount of data transmitted in a wireless sensor network (WSN), and efficient routing can reduce the network traffic. Thus, this paper presents a Random projection-Polar coordinate-Chain routing (RPC) method. The method uses polar coordinates to locate nodes, establishes a chain structure to form a route, and applies random projection to achieve the compressed data collection. In a WSN, the sink is the center of the data collection. With the sink as the pole, the polar coordinates can be used to determine the orientation of each node relative to the sink so that nodes can be searched under certain conditions. By adopting the chain topological structure, the establishment of the chain through the greedy algorithm reduces the energy consumption and complexity. Based on the comparative analysis, a four-quadrant chain routing method combining the polar radius and polar angle is proposed for smaller networks. For large-scale networks, a routing algorithm combining the sector and inner circle is proposed. Then, according to the random projection theory, the weighted sum of the random projections of each row of the corresponding measurement matrix in each partition is transmitted to the sink. The sink has collected all measurements of each partition to complete the signal reconstruction. In this method, the route is formed by searching in the zones according to the polar radius and the polar angle, which avoids the roundabout route between distant nodes and reduces the energy consumption of the network. By comparing the RPC method with other related methods and the simulation experiments for different types of routing, the proposed method is proved to be time and energy efficient.

INDEX TERMS Chain, compressed sensing (CS), polar coordinates, random projection, routing, wireless sensor networks (WSN).

I. INTRODUCTION

A Wireless Sensor Network (WSN) consists of a large number of nodes with limited energy supply, storage, computing resources, and communication capabilities. The collected data have spatiotemporal correlations, simple terminal functions, and strong performance of sink nodes. Compressed Sensing (CS) theory combines sampling and compression, which is in line with the characteristics of WSN. Compression Data Gathering (CDG) for WSNs based on CS can convert N samples to collect M ($M << N$) weighted sums of local samples. It has good data compression performance, and it also effectively reduces the amount of data transmitted in the network. Since communication energy consumption in WSNs is much higher than other aspects of energy consumption, how to reduce the traffic is an important issue in WSNs.

CS-based WSN data collection has played a positive role in energy savings of the network. On the one hand, WSN energy consumption is reduced by reducing the amount of data. The application of CS theory to data collection in WSNs can recover the original signal with a small amount of measurement, thus reducing the amount of data transmitted by the network and reducing the system's energy consumption. Therefore, since Bajwa and Haupt et al. applied CS theory to the data collection in WSNs in 2006 [1], it has become a hot research topic. A large volume of literature has studied the application of CS in WSNs from the perspective of energy efficiency [2]–[6].

On the other hand, WSN energy consumption is reduced by sparse random projection. The amount of data to be transmitted in a CS-based WSN is determined by the measurement matrix. For dense Gaussian random matrices, each sensor node transmits M weighted sums. However, most of the elements in the sparse random projection matrix are 0. Thus, the corresponding nodes do not have to transmit data, which greatly reduces the traffic. Therefore, data collection based on sparse random projections becomes an option to reduce energy consumption.

Haupt and Nowak first showed that the relatively small number of random projections of a signal can contain most of its significant information. Therefore, if a signal is compressible on some orthonormal basis, the reconstruction from random projections can be very accurate [7]. Moreover, this ‘‘compressive sampling’’ method can accurately recover from random projections of noise pollution. In many cases, it may be more accurate than using the conventional method of sampling the same number of points, and it can be effectively applied to remote wireless sensor networks [8].

MSTP [9] is the minimum spanning tree proposed in compressed data collection using random projections. That is, the MSTP selects the projection node first, and then it transmits the weighted sum of the non-zero nodes of each row in the measurement matrix to the projection node through the tree route. The projection node then transmits the weight sum to the sink. In the improved MSTP method proposed in this paper, the sink is used as the root node, and thus, the weighted sum can be directly transmitted to the sink. However, the sink as the projection node of all clusters greatly increases the energy consumption of the sink and becomes the bottleneck of the system.

In addition, choosing a suitable routing topology reduces the WSN's power consumption. The application of CS in WSN data collection cannot be separated from the routing structure of the network. The energy consumed by different paths from the sensor node to the sink is different. How to build an energy-efficient topology and routing mechanism in CS applications is an important issue.

Reference [10] showed that finding the best routing path and minimizing the data flow is an NP-complete problem. This paper presents a distributed algorithm that uses the local minima to dynamically construct routes to reduce the flow of data in CS-based aggregations. The algorithm does not need to know the global network's topological knowledge, and it has less overhead than the nearest optimal solution. Therefore, it is more suitable for practical applications.

PEGASIS is a type of chain structure with less energy consumption in hierarchical routing [11]. Starting with the node farthest away from the sink, PEGASIS chooses the next node according to a greedy algorithm. It searches gradually to form a chain, and then randomly selects a node in the chain as a cluster head. The aggregated data are sent to the Sink. However, since all of the nodes in the network form a chain, the delay is large and the cluster heads are randomly selected, which also increases the network's uncertainty and unbalanced energy consumption.

GEM is a routing structure of graph embedding using virtual polar coordinates [12] that determines the radius of each node according to the number of hops in establishing the tree structure. The polar angle is assigned by the network in the range of $0\sim2^{16}-1$ or $0\sim2^{32}-1$. The data of the node must be transmitted within a certain angle range according to the tree path. Once a route is established, it needs to be kept as much as possible. Otherwise, the costs of changing the structure are huge, and thus, it is suitable for a WSN network in a stable state.

Data collection combining the CS and cluster structures has proven to be an effective way to reduce WSN energy consumption [13]. The idea is that the WSN is divided into several clusters, and the intra-cluster sensor readings collected by each cluster head form a CS measurement value that is sent to the sink or the base station. The tree structure is also a typical WSN routing structure, and the most commonly used is the minimum spanning tree. The entire network takes the sink node as the root node and the sensor node as the leaf node in order to construct an aggregation tree [14], [15].

Random Walk (RW) has been effectively used for data collection in wireless sensor networks [16], [17]. It does not require global information to form the shortest path route and achieves network load balancing. The literature shows the effectiveness of this scheme in signal reconstruction and reducing the routing energy consumption. However, [16] only selects routes in the upper left direction, and thus, the route is too singular. Because sparse random projection has proven to be as effective as a dense Gaussian matrix, the combination of RW and CS becomes a powerful routing method that helps to save energy and extend network life effectively [18]. Fletcher [19] also introduces RW into WSNs based on distributed compression sensing, which proves that RW performs better than shortest path routing.

Literature [20] used the integration of CS and RW to reduce network energy consumption. Each CS measurement is collected by RW routing with a predetermined length. All sensing data are reconstructed by applying a small amount of CS measurements at the base station (BS). This paper studied the trade-off between sensor transmission range and RW length to achieve the minimum energy consumption, and it further developed the average energy consumption per random walk according to the sensor transmission range. The average energy consumed to send measurements from the RW to the BS (either directly or via the multi-hop relay mode) is developed and analyzed, and the total energy consumption under different conditions is acquired. However, the obtained conclusions are based on experiments and have not been effectively proved.

Reference [21] proposed a random walk algorithm for data acquisition in wireless sensor networks. From the perspective of CS theory and graph theory, it provides a mathematical basis for random measurements to be collected in a random walk. The simulation results show that the proposed scheme can significantly reduce communication costs compared with the traditional scheme that uses dense random projections and sparse random projections.

Moreover, CS combines artificial intelligence optimization methods for WSN data acquisition [22]–[23]. As CS-based WSN data collection continues to evolve, its applications are also becoming more widespread. In addition to the application of military and harsh environmental parameter detection, WSNs are also used in modern life, such as agricultural management, smart homes, traffic automation, and so on [24]–[28].

According to the CS theory, collecting a small amount of weighted measurements can reduce the amount of data transmitted by the WSN. Using sparse random projection further reduces the amount of data. However, the sparse random projection is derived from the nonzero coefficients of the measurement matrix, and the data collection and routing are closely related. How to realize the energy-efficient projection process and how to choose an effective and simple routing structure are still urgent problems to be solved for CS applications.

The center of WSN data acquisition is the sink. In order to find a simple and quick path and reduce the system power consumption, this paper locates the sensor nodes using polar coordinates, which can determine the distance and azimuth from the sensor nodes to the sink to facilitate clustering and routing. The sparse random projection is used to determine the sensing nodes and reduce the amount of data to be transmitted. Since the sparse random projection matrix has a small number of non-zero coefficients and since the data only need to be transmitted among non-zero nodes, a chained structure is adopted. The nodes that satisfy the condition are directly formed into the transmission path, and the weighted data are transmitted to the sink. Furthermore, according to the theory of RW and the number of measured values of CS, multiple chains can be formed. Since the method involves the three aspects of Random projection-Polar coordinate-Chain routing (RPC), it is called the RPC method for short.

The rest of this paper is organized as follows. Section II briefly introduces the basic theory of CS and the problem's formulation. Section III describes the establishment of polar coordinates. Section IV illustrates the formation of simple chains. Section V conducts a performance evaluation of the proposed method. Section VI presents the building of complex chain and discusses the dynamic problem of chain routing. Section VII gives the conclusion.

II. BACKGROUND AND PROBLEM FORMULATION

A. COMPRESSED SENSING THEORY

Compressed sensing [29] (or compressive sensing [30], CS) theory states that for sparse or compressible signals, the data can be sampled much below the Nyquist sampling frequency and then perfectly reconstructed by a nonlinear reconstruction algorithm [31]. The N-dimensional signal x can be represented under an N×N dimension sparse transformation matrix Ψ as:

$$x = \Psi\theta \tag{1}$$

where θ is a k-sparse N×1 column vector with K sparser. That is, there are only K non-zero terms in θ, and K≪N. Then, x is projected on an M × N dimensional measurement matrix Φ (called a projection matrix or observation matrix) to obtain M observation values y, and M≪ N. That is,

$$y = \Phi x = \Phi\Psi\theta = T\theta \tag{2}$$

where T is called the sensing matrix and y is the M × 1 column vector, which is the measurement.

Compressive sensing theory states that the sufficient condition for the existence of the definite solution in (2) is that T satisfies the Restricted Isometry Property (RIP) [32]. That is, $\delta \in (0, 1)$ exists such that all k-sparse signals θ satisfy

$$(1-\delta)||\theta||_2^2 \le ||T\theta||_2^2 \le (1+\delta)||\theta||_2^2. \tag{3}$$

The reconstruction signal $\hat{\theta}$ can be obtained by solving the following convex optimization problem [26], [27].

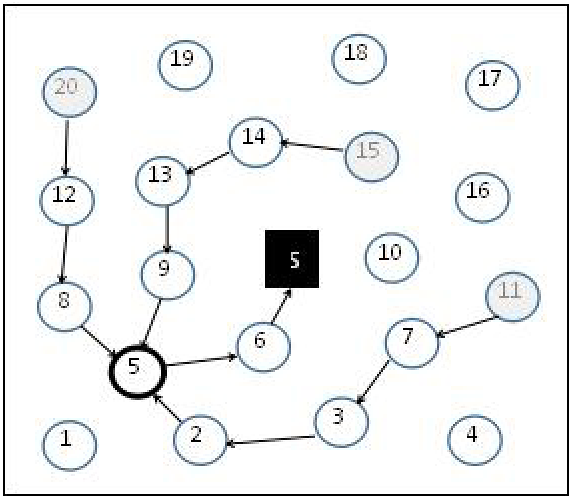
$$\hat{\theta} = \arg\min ||\theta||_1 \text{ or } \hat{\theta} = \arg\min ||\theta||_0 \\ \text{s.t } y = T\theta. \tag{4}$$

The above equation can be solved by using methods such as Basis Pursuit (BP) or greedy algorithms to reconstruct the original signal $\hat{x}$.

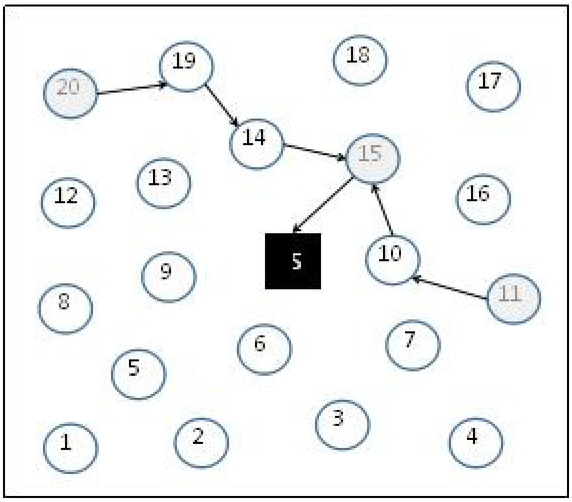
B. PROBLEM FORMULATION

It is assumed that N wireless sensor nodes are randomly deployed in a monitoring area. Each node is equipped with sensors that can collect the required parameters, obtain the measurements x_j, and ultimately send it to sink nodes or base stations. Therefore, the sink needs a total of N data vectors ($x = [x_1, x_2, \ldots, x_N]^T$) from all the nodes in the network. Each node can send the data to its neighbors within its communication radius, and since not all nodes are hop-to-hop with the sink, most of them must forward their readings to their destinations over multi-hop routes. However, according to CS theory, the sink only needs to collect M (M=O(klogN/k)) weighted measurements. In this paper, a method based on the M×N sparse random projection matrix is adopted, and there is only one non-zero value in each column of the measurement matrix. Therefore, each node can transmit at the same time without waiting for the time slot. All nodes of each row in the measurement matrix corresponding to non-zero elements are taken as a group (cluster). Each non-zero node weights and transmits the collected data, and it finally reaches the sink node to obtain M measurement values.

The above problem can be expressed as follows. Consider a given undirected graph G (V, E), its vertex set is V, and the edge set is E. The non-zero coefficients in each row of the measurement matrix Φ are projected onto the corresponding vertices and then form a chain that sends the weighted sum of the corresponding vertices through the chain to the sink. For example, for the same measurement matrix, the process



(a)



(b)

FIGURE 1. **Comparison of the MSTP data collection methods in [9] and the RPC data collection methods presented in this paper. (a) MSTP compressed data collection method [9]. (b) RPC data collection method proposed in this paper.**

of projection measurement is shown in (1). Fig. 1 shows the comparison between the MSTP data collection method in [9] and the data collection method proposed in this paper. The MSTP collection method shown in Fig. 1(a) is as follows. For each row of the measurement matrix, a projection node is randomly generated. The projection node is taken as the root node, the node corresponding to the non-zero coefficient of the row is a leaf node, and a tree route is formed. Then, the root node collects the weighted sum of the leaf nodes and sends it to the sink.

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{20} \end{bmatrix} = \begin{bmatrix} 0 \cdots 0 \ \Phi_{11} \ 0 \cdots 0 \ \Phi_{15} \ 0 \cdots 0 \ \Phi_{20} \\ \\ \\ \\ \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{20} \end{bmatrix} \tag{5}$$

In Fig. 1(a), S is the sink node, node 5 is a projection node, and nodes 11, 15 and 20 are nodes corresponding to non-zero coefficients. Here, by using 5 as the root node and 11, 15 and 20 as the leaf nodes, the tree route is established to transmit the weighted data. Projection node 5 sends requests to 11, 15 and 20, which reply to the request, send weighted data to node 5, and node 5 computes the sum of the received weighted data and sends it to the sink. Fig. 1(b) shows the method in this paper. Nodes 11, 15 and 20 corresponding to non-zero coefficients are connected as a chain. The weighted data of non-zero nodes are transmitted along the chain from the two ends of the chain to the sink. The node closest to the sink sends the weights' sum directly to the sink. The two methods transmit the same amount of data. The number of hops in [9] shown in Fig. 1(a) is 4 for Node 11 to Projection Node 5, 4 for Node 15 to 5, and 3 for Node 20 to 5 for a total of 11 steps. It takes 2 steps for the projection node 5 to the sink, and the total transmission distance is 13 steps. The method in this paper is the number of hops in Fig. 1(b). It can be seen that the chain routing only needs 5 steps, and it then adds one hop to the sink for a total of 6 steps. This method does not need to generate projection nodes, the routing is simpler, and the transmission path is short, which is obviously a more efficient compressed data collection scheme.

III. POLAR COORDINATES SPACE

A. THE ESTABLISHMENT OF POLAR COORDINATES

In order to clarify the distance and azimuth of each node from the sink, this paper uses a combination of distance and angle to establish the polar coordinate system and determine the position of the node using the polar coordinates. With the sink set as a pole, each sensor node is expressed as (r, α) that represents the polar radius and polar angle. Corresponding to the spatial region, the node distribution can be regarded as a sphere network and the sink as the sphere center. For the convenience of explanation, this paper describes the state of the nodes using a planar diagram.

Suppose that 50 nodes are randomly deployed in a range of 50 m $\times$ 50 m (as shown in Fig. 2), and the central star is the sink. Now, it is placed on the polar coordinate system as shown in Fig. 3, and the sink is the pole as shown in Fig. 4.

Different colors or shapes are used to distinguish nodes in different groups (clusters), assuming that the nodes in different rows of the measurement matrix correspond to non-zero coefficients. The central star represents the sink. According to the system model, there is only one non-zero element in each column of the measurement matrix. Therefore, each group of nodes will not be the same. Now, 50 nodes are divided into 5 groups, and each group contains 10 nodes.

B. POLAR COORDINATE-BASED CHAIN ROUTING

In [12], by using the method of virtual polar coordinates, the radius value is obtained through the formation of a tree. From the root node, the child nodes are searched step by step. Then, 0, 1, ... are used to determine the number of stages so that each

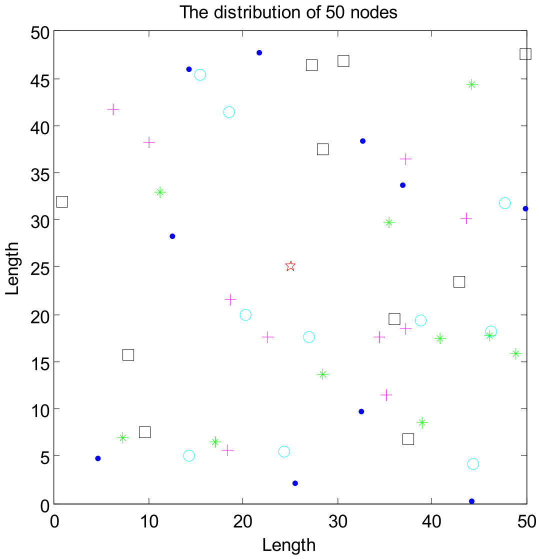


FIGURE 2. 50 nodes in Cartesian Coordinate Space.

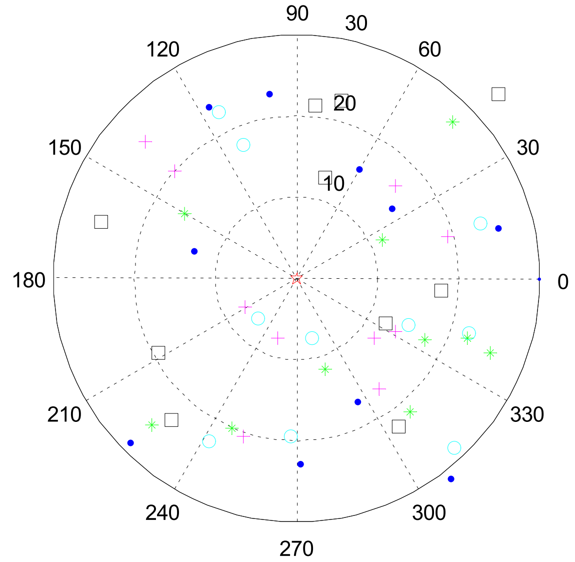


FIGURE 4. Nodes in polar coordinates space with the sink as the pole.

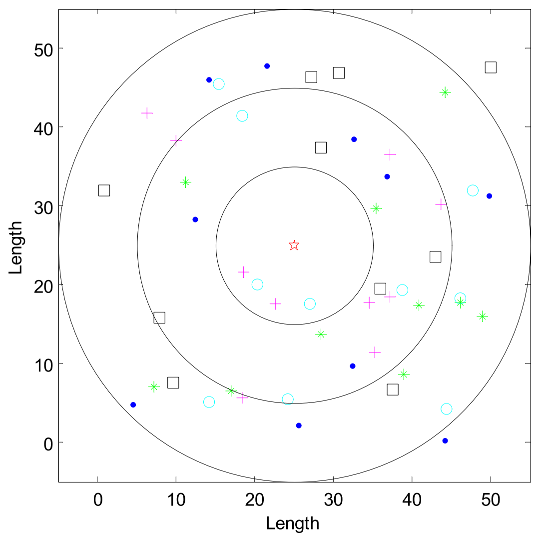


FIGURE 3. 50 nodes in polar coordinate space.

node knows its own parent node, child node and hop count to the sink (namely, the radius). Moreover, each parent node needs to know the size of all its subtrees (that is, determine the feedback size of the sub-tree). The virtual angle is assigned an angular range by the base station or the sink to each child and is proportional to the size of the sub-tree. Obviously, this process of determining radii and angles is complicated. The length of the radius determined by the number of hops is not uniform and takes up a significant amount of overhead. Furthermore, in the transmission process, the destination node can only be found through the tree route.

Since the number of non-zero nodes in the random projection is not very large, this paper adopts the chain structure. Non-zero nodes in each row of the measurement matrix act as a group (cluster). The chain starts from the farthest node in a group and is constructed using a greedy algorithm. Whenever a node meets the conditions within the communication radius, as long as the nodes that meet the conditions are detected, the weighted sum of the readings is passed to it. If you search from far to near according to the radius, the nodes that join the chain get closer to the sink. The last node in the chain is equivalent to the cluster head, and the data can be transmitted to the sink in one step. Thus, the cluster head does not need to consume extra energy. The closer it is to the sink, the less power that is required to transmit the weighted sum to the sink, and the lower the energy consumption. In this way, the energy consumption of all nodes is lower and balanced. As in Fig. 1(b), because the sink is at the center of the network, the chain structure begins at the farthest nodes of 20 and 11, converges towards the center, connects to the intermediate node 15, uses it as a cluster head, and sends the weighting sum with one hop to sink.

In the next time slot, another group of nodes also start transmitting from the farthest node and still reach the Sink after gradually detecting it. After M times the weighted sum transmission, M measurements can be obtained in the Sink, which can reconstruct the signal. If there is only one non-zero value in each column of the measurement matrix set by the system model, the weighted sum of M groups can be concurrently transmitted. Each group of nodes is numbered separately, and the weighted sum of the collected data of all nodes of the same number is a measured value. In the illustration, different numbered nodes are represented by different shapes.

IV. SIMPLE CHAIN ROUTE

A. THE BUILDING OF A SIMPLE CHAIN ROUTE

Here are two ways to build a chain. One way is to search by the radius from far to near, and the other way is to search by the angle either clockwise or counterclockwise. For the entire monitoring area within the communication radius, the chain is established by the following steps.

1) Assign each node a unique polar angle α and polar radius r. The polar angle range is $0 \sim 2\pi$, but each node has a certain radius of communication. In order to save storage space, it only needs to take up a unit of storage space, expressed as $0 \sim 2^8$-1. The radius range is 0 to the maximum radius of the node. An identifier is assigned to the nodes corresponding to each non-zero value in the measurement matrix. That is, a group of nodes has an identifier.

2) According to some search rules, determine the head node of the chain. For a search by radius starting with the farthest node and for a search by angle starting at 0°, this node is the head node of the chain.

3) From the head node of the chain, create a chain. Within the transmission power radius of the head node of the chain, the node satisfying the same identifier is detected as the next node of the chain and added to the chain. In turn, the search continues to add the next node into the chain until it reaches the node closest to the sink, which is the tail node of the chain.

4) In the process of data collection, each node in the chain (starting from the head node of the chain) forwards the weighted value of the collected data to the next node. The next node calculates the weighted value of the data collected by itself and the data from the previous node and sends it to the next node. In this way, the weighted sum of the nodes in the group is sent to the tail node of the chain. The tail node sends the data to the sink or base station by one hop.

B. CHAIN SEARCH BY POLAR RADIUS

The chain searched by the radius starts from the farthest node and propagates along the node whose radius is gradually shortened. In the example of the nodal distribution in Fig. 2, the chains of two groups of nodes using the radius search method are shown in Fig. 5. Starting from the farthest node, the chains are sequentially formed according to their radii. The weighted sum collected at the tail of the chain is sent to the sink. The dashed red line shows the last hop from the tail node of the chain to the sink.

Fig. 5 shows two illustrations of two groups of nodes that are forming two chains of networks that were given in Fig. 4. By setting the sink as the pole and starting from the farthest node from the sink, the chain is built according to the polar radius from far to near point by point, which is called the unidirectional chain. The nodes that are joined later are closer to the sink. The tail node of the chain is the node closest to the sink. The weighted sum is passed to the sink by one hop, and the last hop is indicated by a dotted line. As can be seen from the figure, according to the unidirectional chain formed by the polar path, the node span is relatively large, and the transmission energy consumption is also large.

Therefore, consider forming a chain from two ends and separating the two ends from 0° with one searching clockwise and the other searching counterclockwise, which is called a bidirectional chain. At a polar angle of 180°, the two ends of the chain meet. Then, one of the nodes near the sink is set as the cluster head. The weighted sum is transferred to the sink, which is still the last hop indicated by the dotted line.

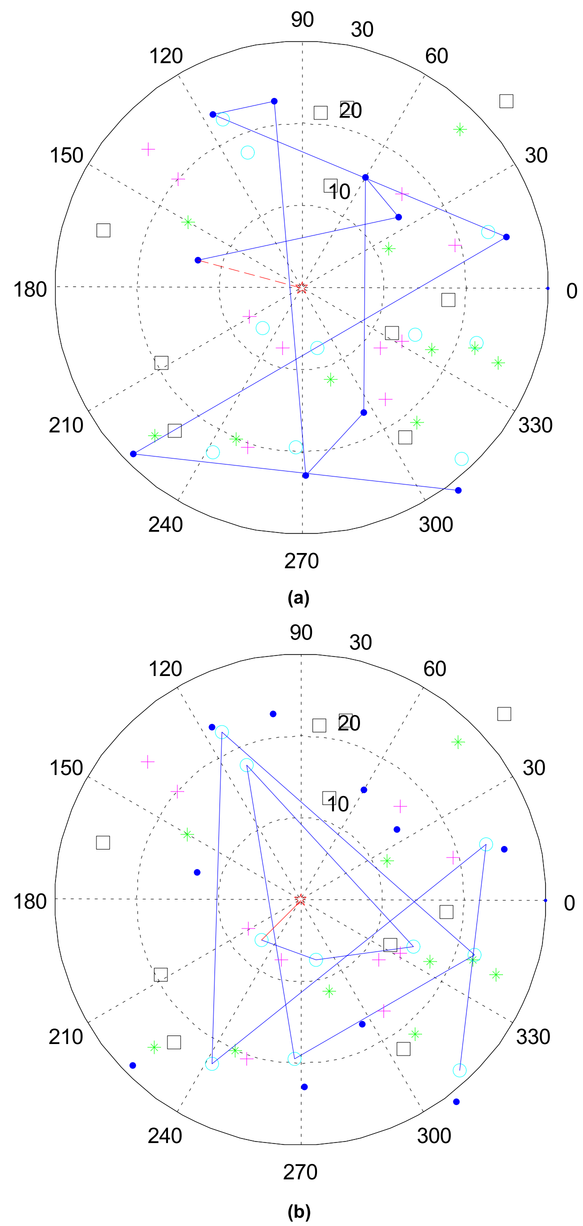


FIGURE 5. Schematic diagram of chain routing for two groups of nodes (single directional chain). (a) I TGroup. (b) II U Group

Fig. 6 shows the bidirectional chain formed by the two sets of nodes in the network. From Fig. 6 and Fig. 5, it is clear that the path of the bidirectional chain in Fig. 6 is shorter than that of the unidirectional chain in Fig. 5. However, some paths are still circuitous, so the introduction of the polar angle and clustering will continue to shorten the transmission distance.

C. CHAIN SEARCH BY POLAR ANGLE

Search the chain using the polar angle, starting from 0°. Search in a clockwise or counterclockwise direction in the corresponding group by using the polar angle to form a chain. After searching the $0 \sim 2\pi$ range, the last node is the tail node of the chain, and the weighted sum is sent to the sink

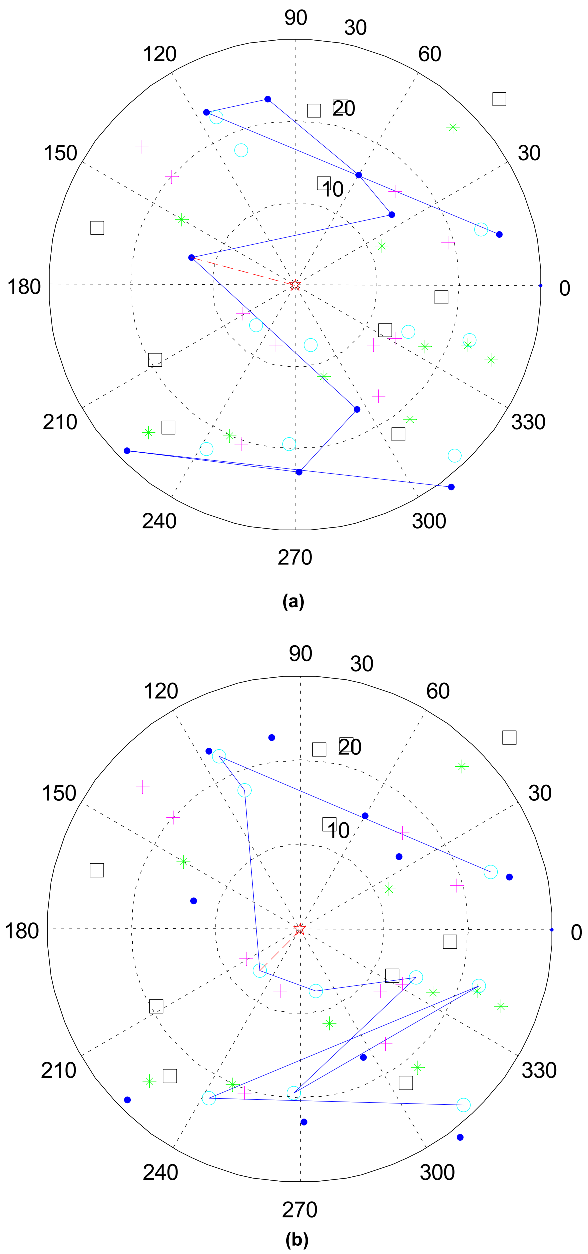


FIGURE 6. **Chain routing diagram of two groups of nodes (bidirectional chain). (a) I TGroup. (b) II U Group.**

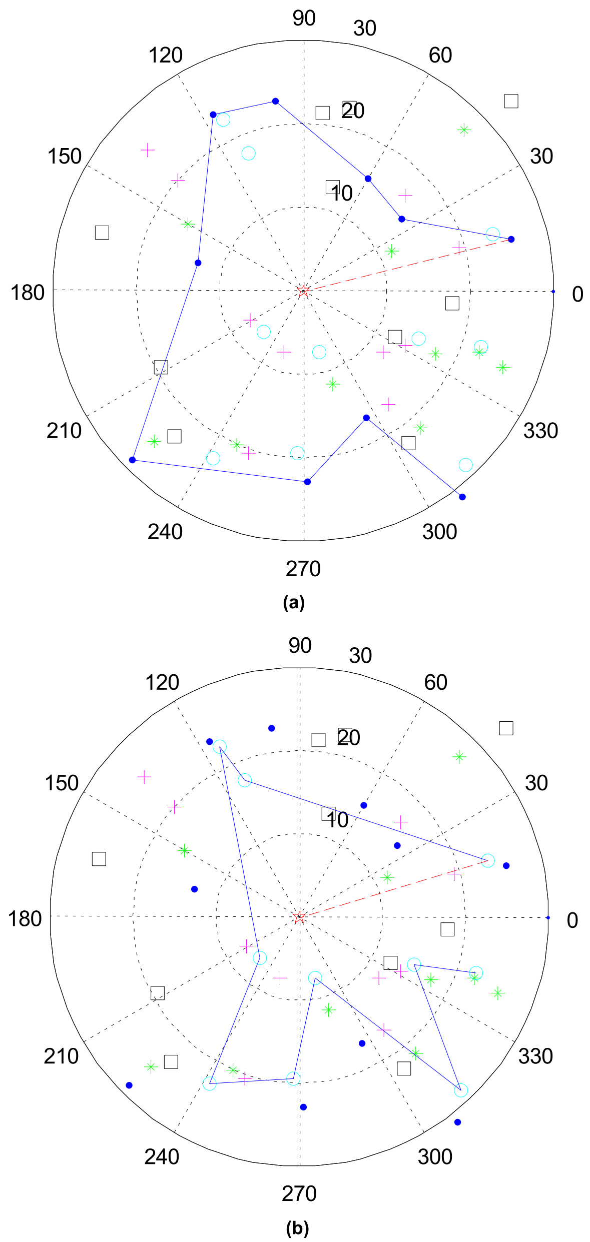


FIGURE 7. **Chain routing based on polar angles. (a) I TGroup. (b) II UGroup.**

by one hop. Fig. 7 shows the two sets of nodes forming bidirectional chains by polar angles, with the search starting at 0°clockwise and the dotted line representing the last hop from the tail node of the chain to the sink. As can be seen from the figure, the circuitous route of this method is shorter and saves energy. The disadvantage is that the end of the chain may be far away from the sink. As a result, the node that sends the weighted sum consumes more energy by either increasing the power to send or transmitting the sink by multi-hop. If the radius of the network is large, the path of this method will also turn sharply back and forth. Therefore, this method is not suitable for large-scale networks, and we need to consider a more appropriate approach.

In order to select a node closer to the sink as the tail node of the chain, we need to consider the polar radius and polar angle. Then, the weighted data are forwarded towards the sink from both ends. That is, within the radius of the transmission power of the node, the nodes of the same identifier can all be transmitted according to the nearest principle, thus avoiding the path turning back and forth, reducing the transmission distance, reducing the power consumption, and prolonging the lifetime of the network.

D. CHAIN ROUTE BY FOUR QUADRANTS

In order to get the path and energy consumption's optimal routing structure, it must be measured synthetically. In this paper, considering the joint effects of the polar radius, polar angle and clustering, the polar radius determines the extension direction of the chain and the final choice of the tail node of the chain. The polar angle reduces the twists and turns of the route, and clustering can further reduce the roundabout of the route. Therefore, the whole network can be directly divided into four clusters according to four quadrants. Each cluster starts from the farthest node as the head node of the chain, and it selects the next node of the chain according to the greedy algorithm in order to gradually form a chain. The last node of the chain sends the collected weighted sum to the sink by the last hop. Thus, it avoids the pre-selection of cluster heads, and the chain is formed once to minimize the power consumption. The routing effect based on this method is shown in Fig. 8.

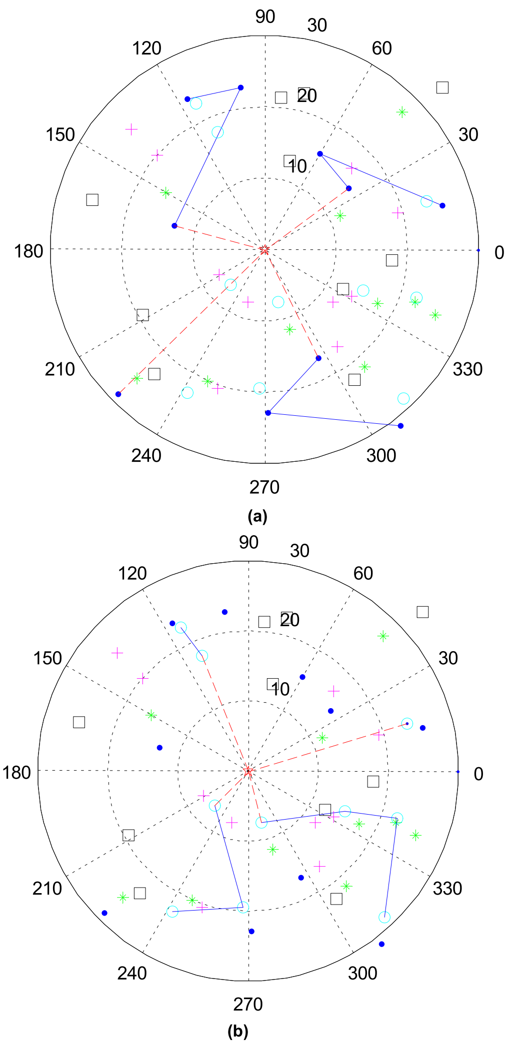


FIGURE 8. Schematic diagram of the four-quadrant chain routing. (a) I Group. (b) II UGroup.

Fig. 8 shows the network in Section II. The two groups of nodes are distributed in four quadrants. Each quadrant is distinguished by different ranges of polar angles. Therefore, within a quadrant, it can be searched according to the polar radius. Each quadrant searches by the polar radius to form a chain, and the tail node of the chain transmits the collected weighted sum to the sink by one hop. After the chain of each quadrant sends the data to the sink, the sink sums up the weighted sums of the same identifier and gets a measurement. When the sink gets the weighted sum of each group, it can be reconstructed.

Fig. 8(a) and Fig. 8(b) are four-quadrant routing diagrams formed by the previous two groups of nodes, respectively. As can be seen from the figure, the route is less circuitous, and the tail node of the chain is the node closest to the sink. Although the route of individual nodes is not optimal, the complexity and power consumption of the algorithm will be increased if the selection is increased. Therefore, this method is a simple and efficient energy-saving comprehensive scheme choice.

V. IMPROVED CHAIN ROUTE

If the monitoring area is large, the route search in Section IV cannot reach the target node in one step, which needs to be forwarded through the relay node. Therefore, the energy consumption and complexity of the network will greatly increase. This section gives the general route building method.

A. 'SECTOR-INNER CIRCLE' ROUTE

Suppose that 200 nodes are randomly deployed in a range of 200 m×200 m, and the communication radius R of the node is set to 50 m. As a result, you cannot use the one-step search method to find the next node and can only accomplish this within the radius of the communication point by point. Within the communication radius, according to the analysis in Section V, the route by the polar angle and the four-quadrant are better than the unidirectional chains and bidirectional chains by the polar radius. However, for the set scenario, each quadrant is still not within the direct communication radius. Therefore, the routing method based on the four quadrants and polar angles is improved by dividing the outermost circumference of the monitoring area by the communication radius. In the vicinity of the pole, the radius decreases. When the radius is smaller than the communication radius R, the node entering this radius can hop to the sink by one step. Therefore, by taking the pole as the center, the radius of the communication radius R is drawn as a circle. Within this circle, it can be searched according to the chain by the polar angle. Finally, the weighted sum of the collected data of the nodes with the same identifier is transmitted to the sink by one hop.

Fig. 9 shows a schematic diagram of building an improved chain route. Since the monitoring area is 200 m×200 m, the sink is located at the center as a pole, and thus, a polar coordinate is established at a radius of 100 m. Since the communication radius is 50 m, the circle is divided by a circle with a diameter of 100 m. By using the line from the intersection of the outer circumference and the small circle to the pole as the dividing line, the monitoring area is divided into different sectors. Then, make an inner circle at the center

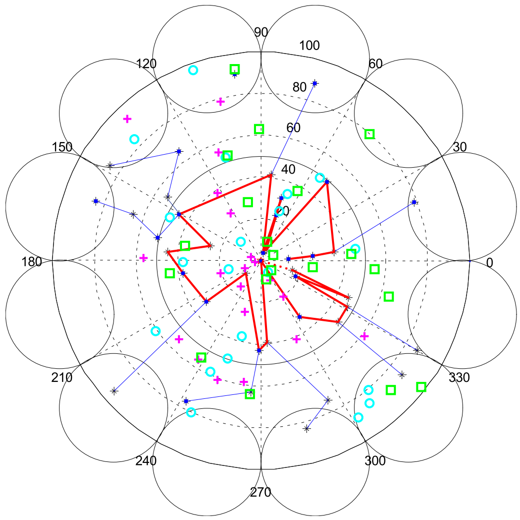


FIGURE 9. Schematic diagram of the improved chain route.

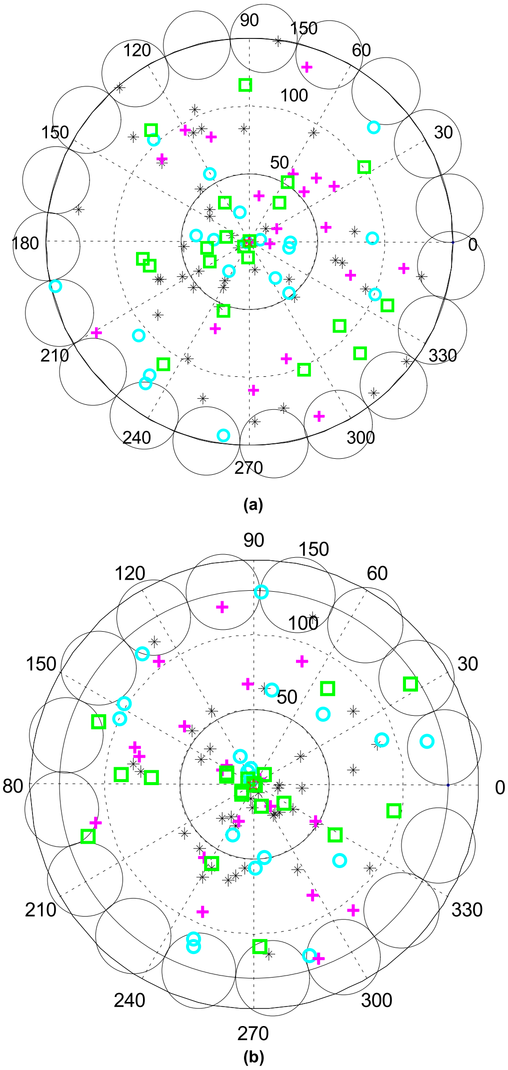


FIGURE 10. Sectors in monitoring areas of different sizes. (a) R = 150 m, Count = 19. (b) R = 130 m, Count = 16.

of the pole with a radius of 100 m. The set area is thus divided into 12 sectors. The chain of each sector is searched by the polar radius from the farthest node, and when the polar radius is less than 100 m, it enters the inner circle. After each sector's weighted sum is delivered to the inner circle, it searches using the polar angles to form a chain, and then the tail node sends the weighted sum of all nodes of the same identifier to the sink. There are 40 non-zero coefficients in the row of the measurement matrix shown in Fig. 9, which correspond to 40 nodes of the same identifier.

If the nodes in some sectors have a large polar radius and cannot search the next node by one hop within the communication radius, it is necessary to find a relay node to do only the data forwarding until the node with the same identifier is found or the inner circle is entered. The relay node should also be identified in order to completely transmit the data.

If the area's circumference cannot be exactly partitioned by a small circle whose diameter is exactly the communication radius, the small sector with less than one communication radius is either merged into the adjacent sector or the remaining part is divided into a single smaller sector.

Let the monitoring area be a circle with a radius of R and the communication radius of the sensor node be D. Due to the large radius of the monitoring area, the length of a circular arc on the circumference can be regarded as a straight line. The center of the circle is on the circumference of the area, the radius of the circle is D/2, and the angle of the sector corresponding to the circle is α. On the circumference, Count circles can be made based on the number of sectors. Then,

$$\frac{2\pi R}{2\pi} = \frac{D}{\alpha} \tag{6}$$

$$\alpha = \frac{D}{R} \tag{7}$$

$$Count = \frac{2\pi}{\alpha} = \frac{2\pi R}{D} \tag{8}$$

For Count rounding, if there is less than one communication radius after making an integer number of small circles on the circumference, the part will be classified into the adjacent sectors if the arc of the remaining part is less than D/2. If the remaining part of the arcs is greater than D/2, it is individually zoned as a small sector. The sector division is shown in Fig. 10, where R=150 m in Fig. 10(a) and R=130 m in Fig. 10(b).

B. DYNAMIC ROUTING PROBLEM

During the network running, the network will dynamically change due to the death of a node or the joining of a new node and the randomness of each group of nodes. For the chain structure used in this paper, regardless of the type of change, the establishment of the routing is very simple and convenient.

When a new node is joined, it is always detected as long as it is within the radius of the communication, and then it can be directly transmitted without any predesign. As shown

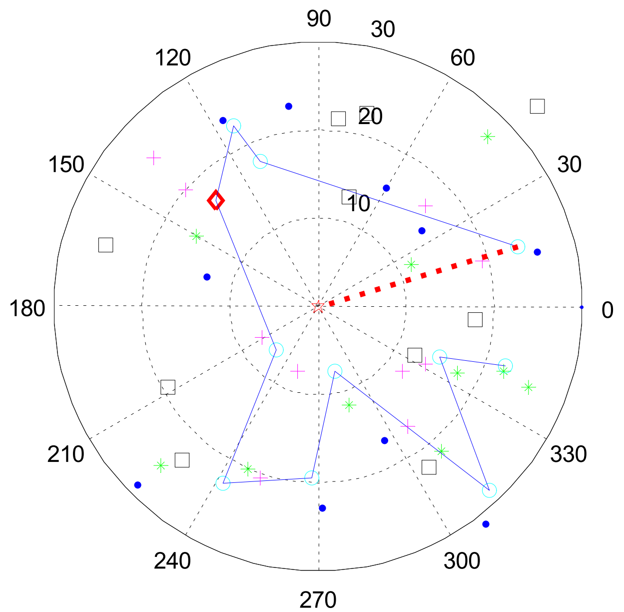


FIGURE 11. The new node joined into a chain.

in Fig. 11, a diamond node is a newly added node. When a chain is formed, it is naturally added to the chain according to the greedy algorithm.

When the node dies, it cannot be detected naturally and does not participate in the data transmission. The nodes that transmit data will search for energy-efficient nodes within the radius of the transmission's power without any other burden.

If the current cluster head dies, one can adopt the next node closest to the sink as the cluster head since it is still relatively close to sink and therefore does not consume much energy. If the communication radius is exceeded, it can be forwarded according to the shortest path algorithm through adjacent nodes closer to the sink.

Therefore, compared with the situation where the tree structure leads to the whole body, the topological change in the chain structure is a method that needs to be built immediately with little extra overhead. The only drawback is that there is a delay, but it is very effective for sparse random projections with fewer nodes.

C. SINK OUTSIDE THE MONITORING REGION

The proposed chain routing structure based on polar coordinates has the advantages of fast construction, less energy consumption and more efficient route formation according to the radius and angle, which can select the simplest route. However, the above studies only consider the situation of the sink in the center of the region, and for the case of a sink outside the monitoring area, a two-quadrant routing approach can be used. The sink at the bottom can be clustered in two quadrants, as shown in Fig. 12.

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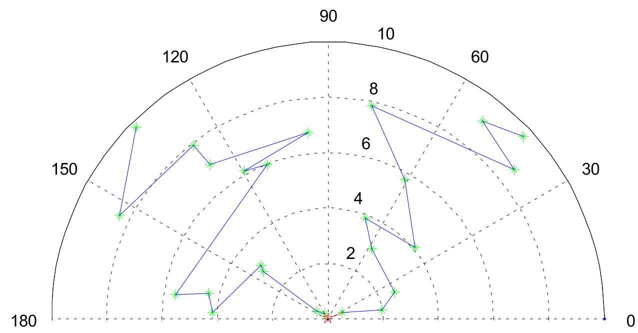

FIGURE 12. Two-quadrant chain routing with the sink on the outside of the network

TABLE 1. Comparison of this method with three other methods.

Method	Positioning	Routing Structure	Dynamic	Delay	Consumption	Disadvantages
MSTP	Each node has location information	Tree	Reconstruction tree structure	Less	Small	Projection node occupies additional resources
PEGASIS	Each node has location information	Chain	Change easily	Long	Small	Only forms a chain, long delay
GEM	Polar coordinate positioning	Tree	Change is expensive	More	More	Tree routing is complex, expensive to change
RPC (this paper's method)	Polar coordinate positioning	Subarea + chain	Change is quick and easy	Less	Small	Suitable for smaller networks

However, the above studies only consider the situation of the sink in the center of the region, and for the case of a sink outside the monitoring area, a two-quadrant routing approach can be used. The sink at the bottom can be clustered in two quadrants, as shown in Fig. 12.

VI. PERFORMANCE EVALUATION

The proposed RPC method in this paper involves three aspects: random projection, polar coordinates and chains. Tab. 1 shows the comparison with MSTP [9], GEM [12] and PEGASIS [11].

In the WSN application, the sensor has the same acquisition process and the same transmission mode. Therefore, the amount of data transmitted and the transmission distance are regarded as the power consumption index of the sensor node. The more data that are transmitted by the sensor node, the longer the transmission distance is, the more energy it consumes, and the faster it disappears.

In this method, because of adopting the chain route, if there is no relay node, the hops of each method are the same, and the difference is only in the transmission distance. Since the sum of squares of distances reflects an index of energy, its performance can be measured from the sum of the squares of the distances traveled by each route in total. The network

TABLE 2. The performance comparison of different types of chain routing.

Routing structure		The sum of the squares of the distances of the chain nodes		
		I Group	II Group	Average (10 groups)
Chain route by polar radius	Unidirectional chain	3.9019	3.6179	3.7501
	Bidirectional chain	2.1913	2.0432	2.1165
Chain route by polar angle		1.1461	1.4071	1.2836
Chain route by four-quadrant		1.1410	0.9714	1.0526

node's layout is object-oriented and unique, and thus, only a specific instance needs to be analyzed. First, the polar radius of each node is normalized to the largest polar radius, and then the squared sum of the distances between each two adjacent nodes of each route is calculated, including the distance between the end of the chain and the sink. As shown in Tab. 2 below, the square sum of the distances for different route search methods of the two groups of nodes in the above Figs. 5∼8 are compared.

As shown in Tab. 2, regardless of the set of paths, the squared sum of the distances of the unidirectional chains is the largest, which results in its energy consumption being the largest. This is because when searching by the radius, the nodes' positions may be far away from each other and twist back and forth. Thus, the route is not energy efficient. The bidirectional chain reduces the interconnection of the nodes on both sides of the pole, and thus the energy consumption is significantly reduced. However, there may be chains turning back and forth between nodes in a half plane, and thus, it still consumes a lot of energy. The chain formed by the polar angle can be a clockwise or counterclockwise search in one direction, and the last link is to the sink. This method does not link the nodes on both sides of the pole, and it only sequentially links them on one side. Therefore, the path becomes shorter.

However, in practical applications, if the radius of the area is relatively large, this energy consumption may also increase. Furthermore, the location of the tail node of the chain is uncertain. This means that you may encounter a large radius of the tail node, and thus, energy consumption will increase a lot. Therefore, this method has great uncertainty. The four-quadrant chain consumes the least energy because the method distinguishes between quadrants and then searches by the radius. There are no nodes that are far apart, and the tail node of the chain is closest to the sink so that there is no particularly serious energy consumption. The method focuses on the angle and radius and is an ideal choice for routing. It can be seen from Tab. 2 that the energy consumption of the routing based on the polar radius is 2∼3 times the energy consumption of the four-quadrant routing, and the energy consumption of the routing based on the polar angle is about 1.2 times the energy consumption of the four-quadrant routing, thus verifying that the four-quadrant clustering method is energy efficient.

For larger networks, an improved 'sector-inner circle' routing method is used. For two different scale networks, the following shows a comparison of the energy consumption between the presented method in the article and the other three methods shown in Tab. 1. The energy consumption is still represented by the squared sum of the distance between nodes. The results of the comparison are shown in the Fig. 13.

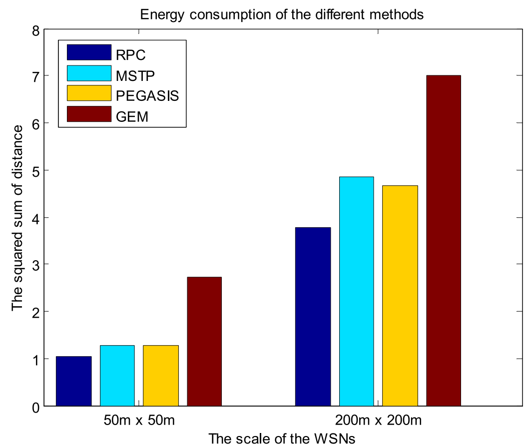

FIGURE 13. Comparison of the energy consumption of the different methods.

As can be seen from the figure, The energy consumption of the GEM method is the largest because the transmission of the projection nodes corresponding to the non-zero coefficient of each row of the measurement matrix must pass through a pre-established routing tree, so that the path needs to pass through many intermediate nodes and consumes energy. The MSTP method has small energy consumption in a small-scale network. However, in a large-scale network, the distance of the projected nodes may exceed the communication radius. It is necessary to forward data through intermediate nodes, which increases energy consumption. Although the PEGASIS method can search unrestrictedly with a greedy algorithm, its routing has no directional choice, thus the energy consumption is very unbalanced. However, no matter what the scale of the network, the energy consumption of the RPC method is lower than the other three methods, which indicates the effectiveness of the proposed method.

VII. CONCLUSION

In view of the compressed data collection of WSNs, we propose a Random projection-Polar coordinate-Chain routing (RPC) method based on polar coordinate positioning and chain structure. The RPC method uses the sink as the pole to form polar coordinates. The network energy consumption is reduced by the weighted sum of the data collected by the sparse random projection nodes. We mainly study the chain route that searches by the polar radius and the polar angle and the four-quadrant route that combines the polar radius and polar angles and analyze the performance of these types of routes. It shows that the four-quadrant route is more energy efficient. Then, for the larger network, we establish an effective chain route through the combination of the sector and the inner circle and discuss the dynamic problem of routing and the situation with sinks outside the monitoring area. The proposed four-quadrant route and sector-inner circle routing algorithm avoid back and forth routing between nodes far away from each other and save energy. Compared with the related algorithms and the simulation of different types of chains, the methods in this paper have been proven efficient and energy saving. However, for more larger networks, the sectors will become very narrow. Only the routes formed within the sectors may not be optimal route, and they need to be considered in conjunction with neighboring areas. The project will continue to be studied in future work.

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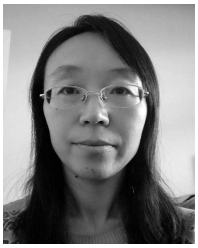

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