Artificial Intelligence-based Optimization of Sink Localization for Self-powered Sensor Networks

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Abstract. Wireless sensor networks (WSNs) are mainly communication networks comprised of a large number of miniature sensors using collaboration and self-organization, which have the characteristics of high reliability and low deployment cost. However, the mobile Sink nodes of traditional WSNs have problems such as large network energy consumption and data latency, so this paper introduces the deep learning method, an essential technique of artificial intelligence, and proposes a clustering-based energy optimization CEOMS algorithm by considering the mobility characteristics of Sink nodes and energy consumption-related parameters of sensor nodes and constructing energy consumption functions and performance enhancement functions, respectively; subsequently, we build the standard values of cluster head selection that include energy consumption functions and performance enhancement functions; finally, we calculate the Finally, we calculate the mortality rate of Sink nodes to design the adaptive cluster head self-selection function, and then adaptively adjust the cluster head selection criterion value. The proposed algorithm not only improves the process of cluster head standard value selection and the data transfer efficiency, extends the Sink node network life cycle, reduces the network energy consumption, but also provides a basis for optimizing the localization function of Sink nodes.

Keywords: Sensor network, artificial intelligence, CAD, sink node.
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1 INTRODUCTION

In the global automation industry continues to develop at the same time, industrial equipment systems constantly update their structure, increasingly complex, increasingly harsh working environment, greatly enhance the equipment loss, failure frequency becomes larger because, whether the equipment system can safely run, depending on the maintenance guarantee level, so, in the increasingly fast-paced, more intense modern industrial production, the traditional regular inspection and maintenance system and after-the-fact maintenance technology has been stretched to the limit. Globally, industrial equipment systems are evolving towards condition-based maintenance (CBM) based on real-time condition monitoring. For data transmission and power supply of condition monitoring systems, cables and wires are widely used; however, industrial equipment is becoming increasingly complex, and its measurement points are also changing. Meanwhile, if it is in a corrosive or high-temperature environment, it is impossible to connect through the wire, which significantly increases operation difficulty. A continuous development in embedded technology, systems on chips (SoC), microelectromechanical systems (MEMS), and wireless communication technology also led to an advancement in wireless sensor networks (WSNs), which laid the groundwork for monitoring industrial equipment in real-time and maintaining the systems.

WSNs play an essential role in the Internet of Everything. In particular, the introduction of mobile Sink nodes to alleviate the transmission hotspot problems caused by stationary Sink nodes, expanding WSN applications, and making WSNs more widely used in military, medical, civilian, and other fields. The limited energy of Sink nodes themselves makes frequent broadcasting of Sink node location information problematic, as it causes rapid node energy consumption, data transmission congestion, and other problems, resulting in reduced monitoring performance of the entire network and reduced network life cycle, which makes it difficult to locate the network accurately. Therefore, it is essential to study how to design efficient routing algorithms to optimize node energy, balance the network load, extend the network life cycle, and thus optimize the sink node localization function. This paper focuses on WSN energy optimization, combining changes in node energy consumption with changes in parameters of mobile Sink node motion, and proposes an adaptive cluster head selection strategy to make cluster head selection more dynamic and energy efficient. It reduces data delay, prolongs network lifetime, reduces network energy consumption, and optimizes sink node localization function.

2 RELATED WORK

WSNs, which are composed of a large number of small sensors combined, play a vital role in the Internet of Everything. In general, sensor nodes randomly deployed in large monitoring areas communicate with each other via wireless transmission. Sensor nodes are interconnected in a collaborative, self-organizing manner to form a sensor network and send the monitored data to Sink nodes, sending the received data to users or control centers via the Internet and satellites. However, due to the small size of the sensors in general, the energy is minimal. In addition, sensor nodes are generally deployed randomly to machines with harsh survival conditions, rugged terrain, complex and changing environments, and vast areas. Once the energy of a sensor node is depleted, it cannot be replenished in time by replacing batteries or other means. This results in the loss of some of the monitoring data for the entire monitoring area, which leads to degradation of Sink positioning performance. In addition, in traditional WSNs, Sink nodes are unchanged after random deployment. Sensor nodes of WSNs transmit their sensing data to fixed Sink nodes. Sensor nodes located around Sink nodes not only send their localization data to other nodes but also receive and process localization data from other sensor nodes, which leads to node energy consumption excessive node energy consumption, premature node death, and the formation of energy black holes, i.e., hotspot problem [1]. In addition, in complex terrain scenarios, fixed Sink nodes cannot meet the requirements of practical and particular complex scenarios. Therefore, in order to achieve higher monitoring performance of WSNs, how to improve the power generation capacity of network nodes, reduce the energy load, and extend the life cycle of nodes to meet the needs of practical scenarios is an essential issue of concern and research for domestic and foreign scholars in the field of WSNs [2]. Therefore, for WSNs with mobile aggregated nodes, many well-known scholars at home and abroad have designed a large number of efficient routing algorithms to reduce network energy consumption, improve network lifetime, and balance the load of the whole network. Routing algorithms are generally classified into two categories: planar routing algorithms and cluster routing algorithms.

In order to reduce the overhead of routing protocols, some scholars have studied planar routing algorithms. Zhang et al. [3] proposed the Sensor Protocol for Information via Negotiation (SPIN) algorithm. This algorithm interrogates packets in the form of broadcasts. It introduces a negotiation mechanism to purposefully select the next node that is willing to receive its data to build an efficient data transmission path and reduce the blindness in the data transmission process. However, such algorithms easily consume too much energy by broadcasting by nodes. They do not consider the negotiation of sending packets during transmission, which causes a large data delay problem. Based on the location information, Sivaram et al. [4] proposed a Greedy Perimeter Stateless Routing (GPSR) algorithm. The GPSR algorithm does not need to obtain global topology information but only uses the information of direct neighbors of nodes in the network topology to make greedy forwarding decisions, which have good scalability and fault tolerance. Muruganantham et al. [5] proposed a Directed Diffusion (DD) algorithm that does not consider the power consumption capacity of the nodes during data forwarding, which leads to the problem of unbalanced energy load of the entire node network. In this algorithm, multi-hop transmission paths are designed for the global nodes to the aggregation nodes by sensing the nodes' locations and other information. Moreover, all nodes can temporarily cache and process data, which is energy efficient and scalable. However, when there are multiple source nodes, data redundancy is likely to occur, resulting in a waste of resources. In addition, the network topology between nodes in the planar routing algorithm is relatively simple, low cost, and easy to maintain. However, in the planar routing algorithm, all network nodes have the same status, and it is not possible to effectively classify and manage the data of the nodes, which prevents effective utilization of network resources, increases data transmission delays, and increases unnecessary energy consumption.

On the other hand, the advantage of the design of the clustered routing algorithm is that it achieves hierarchical transmission of Sink nodes, which has obvious advantages in saving network resources, balancing power generation consumption, and improving the survival time of nodes. Among them, Pandey and Hegde [6] proposed the low-energy adaptive clustering hierarchy (LEACH), where the idea of running in rounds and clustering all network nodes is introduced. A cluster head selection criterion value is raised and some nodes are selected as cluster heads in each node rotation process. Then, based on the distance between the Sink node and the cluster head, the cluster in which the nearest cluster head is located is selected to join, i.e., by dividing the Sink node network into different cluster heads and replacing the cluster heads according to the actual situation, the energy consumption of the nodes for power generation is reduced and their survival cycle is extended. However, in this algorithm, there is often a large randomness in the selection of nodes without considering the Sink nodes and the distance to other nodes, which leads to problems such as premature death of some nodes and excessive power generation consumption. Therefore, Ding et al. [7] proposed the distance-based cluster head (DBCH) algorithm, which considers the power generation efficiency of Sink nodes in cluster head selection and increases the probability that nodes with high power generation capacity are selected as cluster heads, thus extending the survival cycle of the whole node network. Zou et al. [8] proposed the distance-based threshold (LEACH-DT) algorithm, which takes into account the relative distance, maximum and minimum distance between Sink nodes and other nodes as well as the current power generation efficiency of the nodes in cluster head selection, thus making the distribution of nodes more systematic and extending the survival cycle of the network. In conclusion, the algorithm considers the generation efficiency, relative distance, and average distance of nodes to design the cluster head selection criteria values when performing cluster head selection, which provides a methodological basis for extending the node network survival cycle. However, the cluster head, as a transit station for data transmission, needs efficient power generation capacity to process the localization of Sink nodes within the cluster and send them to other Sink nodes. In this algorithm, although the node-to-node distance is considered, the network density of nodes is not taken into account, and it results in huge fluctuations in the energy load of the whole network [9].

In WSNs, many studies on cluster routing algorithms have focused on aggregation nodes and sensor nodes to address the problems of unbalanced energy consumption and short network lifetime. However, the limited energy of sensor nodes and the high traffic load of nodes close to aggregation nodes can lead to increased energy consumption and premature death. Many scholars have considered introducing mobile Sink nodes to solve such problems. Palani et al. [10] proposed a node density-based clustering and mobile collection (NDCM) algorithm. This algorithm effectively combines the design of the cluster routing algorithm with mobile aggregation point collection. In the cluster head selection process, the average distribution density of the network of Sink nodes is chosen as an essential algorithm to increase the probability that nodes located in the dense node area are selected as cluster heads. The mobile Sink nodes are used to collect the localization data, which effectively avoids the energy consumption of long-distance transmission, improves the network survival cycle, and reduces the data transmission delay. However, such algorithms do not consider the impact of frequent changes in mobile aggregation node mobility parameters on network energy consumption when selecting cluster heads, which leads to excessive distance and energy consumption during transmission of some cluster heads; meanwhile, data delay problem occurs when cluster head nodes send data directly to mobile aggregation nodes.

In summary, the current packet clustering routing algorithm still has some problems. 1) The cluster head selection is unreasonable, resulting in some cluster heads being far away from the mobile aggregation nodes, leading to unbalanced energy consumption. 2) The location information of the mobile Sink nodes is updated frequently, resulting in the sensor nodes needing to receive frequent information packets from the mobile aggregation nodes, leading to unnecessary data transmission congestion. 3) The Sink nodes use a single transmission method to send location data to the mobile Sink nodes, leading to a decrease in the efficiency of point generation of other mobile Sink nodes, thus reducing the survival cycle of the entire node network.

3 THE PROPOSED MODEL AND ALGORITHM

Based on the classical cluster routing algorithm, we propose a network energy optimization algorithm CEOMS considering mobile aggregation nodes, which can enhance cluster head selection adaptivity of mobile aggregation nodes, extend the network lifetime, and reduce data latency due to mobile aggregation nodes' mobility characteristics.

3.1 The Structure of the Proposed Model

We assume that the distribution of Sink nodes in the sensor network is characterized by randomness within the network area. More importantly, the data transmission pattern of Sink nodes is constantly changing according to a specific algorithm design and collecting localization data from other nodes in real time. Due to individual Sink nodes' low power generation efficiency, when they all transmit data to the Sink nodes, the nodes consume too much energy and die prematurely. Therefore, nodes in the network should be clustered using a reasonable routing algorithm.

We tried to use classical clustered routing algorithms and clustered the network nodes to construct a WSN network model based on a policy of running processes in a cluster. First, the localization data collection used to monitor the network is divided into several rounds. Each round includes the complete localization data collection process for all nodes. The complete data collection consists of cluster construction and stable inter-node data transmission. First, some nodes are selected as cluster heads based on the constructed cluster head selection criteria values; second, when the cluster head selection is completed, the sensor nodes are selected to join the closest cluster by the relative, maximum and minimum distances of different cluster heads; then, the Sink node in each cluster transmits the processed localization data to the cluster head according to the algorithm, and the cluster head performs secondary processing and analysis of the localization data; meanwhile, the cluster head sends the At the same time, the cluster head sends the processed data to the cluster head. Finally, the Sink node aggregates the positioning data to the control center or user via satellite and network.

Nodes in WSNs are deployed in random equal parts, and their positions do not change. During each round, the mobile aggregation node's trajectory changes, as does its relative distance from the node. When collecting, processing, and delivering data from sensor nodes farther away, more energy is consumed (Figure 1).

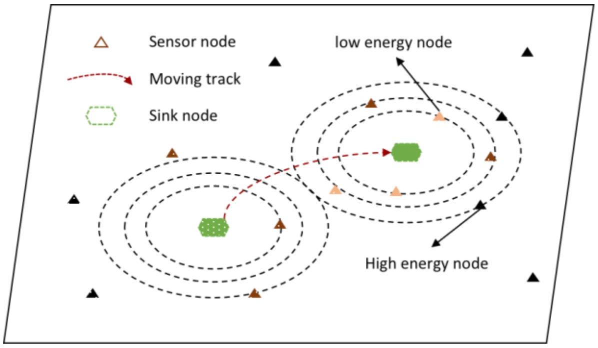

Figure 1: Distribution of energy intensity.

3.2 Algorithm Design

Since Sink nodes have different energy consumption depending on the distance from the Sink node, it is necessary to introduce the relative distance between different Sink nodes (Figure 2). When the distance of a Sink node in round r becomes more distant compared to the distance in round r-1, i.e., the Sink node moves in the direction away from that node, its cluster head selection criterion value will increase, and accordingly, the possibility of that Sink node becoming a cluster head will increase. The number of cluster heads will be redistributed within a fixed area in the region where the distance from the Sink node becomes progressively more distant. Conversely, suppose the criterion value of cluster head selection decreases. In that case, the probability of a Sink node becoming a cluster head will decrease, and the number of cluster heads in the region where the distance from the mobile aggregation node gradually decreases will decrease, resulting in more balanced energy.

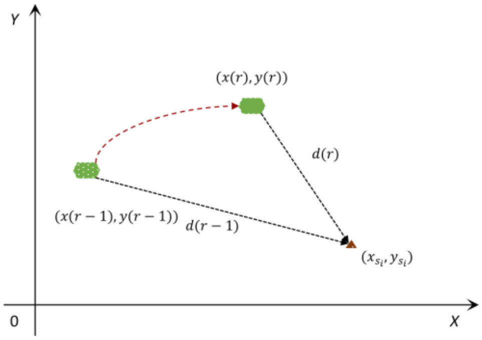

Figure 2: Change in relative distance.

With the distribution and operation of the node network and the dynamic change of the output node data of the Sink node, the energy consumption of the whole network for power generation is also increasing. The number of surviving nodes in the WSN will also change accordingly, so the algorithm in the selection criteria value needs to be adaptively adjusted; considering the parameter change law of the algorithm, combined with the sigmoid function, the function of the cluster head selection criteria value is introduced as f(g), with the operation of the node network, the cluster head selection criterion value decreases with the increase of the number of Sink nodes at the end of their life cycle. Furthermore, when the adaptive cluster head selection criterion value is obtained, the cluster heads in the region are determined by calculating the cluster head selection criterion value in the node network. The Sink nodes selected as cluster heads are added to the next cycle of cluster heads in the region for the dynamic localization data transmission process. In contrast, the Sink nodes not chosen as cluster heads are added to the set of non-cluster heads. The flow of the proposed algorithm is shown in Figure 3.

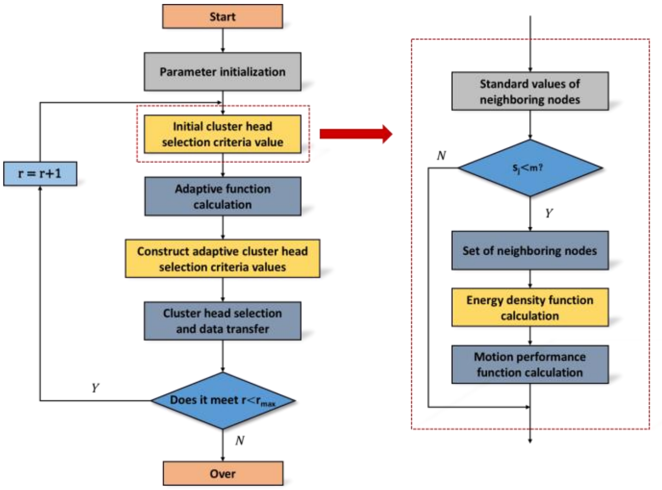

Figure 3: Algorithm flow.

4 SIMULATION EXPERIMENTS

We compare and analyze the proposed CEOMS algorithm with the conventional algorithm. The simulation experiments are validated on MATLAB 2019a simulation platform and are compared and analyzed in terms of the number of survival cycles of the Sink nodes, the energy consumption of the nodes for power generation, and the energy distribution strategy of the node network, respectively. In addition, to verify the effectiveness of the CEOMS algorithm in terms of the number of remaining nodes and the energy consumption of the node network for power generation, the energy consumption gradually increases during the network operation due to the continuous localization data transmission between Sink nodes. The number of remaining Sink nodes also decreases; some Sink nodes consume their energy and die. The variation of the number of nodes surviving in different algorithms is shown in Figure 4.

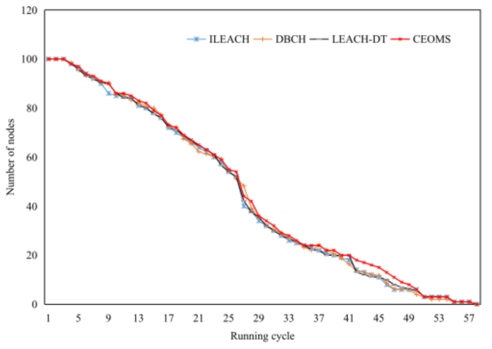

Figure 4: Trends in the number of surviving nodes.

In the initial stage, the number of remaining Sink nodes in WSN is 100. as the node network continues to meta-rotate, it can be seen that the curves of these four algorithms start to show a decreasing trend, where the number of rounds with the first dead node in ILEACH, DBCH, LEACH-DT, and CEOMS algorithms is 73, 99, 73 and 144 respectively. The number of cycles with the first dead node in ILEACH, DBCH, LEACH-DT, and CEOMS algorithms has 1121, 1111, 1225, and 1645 rounds of all node deaths, respectively, and the CEOMS algorithm is 46.58%, 48.1%, and 34.2% longer than the other three algorithms.

With the continuous extension of the node network operation cycle, the number of nodes transmitting location data to each other increases, and accordingly, the power generation energy consumption gradually increases. Therefore, the power generation efficiency and energy consumption of the whole network will gradually decline, and Figure 5 shows the trend of power generation energy consumption as the number of cycles increases.

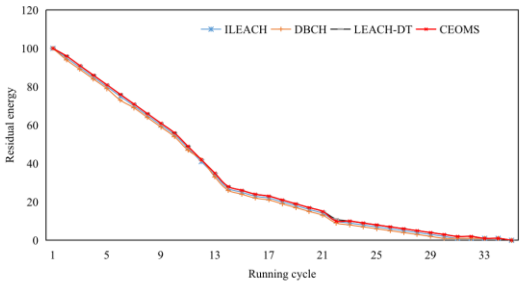

Figure 5: Trend of total residual energy.

We assume that the initial power generation energy consumption of Sink nodes in different algorithms is the same, i.e., 1J, and the total power generation energy consumption of all network nodes is 100J. As the network cycle is extended, the power generation energy consumption of nodes increases continuously and the power generation energy efficiency of the four algorithms show a decreasing trend. Meanwhile, the CEOMS algorithm is always higher than the other algorithms in the same cycle, which also indicates that the CEOMS algorithm generation energy efficiency is higher than the other three algorithms. When the network runs to 1121, 1111, 1225 and 1645 rounds respectively, it can be seen that the remaining energy of these four curves does not have a decreasing trend, mainly because the energy of all nodes in the whole network has been consumed. the CEOMS algorithm can effectively improve the power generation efficiency, reduce the power generation energy consumption and extend the network operation cycle.

Figure 6 shows that the CEOMS algorithm has better performance than the other three algorithms, which indicates that the algorithm can effectively save power consumption and extend the entire node life cycle.

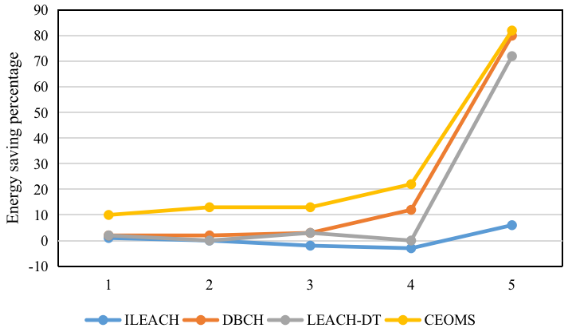

Figure 6: Four algorithms for power energy consumption.

We further examine the generality of the proposed algorithm in enhancing the node generation efficiency, reducing the energy consumption of generation and extending the network operation cycle, we randomly changed the distribution positions of the network nodes and conducted several experiments. Figure 7 shows the comparative analysis of the network lifetime of different algorithms by changing the node positions randomly several times.

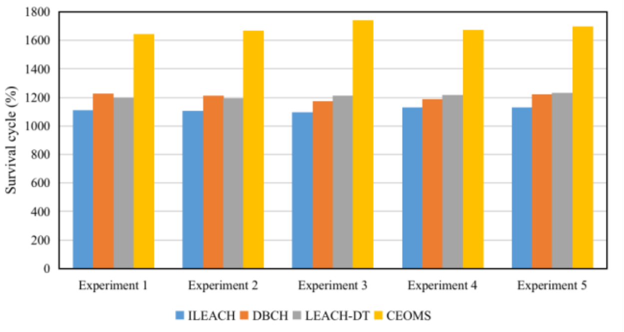

Figure 7: Four algorithms for percentage of energy savings.

We further conducted several experiments by changing the position of the Sink node several times. Figure 7 shows the number of cycles (network lifetime) in the network of nodes corresponding to the CEOMS algorithm as 1633, 1671, 174, 1674 and 1697 rounds. Compared with the other four algorithms, the CEOMS algorithm has the most extended network lifetime, which indicates that the CEOMS algorithm can node power generation efficiency, reduce power generation energy consumption and extend network operation cycles with universal applicability.

5 CONCLUSION

The traditional routing algorithm involves the Sink node sending location data to the cluster head, while the cluster head sending processed location data to other Sink nodes for algorithmic changes, which reduces the node network's power consumption. As a result of the mobile Sink nodes, the high energy consumption and high load issues caused by traditional Sink nodes are effectively mitigated, and the whole network's energy consumption is further reduced. Despite this, the following problems still persist. 1) The regional distribution density and power generation energy consumption among sensor nodes are not considered, resulting in the nodes elected as cluster heads often have compressed survival cycles due to high energy consumption. 2) The location state of sensor nodes does not change after random assignment in the regional network, and mobile Sink nodes are far away from some cluster heads, resulting in unbalanced network energy distribution in the region. 3) When most of the sensor nodes enter the late stage of their survival cycle, the cluster head selection criteria values lack dynamic changes and are difficult to be self-adaptive. We therefore consider the average power generation energy consumption of sensor Sink nodes, the density of regional nodes, the survival cycle of Sink nodes, etc. A cluster-based energy optimization algorithm (CEOMS) using deep learning is proposed in this paper with the support of artificial intelligence technology. To ensure that cluster head Sink node selection is scientific, we construct the node power generation energy consumption function and the cluster head selection criteria value function first; we design the adaptive adjustment function based on the node survival cycle based on the density of the node network in the region using the traditional algorithm. Assist with the optimization of Sink node localization by improving the adaptability of cluster head selection, thereby extending network life cycles, reducing network power generation energy consumption, and optimizing localization data transmission rates.

In addition, this paper proposes an energy-efficient routing algorithm based on Sink nodes, which can effectively optimize the energy consumption of WSNs and save network resources. However, for the energy optimization of WSNs containing mobile aggregation nodes, there are still some issues that need to be studied in depth: the movement path of Sink nodes is predefined, and the proposed routing algorithm is designed under the condition that the movement parameters of the mobile aggregation nodes are known. However, in practical applications, such as dense forests, enemy military environments, etc., the proposed algorithm will not be applicable when the obstacles in the mobile aggregation node's mobile trajectory may be unavoidable, and the original trajectory cannot be moved. Therefore, based on the current research, the change and adjustment of the trajectory of Sink nodes when they encounter obstacles is the next important point to be studied.

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