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RESEARCH ARTICLE - ENGINEERING (MISCELLANEOUS)

Enhancing the Efficiency of Routing Strategies in WSNs Using Live Streaming Algorithms

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Abstract

The application of machine learning in wireless sensor networks (WSN) has attracted much attention. Since references in WSNs are pre-defined, determining how to optimize the utilization of resources and achieve efficient load balancing has become a critical problem in WSNs. The goal of conventional green routing algorithms is to reduce energy consumption and increase network life cycles by improving routing schemes in wireless networks. However, sometimes problems arise, such as poor flexibility, focusing on a single operative, and relying on precise algebraic models. Machine learning techniques can adapt to environmental changes and employ multiple agents to make informed decisions, providing new ideas for energy-saving and intelligent routing algorithms in wireless networks. In this piece, we examine the suggestion of fictitious artificial intelligence. Developing a mathematical framework is an effective approach to formulating an ideal green routing strategy that addresses the shortcomings of conventional green networking techniques. This research summarizes past, present, and future advancements in environmentally friendly routing algorithms within wireless communication networks. The information in this article will be interesting for individuals interested in applications of machine learning in WSNs.

Publisher: Middle Technical University

Keywords: Energy-Efficient; Routing Algorithms; Wireless Sensor; Network; Deep Learning.

1. Introduction

This is a challenging problem that can be addressed using soft computing and optimization techniques. Consequently, recent years have seen the proposal of numerous intelligent algorithms, such as ERA and AFSRP, to enhance energy consumption in sensor network clustering and routing. Despite the many benefits of using such algorithms, there are also problems, such as low convergence speed, high processing costs, and computational complexity. Additionally, an imbalance between local and global searches may occur. Such phenomena can cause the algorithms to behave randomly during the location update phase, potentially leading to blind reactions and the risk of becoming stuck in place. In this paper, the intelligent optimization algorithm of the fruit fly is selected as the main algorithm of the proposed method, and the intelligent algorithm (AFSRP) is selected as the known intelligent protocol for comparison to simulate the network [1]. Both algorithms suffer from the problems mentioned above. Solving the above fuzzy logic challenges is used to improve the performance of a fruit fly-based optimization algorithm with one topology (150 nodes). Considering the use of fuzzy logic in the structure of the fruit fly optimization algorithm, compared to the AFSRP algorithm, which only uses the fish swarm algorithm, the proposed method is expected to find optimal cluster heads and more suitable paths with minimal overhead [2]. The expected results will solve the blocking problem in the local optimum and slow convergence in the optimization algorithms. The structure of this article is as follows: The second part outlines the research background, discussing the subject and previous studies aimed at enhancing energy consumption in WSN. The third part reviews the use of the fruit fly algorithm and fuzzy logic for clustering. The simulation results of the proposed algorithm are presented in the fourth section, and finally, the fifth section deals with the conclusion [3]. Power consumption: Many efforts are underway to optimize power consumption in battery-constrained sensor systems. These protocols were developed considering application requirements and network architecture. However, some factors should be considered when designing WSN routing protocols. The sensor's energy consumption is crucial since it influences the network's overall endurance. The present research addresses how much energy an average person has. The four primary components of sensor nodes are a radio component, a sensor component, a source of electricity, and a processor component. In a recent study, researchers looked into power-aware broadcasts and spreading difficulties to divide methods into two groups: the MLB/MEM challenge, which is defined in terms of minimal broadcast/multicast power, and the longest possible lifespan of broadcast/multicast (MLB/MLM) issues related to ad hoc wireless connections. Initial elections: who is conscious of energy? Minimize the total energy consumption of all nodes participating throughout and extend the computation duration until the first broadcast node's batteries run out [4]. The authors emphasize the difficulties in creating efficient WSN techniques for medium-access controls (MAC). It also addresses and evaluates various WSN MAC standards. The researchers provide three categories of issues: distribution and execution, network amenities, internal architecture, framework, and connectivity stack protocols. The researchers suggest a strategy that uses sensor node grouping [5]. The remaining power terminals and sensors at a distance are part of the grouping approach. Highly sensitive thresholds, environmentally friendly sensor protocol for networks [TEEN], adaptable periodic thresholds, energy-effective sensor system

Nomenclature & Symbols			
WSN	Wireless Sensor Networks	FL	Fuzzy Logic
APTEE	Adaptive Periodic Threshold Energy Efficient Sensor Network Protocol	EFMRP	Environmental Multipath Fusion Routing Protocol
MAC	Medium Access Control	LSA	Lightning Search Algorithm
MLB	Maximum Lifetime Broadcast	PSO	Particle Swarm Optimization
LEACH	Low Energy Adaptive Clustering Hierarchy	CHA	Category Head Selection Algorithm
TEEN	Threshold Energy Efficient Sensor Network Protocol	RNPP	Relay Node Placement Problem
HEED	Hybrid Energy Efficient Distributed Clustering	KNN	K-Nearest Neighbors
PEGASIS	Energy-Efficient Harvesting in Sensor Information Systems	CH	Cluster Head

protocol (APTEEN), hybrid, and low-energy adaptable grouping hierarchy (LEACH) are just a few of the recognized protocols that the researchers of the current research compare and contrast. Energy Efficiency Gathering in Sensor Data Systems (PEGASIS) and Power Efficiency Heterogeneous Clusters (HEED). The researchers developed an approach to the relay node positioning issue (RNPP) protocols in WSN using two multiple-goal interpretations comprising cost of energy, median sensibility, and network dependability to look for suitable methods to tackle the placement issue from an operational viewpoint [6].

The academic literature includes several research studies on WSN routes, as listed below. The researchers distinguished the following types of network-based forwarding techniques—hierarchical, planar, and geographic routing protocols—in their evaluation of wireless sensor networks. These procedures are divided into query-based, multiple-route, negotiation-based, and QoS-based network routing techniques. Despite going into detail about each protocol, the authors provided a taxonomy of forwarding and strategy design difficulties, along with an approach to routing determined by its methods and attributes. To organize information packets to reach the recipient, the researchers developed green multiple pathways by fusing routing algorithms incorporating a potential field modelling technique. They created systems for sustaining, allocating, and withdrawing traffic [7]. The researchers addressed the topics of energy balancing and WSN optimization. Furthermore, the researchers provide a suite of optimization techniques to determine the most effective route of origin for every individual cluster, and they offer the successful outcome length as a gauge of the ideal length of transmission [8].

By illustrating the physical constraints and suggesting techniques for each tier of the sensor node's configuration networking framework, the researchers addressed the challenges and approaches involved in developing wireless sensor networks that transmit data. They also covered real-world applications of WSNs. Although several sensor network connections are discussed in this research (and they are divided into geographically based, structured, and data-oriented procedures), energy conservation tactics are not the main topic of the paper. Nonetheless, the paper discusses WSN connectivity [9].

Hierarchy-based WSN routing techniques have been suggested previously to promote energy efficiency. Sensor nodes are typically grouped. Fig. 1 refers to each group as a cluster, with an appointed figure known as a head of clusters (CH) leading each group. Wireless sensor networks Grouping: WSNs have employed grouping to improve networking flexibility, share and use resources more effectively, maintain network structure, and save power. By restricting communication diversity, the technique of clustering reduces energy consumption. This is because all nodes interact with an instrumental CH, which functions as a local sink with a longer range and lower energy requirements. The range ratio between the instruments and the sensor is restricted among the detectors and the regional well. To lower energy usage and enable some cluster members to shut down, the CH directs the actual data needed to the Global Sink. [10].

The objectives of clustering are:

- Greater Durability: Scalability is a crucial factor to consider when developing routing strategies for wireless sensor networks. If the method of routing is adaptable and performs well when it periodically modifies the network architecture, we can declare it to be effective. We can expand WSNs by adding network routers after design.
- Data consolidation: Therefore, optimization is required. For effective data aggregation, energy reductions and the simultaneous elimination of superfluous data are required.
- Prevent collisions: Preventing collisions can extend a lifetime and enhance system efficiency. Many collisions result in losses, waste of resources, and retries, which increase expenses, cause delays, and exacerbate the challenges of small WSNs.
- Latency decrease: WSNs are split into categories, with a group commander for each, and only CHs send data to the recipient, reducing the time constraints and possibility of collisions. Furthermore, flooding is a common planar routing mechanism utilized in the hop-to-hop exchange of data. In contrast, CHs are the only ones that employ the group routing system, which allows them to send hops from the origin to the terminal. As a result, there is less delay.
- Load balancing: By avoiding premature cluster leader energy use, equal group implementation extends the duration of the network. We must apply load balancing across CHs, selected from available sensors, to achieve the necessary outcome. The data from each CH is available simultaneously for additional work on the foundation station when clustered with an identical number of nodes.
- Fault Tolerance: Because WSN nodes can function in challenging environments, they frequently encounter disruptions, hostile attacks, hardware malfunctions, transmission errors, and delays. Failure tolerance is required.
- Connectivity Assurance: WSNs' CHs use one- or multiple-hop forwarding to send data to the base station. We must determine whether all nodes are associated with the one after it to ensure effective data transmission to the base station. When no other node can interact with the jumping node, it becomes isolated and is unable to convey information to the BS.

The main contribution of this article is:

Numerous applications utilize WSN, yet energy consumption poses a challenge. Consequently, to extend the lifespan of WSNs, we established a variety of wireless network techniques. In WSN, we have compiled and arranged many approaches to resolving and categorizing energy conservation problems. For each category of methods, we have determined which source reduces energy loss. The amount of traffic, time, delay, and other criteria discussed are verified through WSN simulation software. Using the WSN method and the content-oriented features of the original information method, we intend to perform the tracking operation without imposing additional processing or delaying the update time of the day.

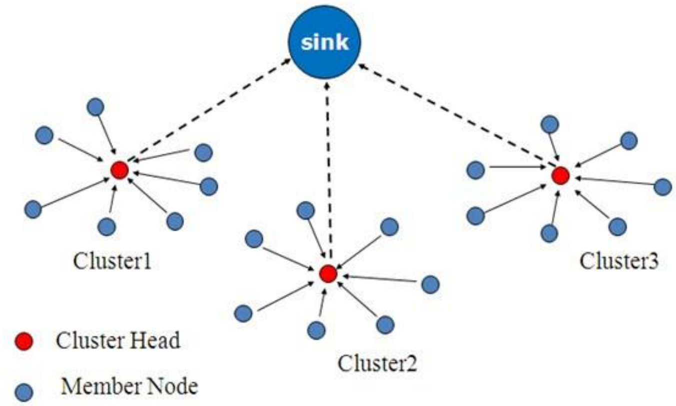

Fig. 1. Clustering in the wireless sensor network [9]

2. Related Works

In [11], a routing protocol using the parameters of sink distance, residual power, and internal distance to select the optimal cluster head was proposed. The proposed protocol is a combination of genetic algorithms and similar techniques. It is this heat production that improves the grid's lifespan. The proposed routing algorithm has some controllable parameters, whose adjustment is an important issue in achieving the best performance in certain applications. The selection of cluster heads in sensor networks can be based on different criteria. According to [12], the two criteria of node energy and node location were simultaneously considered to select the optimal cluster. In the proposed method, normal nodes request to join by sending join messages and sending their remaining energy to the temporary cluster head. Then, the temporary cluster head obtains the residual energy of the whole network based on the energy of the sensor nodes. The cluster head selects the node with the highest energy if the network's remaining energy exceeds x percent. Otherwise, the node with the most neighbors will be the new cluster leader. At the end of the process, the new cluster head sends a message to announce its presence as the cluster head. At the same time, energy and location are the criteria for choosing cluster leaders.

The LEACHY clustering method is used to develop a global search algorithm with a fast convergence rate. This method is a combination of the Harmony Search Algorithm (HSA) and Competitive Swarm Optimization (CSO4) and uses energy criteria for efficient cluster head (CH) selection. Furthermore, the suggested method can increase the lifetime of sensor nodes due to the advanced search capability of the HSA algorithm and the dynamics of the CSO method. The simulation results show that the proposed method is better than HSA and CSO in terms of throughput and residual energy [13].

This algorithm includes the following two steps: the clustering step and the clustering step estimation step. Classification uses the K-means clustering algorithm. The proposed algorithm dynamically adjusts the spatial threshold during the position estimation stage based on the dispersion of reference points, thereby filtering individual reference points and enhancing positioning accuracy compared to other methods. We present the algorithms and simulation results. The positioning accuracy from the ICD-KNN protocol compared to the dynamic threshold algorithms (DH-KNN, K-Means algorithms, and KNN algorithms) is improved by 10, 38, and 39%, respectively. Distributed data clustering based on the K-Means algorithm has a limitation in detecting clusters of arbitrary shape. It needs several pre-defined clusters to compensate for the limitation. The authors in [14] proposed the DN-DBSCANY algorithm for efficient data clustering in wireless sensor networks. This algorithm distributes the selected center points (obtained after performing a local DBSCAN on each node) among neighboring nodes that enable DBSCAN. It is re-executed in these shares, which lead to the formation of global clusters.

Additionally, by observing global clustering patterns, each sensor node adjusts its local clusters through cluster relabeling. Simulation results show that the proposed approach overcomes the limitations of average-based clustering. According to the single-cluster routing technique, the step of directly transmitting data from the cluster head to the base station is achieved by clustering hierarchically. However, this technique does not apply to wide-area networks. To facilitate cluster formation, a new optimized algorithm called Orphan-LEACH (O-LEACH) was presented by [14], which can reduce energy consumption and thus increase the lifespan of the network. In this algorithm, sufficient energy is available. A node that attempts to cover the network is placed. The main advantage of the LEACH protocol is that it covers the entire network with the least number of nodes and has a very high connection rate.

In the above protocol, a hybrid optimization method is used, which includes the Lightning Search Algorithm (LSA) and Particle Swarm Optimization (PSO). The simulation results showed that the proposed method can obtain the optimal path with the lowest energy consumption by selecting the effective cluster head, which will increase the WSN's lifetime. Choosing a cluster head with an efficient energy consumption method, called the Central Category Head Selection Algorithm (CHA), for homogeneous networks was proposed by [15]. The purpose of the proposed algorithm is to reduce energy consumption in wireless networks by accurately determining the cluster head during data transmission. In the proposed method, the cluster heads are selected to be close to the center of the cluster. As a result, energy consumption during packet transfer from the nodes-to-nodes base station will reach the minimum possible value. The simulation results indicate that in the proposed algorithm, on average, 14.68% more nodes are live in the network, and the number sent is 5.187% more than in the LEACH protocol. It should be noted that the residual energy of the proposed method is about 20% higher than the LEACH and PEGASIS algorithms. The authors in [16] proposed a QoS-aware multipath routing protocol. The proposed method clusters sensor nodes using a combination of particle swarm optimization and cuckoo search optimization algorithms, enabling data transmission. This protocol establishes several stable paths via the cluster heads, relying on multi-hop communication. This method relies on paths that do not affect the QoS for fast data transmission. The above algorithm also changes the cluster heads periodically. Based on energy, it increases the remaining life of the network. It uses the optimal number of paths for data transmission, to simultaneously achieve high reliability and better protection of Energy consumption in wireless sensor networks: HECRP routing protocol, was suggested by Zhao et al. It was suggested. In HECRPL, each sensor node selects an optimal set of sending nodes from its set of cluster heads with a hierarchical approach. By simultaneously considering the energy consumption and loss nature of wireless links, the HECRPL protocol can improve topology robustness and enable dynamic routing. Such an approach improves network lifetime and reliability [17].

The authors in [18] introduced a new routing protocol, known as EKF-MRPL, based on the developed Kalman filter. The goal is to provide this protocol to present a unified connection using mobile nodes and also to reduce the number of switches between connection points. Such an approach leads to a reduction in signal overhead and energy consumption in the proposed method to predict the junction point. A new node, moving a nonlinear route based on the proposed Kalman filter and an analytical model, is launched. The simulation results show that the proposed protocol is better than the EC-MRPL algorithm in terms of signalling cost, energy consumption, packet delivery ratio, and delivery delay. To work better to overcome the problems of energy consumption and load balance in the RPL routing protocol in WSN networks, a new method was introduced [19]. This algorithm employs a heterogeneous cluster of varying sizes based on the remaining energy of the nodes and their relative positions. Combining heterogeneous clustering with a cluster rotation mechanism maintains a balance in the energy consumption of the nodes within the network and prevents the creation of energy gaps. To optimize energy consumption in wireless sensor networks, the authors in [20] presented an energy-aware routing protocol that is employed. The popular lawyers are named after the AFSRP that pleases them, the Energy Bank. The simulation results of the proposed service and the ERA. Preliminary consent in the open simulator showed that the proposed protocol has performance in terms of energy consumption, all-over delay, media availability lag, throughput flow rate, sending probability to the well, and the signal was attributed to it.

It is better than the ERA protocol in terms of performance. One of the most important drawbacks is its performance in dynamic environments. The Poisson nonlinear model proves effective primarily in silent environments. However, its utility diminishes in more dynamic surroundings due to a reduction in convergence speed. It presented a routing protocol known as DCRRP to optimize energy consumption. The proposed method increases network lifetime. Using mobile receivers and grouping. In this method, cluster heads increase reliability by choosing the best alternative node as the new cluster head instead of the failed cluster head. Moreover, moving the receiver to the main cluster nodes whose energy is decreasing and receiving their data before turning off reduces the data transmission delay compared to the NDOC method [21].

3. Simulation Entourage

We simulate the proposed method using Open Modeler software and compare it with the AFSRP protocol. In this article, we aim to examine the impact of incorporating fuzzy systems into clustering algorithms to enhance their intelligence. For comparison and simulation, we chose the Drosophila algorithm (base algorithm) and AFSRP. This choice arises from the fact that the two algorithms have similar overall structures, and neither presents significant advantages over the other. Table 1 shows the simulation parameters used in the simulator. As mentioned, in the scenario based on the Fish Algorithm-Based Clustering Protocol in Wireless Sensor Networks (AFSRP), the nodes are distributed in the environment, while in the second (proposed) scenario, the nodes are distributed randomly [22]. It is deployed in the environment and routed by CBFFOF (a clustering algorithm based on the Drosophila algorithm and fuzzy logic). It simulates the proposed ceremony, leaning on a scenario. In both scenarios, the network topology is considered to be 50 nodes.

Table 1. Similar parameters used in the proposed protocol

Amounts	Specifications of the Simulation Environment
50	Number of mobile nodes
200 Second	Duration of simulation
1000*1000 Square meters	Simulated space
250 Meter	The transmission radius of each node
1024 byte	The size of each data packet
30 packets per second	Packet sending rate in the network
Free Space	Diffusion model
IEEE 802.11	Interface access protocol

The following criteria are used to assess the effectiveness of the proposed method: Indeed, the proposed protocol uses the Drosophila algorithm and the fuzzy path control system. Compared to the AFSRP protocol, the higher reliability reduces the end-to-end delay in the network by selecting the appropriate cluster head based on three parameters. In the DCRRP protocol, during the clustering process, a cluster head is selected from the high-energy and short-distance clusters of the mobile receiver. The members are [23] Clusters also join the cluster head based on distance. Still, because of sink mobility, the sink may exist in another area and collect data, forcing the sensor node containing the information to send it to the node that replaces it. Flow at greater distances; Consequently, data transfer operations block intermediate nodes in the path, resulting in data invalidation and loss. Therefore, the end-to-end delay increases in the DCRRP protocol, as shown in Fig. 2. In sensitive real-time applications, such as monitoring safety systems in factories, delay settings are very important, as shown in Fig. 3. This is because high latency reduces response speed and ultimately reduces system performance. Typically, delay settings are highly dependent on the data generation rate and traffic load. Therefore, when the sensor detects an increase in data rate, the delay also rises. This problem arises from the fact that as the data received by network sensors increases, the likelihood of congestion and disruptions also increases, leading to delays in the transmission of encoded data. The aforementioned points indicate a direct relationship between the number of nodes in a sensor network, the amount of data sensed, and the network delay.

3.1. Passage rate

It is defined as the total number of packets received by the receiver divided by the time elapsed between receiving the first and last packet. The throughput of the proposed scenario can be seen in Fig. 4. As seen, with the proposed protocol, the throughput of a network topology of 50 nodes is 16.6% higher than the AFSRP protocol scenario and 31.4% higher than the DCRRP protocol scenario. We can attribute this problem to the proposed protocol's smarter path selection, which employs a fruit fly algorithm and fuzzy logic to identify the cluster head node and forward data through its report. This provides improved data flow. The reason for the lower processing speed of AFSRP compared to the proposed method is node congestion and termination possibilities. Additionally, DCRRP increases processing speed compared to AFSRP because it uses a mobile receiver and transmits data through cluster heads located a short distance from the receiver. In general, the number of sensor nodes and throughput are inversely related because, as the number of sensor nodes increases, the amount of data at the network level increases, and the probability of congestion and disruption increases. This results in reduced data flow.

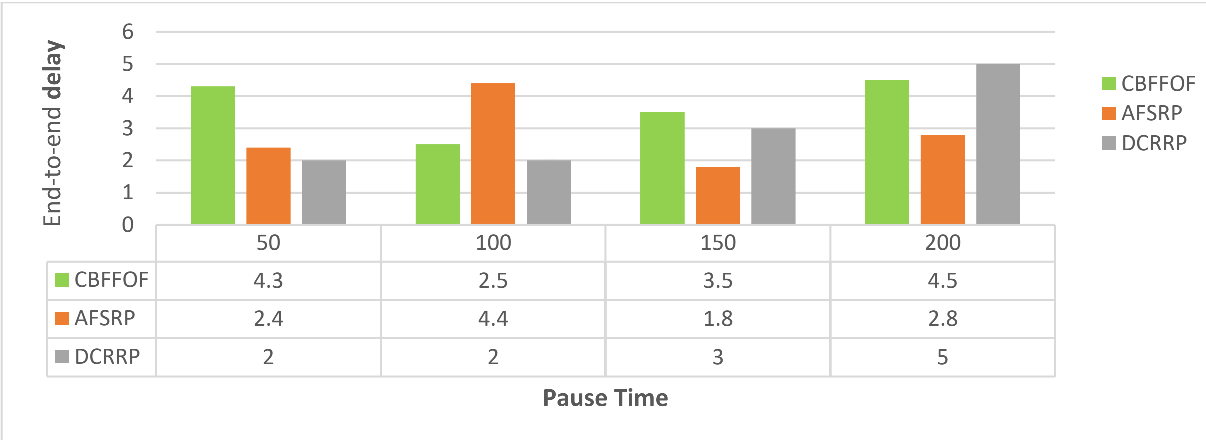

Fig. 2. End-to-end delay

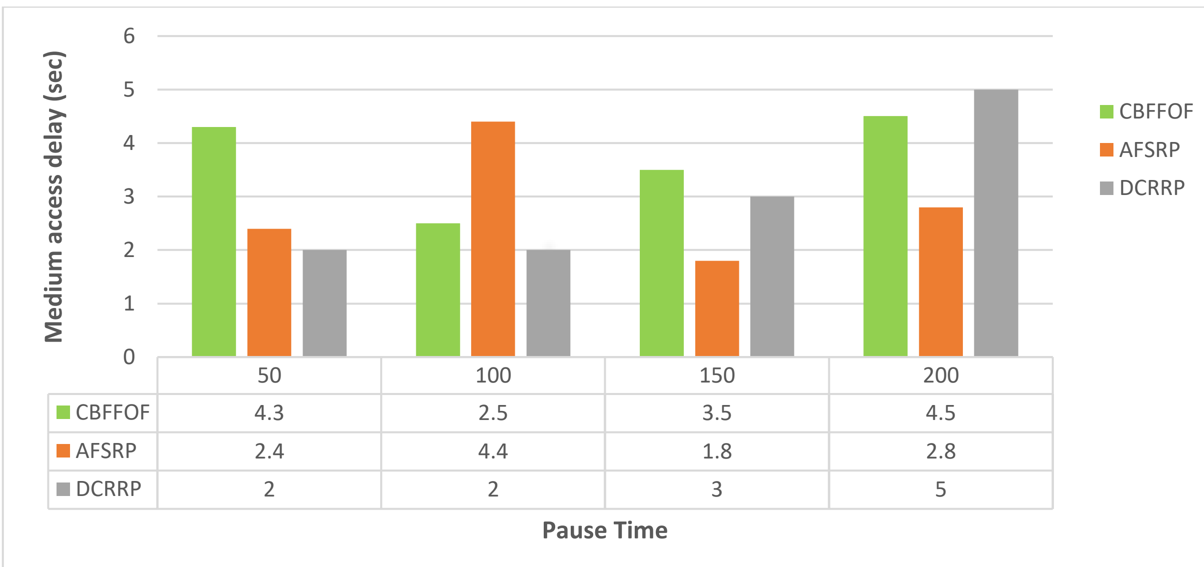

Fig. 3. Media access delay

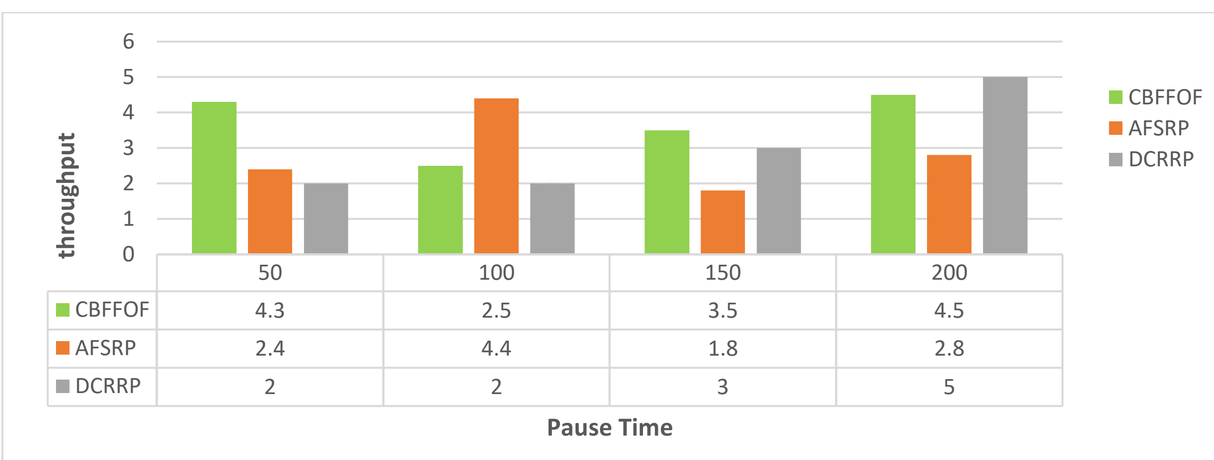

Fig. 4. Passage rate

3.2. The rate of successful delivery of data packets

The transmitter sensor transfers the entire data package securely to the receiver, which then receives it. Fig. 5 shows the successful delivery rate of data packets in the designed scenario. The horizontal axis simulates time, and the vertical axis determines the data packet transfer rate. The proposed protocol demonstrates successful delivery. In a network topology with 50 nodes, the rate of data packets improves by 18.2% compared to the AFSRP protocol scenario and by 93.1% compared to the DCRRP protocol scenario. Lack of access to the path to the destination is one of the most important causes of data packet loss in the network. However, in the proposed method, simultaneous use of the Drosophila algorithm and fuzzy logic means that during the data transmission phase, the target persists at least until the end of the phase. The path is selected to be highly reliable to minimize data loss and improve data transmission rates. Due to battery drain and information transmission, the AFSRP protocol may disable some nodes in the network. The failure to complete the synchronization results in a decrease in the data transfer success rate. Furthermore, the DCRRP protocol employs mobile receivers that relocate to low-battery cluster head nodes, leading to the deactivation of the data cluster heads. Therefore, the more efficient it is compared to AFSRP, the higher the data packet delivery rate. We expect the successful delivery rate of data packets in the network to decrease as the number of sensor nodes increases due to increased congestion, disruptions, and delays.

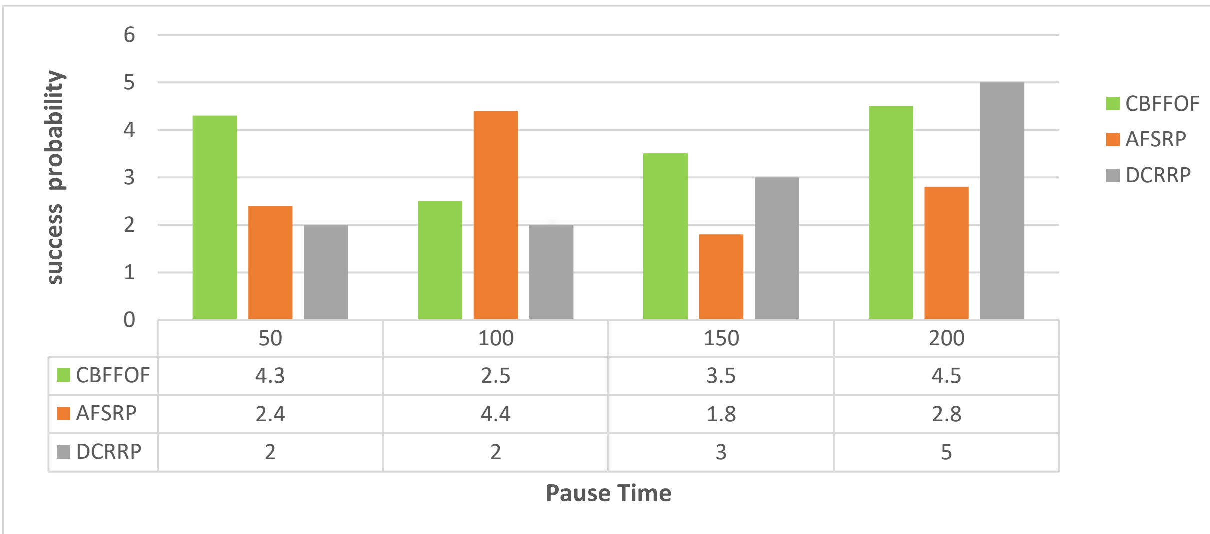

Fig. 5. Successful delivery rate of data packets

3.3. Signal-to-noise ratio

It shows the power of the noise imposed on the signal compared to the power of the signal itself. The signal-to-noise ratio of the simulated structure is shown in Fig. 6. The proposed signal-to-noise ratio, using the protocol, is 93.2% better than the AFSRP protocol scenario and 0.41% better than the DCRRP protocol scenario. As we can see, the proposed signal ratio method performs better than the AFSRP protocol. In Hussain's AFSRP protocol, the number of wrong bits may increase, and the signal-to-noise ratio may increase due to a possible shutdown of the cluster head due to low battery power, resulting in less noise. The reduction is due to the proposed method's node selection process. This corresponds to the reduction of the cluster head using the Drosophila algorithm and fuzzy logic to increase the signal-to-noise ratio. The DCRRP protocol may increase the number of error bits and reduce the signal-to-noise ratio when transmitting information compared to the suggested method. Due to the large volume of data and the high probability of disturbances and data loss, we expect the signal-to-noise ratio to decrease as the number of sensor nodes increases.

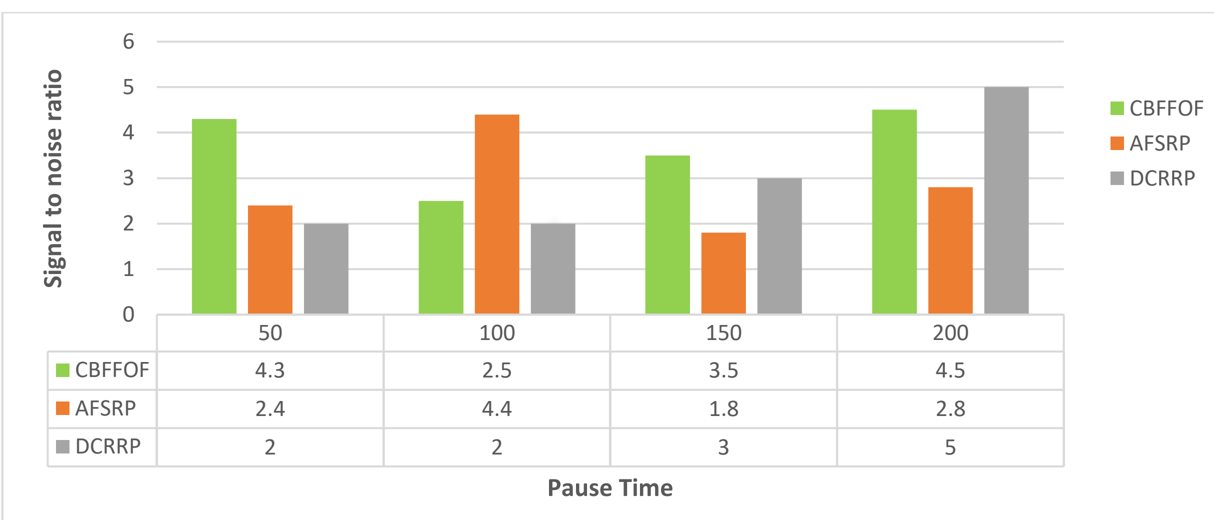

Fig. 6. Signal-to-noise ratio

3.4. Average battery energy consumption of network nodes

This quantity represents the total energy that node networks use for interactions, including transmissions and waiting. Using this procedure, Fig. 7 displays the average battery energy usage for each of the proposed situations. With 50 nodes in the suggested network structure, the median battery energy usage is reduced by 57.9%. This represents a 71.10% increase over the DCRRP protocol scenario compared to the AFSRP methodology scenario. The AFSRP protocol selects the top of the cluster node with the least remaining energy and the closest distance to the trough. If it is not smaller than the limit, it becomes the group head. The network architecture is chaotic. Furthermore, nodes farther away from the sink use more energy for transmitting information since, in this procedure, the cluster head node sends the information-gathered material directly to the sink node. A node is utilized as the group head in the suggested protocol, which uses clustering, sink tracking with the fruit fly procedure, and fuzzy logic. This node has greater distances to the sink and fewer kilometers to the middle of the cluster. Furthermore, there is no need to use a lot of energy to send data from the participant node to the cluster's leader since the node members are associated with the cluster head based on distance. Furthermore, the DCRRP protocol allows nodes distant from the sink to notify the sink of any excess data by having the group head node send the gathered data straight to the sink node. To gather data supplied by other cluster heads, a sink can relocate to a densely populated area and choose nodes aside from its own. The structure of the network is soon destroyed by the group heads' substantial amount of energy usage, which occurs when they have data to send after relocating the sink, and the delay between nodes changing the sink is a considerable issue. Additionally, as the number of sensors rises, so does the number of data streams that are not transferred, which raises energy usage.

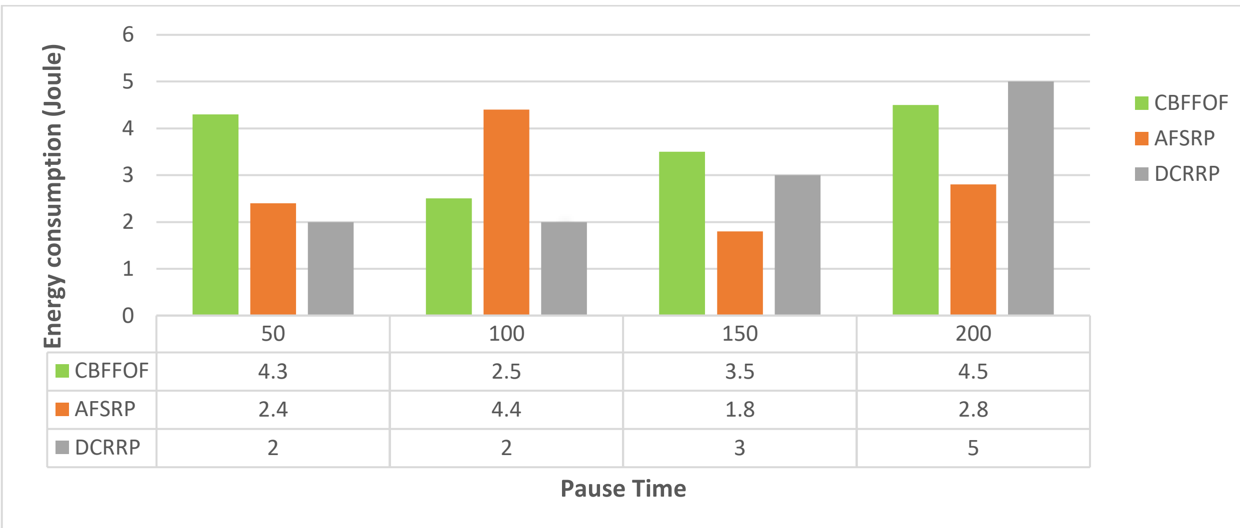

Fig. 7. Energy consumption

4. Challenges of ML-Based Routing Algorithms in WSN

A wireless sensor network consists of sensor nodes distributed in different locations. In addition to one or more sensors, these sensor nodes can communicate directly with other sensors and stations, and each node in the sensor network has a wireless transceiver or other wireless communication device, a microcontroller, and a power source (including a battery). Sensor nodes vary in size and cost. Sensor nodes collect information from sensors and send it to a station, as shown in Fig. 8. Today, the best way to transmit information from nodes in a network to a base station is high-bandwidth dual-band technology, which is the most common method in wireless sensor networks and minimizes transmission. Delay and discreet communication ability between sender and receiver. The design must take into account the high, constant, or rapid errors of nodes or similar issues or Amravati's. Likewise, another approach could be to extend the routing protocol in a way that ensures the provision of the two levels of service required for specific applications. Depending on the importance of the issues raised, design routing protocols for groups. The classification is divided according to the application type, geographic location, receiving service chamber, etc., so that the two-way low-cost transmission from the source to the third party is efficient and minimal; otherwise, the system is described as follows: Service chamber [24].

Wireless sensor networks consist of low-cost sensors that collect and transmit sensitive information. A wireless sensor network consists of several nodes, some of which are known as guide nodes. This node maintains a fixed position and assists in locating other nodes. Packet routing methods in wireless sensor networks represent a crucial area of research, particularly since numerous small-sized sensor nodes depend on batteries for their energy supply. Due to the use of this type of network in difficult and inaccessible areas, it is low-power, and sensor nodes cannot be changed or changed dynamically. In the same way, we get an overview of the energy levels of the batteries and sensors. Nodes are always in scope. Some of them will turn off the radio to conserve energy, become inactive, and then wake up when needed to start sending and receiving information [25]. Efficient routing algorithms are required. Each node that receives a data packet or a control packet sends it to all of its neighbours. After transmission, a packet is sent through all possible routes. In addition, network monitoring is carried out. Unless the packet is interrupted, it will eventually reach its destination, and the transmitted packet will follow the line of sight. Fig. 9 illustrates the principles of the smooth forwarding method in a data transmission network [25].

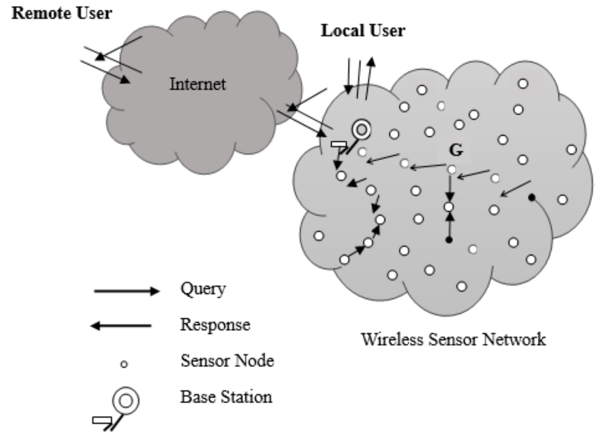

Fig. 8. Data propagation challenges in wireless sensor networks

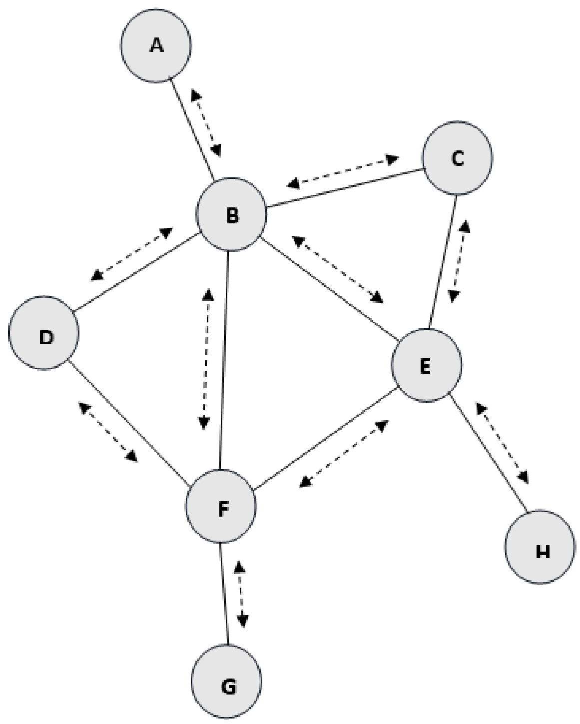

Fig. 9. The principles of the flood-sending method

Sending repeated messages to the same nodes causes this limitation, as in Fig. 10.

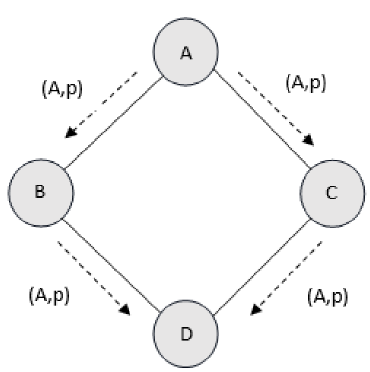

Fig. 10. The number of traffic jams in the flood forwarding method

This problem occurs when two nodes that are monitoring the same area receive packets that contain the same information as in Fig. 11.

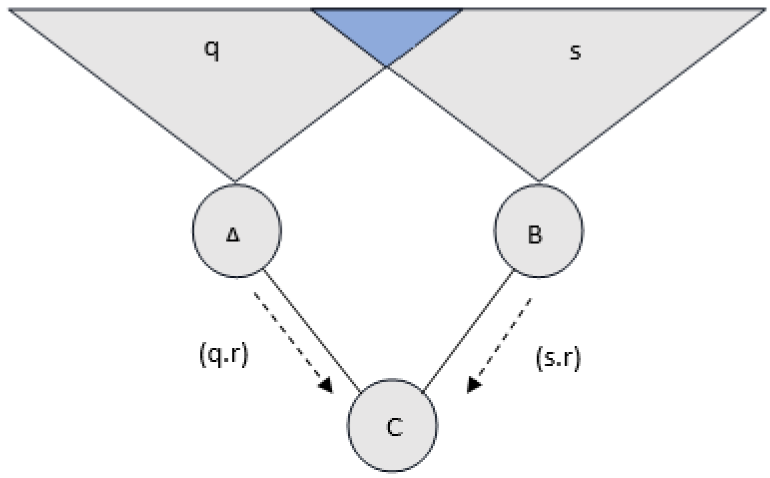

Fig. 11. Friction and overlap in the flood-sending method

A data-driven method where the central node broadcasts its requirements using a query method. After receiving the request, each node sends it to the next node. When the packets want to return to the target node, they select only one path as the best path to send the reply [26]. The LEACH protocol is one of the first hierarchical algorithms. This protocol is self-organizing and consistent. The cluster head node plays the primary role in this protocol. In this protocol, cluster heads rotate randomly with high energy, so activity is evenly distributed among receivers, and sensors consume battery energy equally. Data compression occurs during transmission to the base station, thereby reducing energy loss and enhancing system lifespan. LEACH performs the task of combining data and divides the entire task into periods. Each period includes two phases: deployment and persistence. TEEN Protocol (Receiver Network Energy Efficiency Sensitivity Threshold): The TEEN protocol is a class of LEACH-based hierarchical routing protocols used for time-sensitive applications. This protocol consistently receives average data while frequently reducing data transmission. The TEEN protocol uses the LEACH strategy to create categories in the network. This network includes simple nodes, first-level nodes, and second-level nodes. The cluster head always keeps its transmitter ready, waiting to receive information. This is one of the drawbacks of the Compatible TEEN Threshold (APTEE) protocol [27].

5. Result Analysis

In this article, a new algorithm called CBFFOF is used to select the cluster heads for WSN. Using a combination of the fruit fly algorithm and fuzzy logic, the above protocol can take into account three parameters: battery energy, the distance between the cluster head and the sink, and the distance between the cluster center and the sink. The cluster center selects the best nodes for cluster heads and determines the optimal routes to the sink.3.

The fruit fly optimization algorithm is a novel method for finding the global optimum based on fruit flies' search behaviour. Fruit fly has a stronger sense of smell and vision than other insects. This insect can detect the smell of fruits from a distance of 40 km and uses its senses after approaching the fruit. Use vision and cooperate with other fruit flies to determine the fruit's exact position. In this article, we use the fruit fly algorithm to calculate intensity. Fuzzy logic is used because, in the uncertain conditions of sensor networks, the use of fuzzy logic, which allows inference processes using flexible conditions, in combination with an optimization algorithm, can solve the problem of grouping sensor networks. Quick solution with low processing costs [28].

Additionally, the following assumptions are considered for the simulation process:

- The simulated environment randomly distributes several sensor nodes with unique identifiers.
- Each sensor node is considered a fruit fly, and its position is represented by the vector $(\boldsymbol{x_i}, \boldsymbol{y_i}, \boldsymbol{z_i})$.
- The random direction and distance for finding the path to the sink are set using the fruit fly's sense of smell.
- The receiving node will be considered a fruit.

The network clustering process in the proposed algorithm proceeds as follows:

Each sensor node generates a welcome message to identify its neighbours and broadcasts it within its range. After receiving the message, each neighbouring node sends a wish packet containing the location. Physical and its ID are generated and send greeting messages to the sending node. After receiving the hello response packet, the node sending the hello message extracts the ID and position of the neighbour node and saves them in its neighbour Table 2. The cluster head selection process then begins. It should be noted that the cluster head has been selected centrally in the receiver with fuzzy logic and the fruit fly algorithm, so the sink node sends a route. The request packet contains the receiver ID and its position for all nodes. Upon receiving this packet, it extracts the sink position ID from the packet, and by calculating its distance to the sink (according to equation (1)), the node sends a response to the route request, which includes the remaining energy. In the proposed method, the best answer is defined as a list containing the identifiers of the cluster's main nodes. At the beginning of the clustering phase, it is assumed that all sensor nodes in the simulation environment have the same conditions to be at the head of the cluster, so the ID of all recorder nodes is placed in the best response variable [29].

$$D_i = \sqrt{(x_s - x_i)^2 + (y_s - y_i)^2 + (z_s - z_i)^2} \quad (1)$$

which D_i Comma to sync (x_s, y_s, z_s) Sync's website (x_i, y_i, z_i) Physical location

The sensor's name remains until the termination condition (four hundred rounds of algorithm execution) is fulfilled.

For all sensor nodes in the best answer list, intensity. An adaptive controller uses fuzzy logic to calculate the smell.

Fuzzy Logic: The fuzzy logic [29] tries to model decisions and can provide accurate results according to unspecified and ambiguous reasoning.

The introduction and the results showed that the introduction part for all fuzzy models is the same, but the result is different for each model. In this paper, a GNU fuzzy model is used to select appropriate cluster heads. When designing the fuzzy model of three energy variables, the remaining distance of the well and the distance to the center of the remaining energy cluster are considered fuzzy inputs. The first entry is the most important variable, directly affecting the network's lifespan. If low-energy nodes are left in the decision, they will quickly disappear if they become cluster heads. The higher the residual energy, the more priority the node should have as the cluster head. The cluster head's power consumption is determined by the distance between it and the sink (the second input). The distance between the cluster head and the cluster center (the third entry) is also important because the smaller the distance from the cluster center, the smaller the sum of intra-cluster distances will be, in other words, the variable's fuzzy input energy. To avoid selecting nodes with low input energy, first, bring all the energy consumption of the main nodes to the lowest value in the cluster (the second input) and minimize all non-cluster energy consumption in the main clusters (the third entry). A fuzzy Sogno Law with three inputs x_1, x_2, and x_3 and an output y can be written as (if x_1=a, x_2=b, and x_3=c, then y=f). (x_1, x_2, and x_3) shows that the functions b and a are membership inputs, and y is the intensity of the odor or result. The operation of the fuzzy system to calculate the fitness parameter consists of four parts: normalization, fuzzification, the Sogno fuzzy inference engine, and phase shift. As mentioned, there are three energy input variables remaining: (n) E, distance from the sink (n) D, and distance from the cluster center (d(n)) for each node n [30].

The proposed method's goal is to calculate the penetration coefficient of node n, which is the cluster head. Z(n)) according to three variables is the input. Due to the presence of different ranges for each cluster, the input variables should be normalized between 0 and 1 according to Equation 2.

$$Normalized\ (x_i) = \frac{x_i - Min(x)}{Max(x) - Min(x)} \quad (2)$$

so that x_(i) is the value of the input variable X for node i. Additionally, (min(x)) and (max(x)) display the lowest value and the highest variable value among all nodes in node cluster i.

The fuzzifier transforms normalized inputs into fuzzy linguistic variables using membership functions. Membership functions for the input variables are shown in Figure 2. The fuzzy sets used to fuzzify any input variable is divided into three membership functions: low, high, and medium. In this phase, the fuzzy sets for the input variables, which include the distance from each sensor node (fruit fly) to the sink (fruit), the distance to the center of the cluster, and the battery level energy of the sensor node, and the output blurred, the definition also includes door intensity, which represents the probability of becoming a cluster head [31].

In the inference step, the intensity of the odour is calculated using fuzzy rules, and depending on the parameters considered, each fuzzy rule consists of two parts: a preliminary part such that if the distance to the sink is small, the distance to the sink is small. The cluster centre is high, and the battery energy is high. This also leads to a reduction in the intensity of the odour. Three fuzzy sets are defined for each of the input parameters, which will result in twenty-seven fuzzy rules.

Next, we calculate the fuzzy output for each active rule. Finally, the fuzzifier sums the fuzzy outputs and converts them into a single value (Z(n), or odour intensity).

It uses a fuzzifier to convert the fuzzy output into a numerical value. In this article, the central average fuzzifier is used, which is calculated using equation 3.

$$Smell_i = \frac{\sum_{l=1}^{m} y^{-l} \prod_{i=1}^{n} \mu A_i^l(X_i)}{\sum_{l=1}^{m} \prod_{i=1}^{n} \mu A_i^l(X_i)} \quad (3)$$

The parameters of this relationship are index, node: m; the number of fuzzy rules here is 27. n: number of membership functions for the input variables (here equal to 3). $\mu A_i^l(X_i)$is the is the fuzzy value of the membership functions and $\boldsymbol{y^{-l}}$ and is also the output centre. The best response that has a higher door intensity is determined by the fuzzy system; in fact, a knot that has a small distance from the sink, a small distance from the cluster centre, and more energy will have a higher probability. The candidate is the head of the cluster, and his ID is on the list of best answers. The fuzzy system sorts the sensor nodes according to their door fitness or intensity, then adds the number of cluster heads, represented by spheres with higher fit, to the list of the best answers, updating it accordingly. For approximately 400 sensor nodes that exhibit high fitness or high door intensity, the sink will determine the optimal response variable and subsequently send a notification message to the cluster head. Cluster head nodes broadcast the (new) notification message of becoming cluster heads within their scope. Neighbouring nodes that received this message, if they are not themselves cluster heads, send the connection message containing their identifier and the amount of remaining energy to the cluster head closest in terms of distance, and thus clusters form. The cluster head sets a timer to determine when to send information to the sink for its cluster members and sends a response message to the cluster members. Cluster member nodes issue data to the cluster head.

If the head of the cluster runs out of energy, the algorithm is run from the beginning to replace that cluster head [32].

During simulation iterations of all scenarios, this method has been shown to increase network lifetime by 50–90%. Therefore, applying the proposed algorithm to each scenario improves the performance. The lifetime of the network. The results of Table (2), which shows the results of a single execution of this algorithm on a specific network with the specifications mentioned above and, as an example, shows the truth of this claim, As can be seen in this table in scenario (1), where the objective function for the evacuation of the first node is considered an algorithm, by determining and applying it, the evacuation of the first node can be delayed from 26 cycles to 50 cycles. The discussed coefficients of the PSO algorithm convergence process in this scenario are presented as an example in Fig. 12.

Table 2. The results of the simulation scenarios

Method	Minimum energy coefficient	Coefficient of maximum effective degree	Exit the first node	Exit the last node	The beginning of the breakup	Total live nodes
EA-MCDS-UDG	-	-	26	167	44	7146
Scenario 1	0.2305	0.9358	50	168	50	6037
Scenario 2	0	0.7910	27	168	24	7827
Scenario 3	0.0972	0.9091	39	167	58	6991

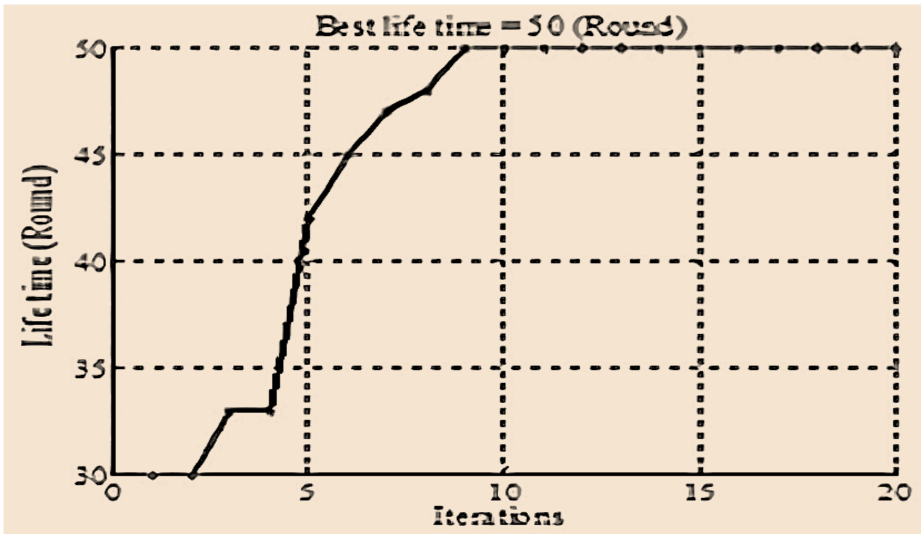

Fig. 12. The convergence process of the PSO algorithm in the scenario

In scenario (2), the proposed algorithm's optimal coefficient determination led to an increase in the total number of live nodes from 7146 to 7837 over the network's lifetime. The breakup increased from 44 to 58.

The results of this scenario are detailed in Table 3. The maximum desired grid degree is 17. It determines the order limit by rounding the product of the most significant order coefficients in each period to the maximum order. For a better comparison of the scenario with the UDG-EA-MCDS algorithm, the order of exiting the nodes from the energy cycle is shown in the diagram in Fig. 13. This figure shows that when the PSO objective function in the EA-MCDS-UDG algorithm and the proposed algorithm are one of the specified scenarios, the coefficients of the proposed algorithm are determined according to these objective functions. What is the number of live nodes in each period? A live node is a node that is still connected to the sink.

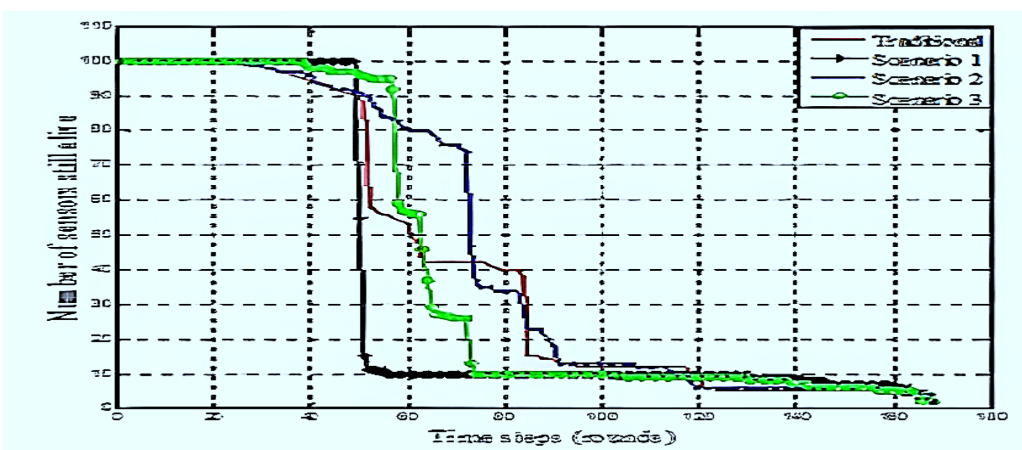

Fig. 13. The number of live rounds according to energy periods in different simulation scenarios

Attention to resource limitations, such as low battery capacity, limited memory, and low computing power, and failure of nodes in WSN networks to form a backbone with a long lifespan, which has a high effect on efficiency and increases the lifespan of the network, is one of the most important challenges ahead. Apart from the importance of a high network lifetime, the network lifetime directly indicates the efficiency of the backbone formation protocol in terms of load and energy balance. CDS networks, one of the common methods for creating backbones, are of great importance. A CDS with a minimum size imposes a large load on the backbone nodes, causing rapid energy consumption for these nodes and creating gaps between the network nodes. To solve this problem, this paper organizes the network backbone into a specific category.

It refers to the connection-dominated set problem as one with degree and minimum weight constraints. The proposed method first considers the objective function of maximizing network lifetime through the PSO optimization algorithm and determines two coefficients: maximum node degree and minimum residual energy. After that, nodes that do not satisfy these two conditions before each cycle of energy and backbone construction cannot compete with other nodes for DS selection. It presented simulation results to validate the effectiveness of the proposed method. As these results show, the proposed method was able to significantly improve the network's lifetime compared to the similar methods presented.

Table 3. The comparisons of ML-based routing algorithms

Scheme	Routing	ML Algorithm	Overhead	Scalability	Delay	QOS	Energy Efficiency
ESDFM	Multi-hop	Kernel linear regression	Low	Limited	High	No	Reducing redundant data
EBS-S	Geographic	SOM+k-means	High	Medium	Medium	No	Optimizing paths
ANNR	Multi-hop	SOM	High	Limited	Medium	Yes	Optimizing paths
WL-DCNN	Multi-hop	CNN	High	Good	Low	Yes	Optimizing paths
SecDL	Geographic	DNN	High	Good	Low	Yes	Reducing redundant data+ Optimizing paths
QLRR-WA	Multi-hop	Q-learning	Low	Good	Low	No	Optimizing paths
Q-PR	Geographic	Q-learning	Low	Limited	High	Yes	Optimizing paths
RLProph	Multi-hop	RL	Low	Good	Medium	Yes	Optimizing paths
DRLSOR	Multi-hop	RL	Low	Good	Low	Yes	Optimizing paths
EL	Multi-hop	Hybrid	High	Good	Medium	No	Optimizing paths

As shown in Table 3, ML-based routing systems use distinct acquisition algorithms such as lineal reflux kernel, SOM, Q-acquirement, reinforcement learning (RL), and complexity to deploy energy-efficient routing tools in B-networks. They use convolutional neural networks (CNN), deep neural networks (DNN), and combinatorial acquisition algorithms that perform other functions. Specifically, ESDFM utilizes a linear regression kernel for information detection, which results in reduced overhead in wireless sensor networks (WSNs). QLRR-WA based on Q-learning can accede to low suspension and low overhead, which is a good potential way to improve energy consumption in wireless networks. RL can access low concealment and low upper, which is a good potential way to improve energy decline in wireless networks. Both CNNs and DNNs have wide overhead but good scalability and low latency. Meanwhile, EL based on combinational acquisition algorithms provides excellent scalability in WSNs.

6. Conclusion

An introduction to routing methods for wireless connections is provided in this article. We present green networking design techniques for WSNs using both conventional and machine learning approaches. It suggests a mathematical example of a machine learning-based networking method to increase the lifespan of WSNs based on thorough evaluation and assessment. This study also looks at the fundamentals and traits of several WSN routing methods. It also covers the advantages and disadvantages of various methods aimed at enhancing the efficiency of routing strategies in WSNs. This paper concludes by outlining the difficulties in applying computational learning to the structure of routing techniques in wireless sensor networks (WSNs) and suggesting future lines of inquiry that merit investigation and should be tackled with the use of machine learning. Investigated. A wide range of people interested in ML and WSN will find this conversation interesting. Future studies could look into the following topics: WSNs' intellectual and energy-consuming constraints prevent extensive use of machine learning techniques for low-power and energy-constrained sensing. Integrated collaborative education, which is highly appropriate for WSNs, removes the mathematical constraint and achieves machine learning-based green transportation with reduced energy usage.

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