Contemporary Mathematics
http://ojs.wiserpub.com/index.php/CM/

Research Article

An Energy-Efficient Learning Automata and Cluster-Based Routing Algorithm for Wireless Sensor Networks

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Received: 9 March 2023; **Revised:** 20 April 2023; **Accepted:** 9 May 2023

Abstract: Wireless sensor networks (WSNs), which may be used for a broad variety of applications, have recently emerged as a prominent data collection paradigm. The fundamental concerns in wireless sensor networks are the efficient use of energy and the reliable delivery of data, both of which are largely determined by the rate at which packets are dropped. When developing an energy-efficient routing protocol, one of the most important steps is selecting a node to act as a successor node in a routing path. The application of learning automata theory to guide the routing decisions made by the sensors in a WSN has recently been the subject of research in the field of WSNs, where it has been shown to have several advantages. In this paper, a learning automata-based PSO relay selection scheme for energy-efficient relay selection and reliable data delivery is proposed. The network is clustered using the LEACH protocol. The random number in the traditional LEACH protocol will be stabilized with the sensor node energy level for CH stability. Every sensor node in the network estimates the best possible routes to the sink node using the PSO algorithm. Instead of retransmissions, here we introduce learning automata for successor node selection during packet loss. The proposed learning automata calculate the next node's selection probability in a routing path using multi-objective parameters like communication cost, residual energy, distance from BS, buffer size, and previous selection probability. Performance evaluation clearly showed that the proposed approach decreases energy usage, transmission delays, and data transfers while extending network lifetime. According to the experimental results, the proposed scheme can improve energy efficiency by 21.68%, delay by 31%, PDR by 87%, routing overhead by 0.5%, and throughput by 18.76% as compared to existing techniques like O-LEACH (Optimized Low Energy Adaptive Clustering Hierarchy Protocol) and EEPC (enhanced energy proficient clustering).

***Keywords*:** WSN, clustering, energy efficiency, PSO, learning automata, network lifetime, LEACH

MSC: 68T05,60A99,94A05,68Q80

1. Introduction

Because of their limited capabilities and resources, sensor nodes are extremely vulnerable to failure [1]. Energy is an essential component in sensor networks because the exhaustion of energy resources is one major cause of this failure.

DOI: https://doi.org/10.37256/cm.4320232654

One of the major energy-consuming tasks of a sensor network is multi-hop routing [2], which is a method of gathering information on each node in every part of the network at the sink. One way to find the path is to choose the path with the least energy consumption. One drawback of this approach is that it requires a method for calculating the amount of energy consumed along each path. Utilizing the technique of data aggregation is yet another approach. In the data aggregation technique, packets with related data are consolidated together at intermediate nodes before being sent to the sink [3]. As a result, less energy is used because fewer packets are being transmitted across the network.

When considering only the information that is local to each node, finding the routing path for each node is not an easy task. Every node in the network makes an effort to deliver its data packets to a neighbor that possesses information that is pertinent to the node's own [4]. If the information that is held by each node changes over the course of the network's lifetime, then the challenge of finding the optimal routing path for each node becomes even more difficult to solve. In such a scenario, the path that each node takes to route data through the network is constantly shifting; as a result, nodes need to be able to adapt to these shifts.

Poor link quality, a lack of a free buffer to hold a packet, and residual energy at the sensor node all have the potential to cause the packets to be dropped. To ensure reliable data delivery, sensor nodes can retransmit dropped packets; however, retransmitting packets increases node energy consumption and delays packet delivery. In time-sensitive applications, packet retransmission is inefficient. The design of an energy-efficient routing protocol relies heavily on the process of selecting a node to act as a successor node in a routing path [5]. Selecting a quality successor node can reduce the packet-dropping rate.

The methods for energy conservation have received the greatest attention, with techniques such as cluster formation and various data transmissions [6]. The conventional clustered network design is shown in Figure 1.

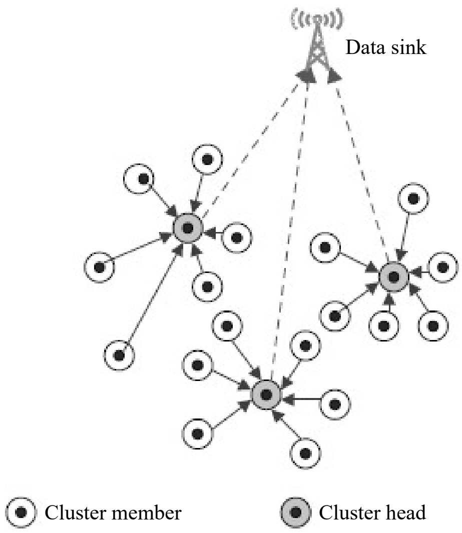

Figure 1. Network topology of a clustered wireless sensor network (WSN)

In general, cluster-based routing methods may utilize the network's sensor nodes more effectively than non-clustering protocols. Eliminating the associated data that might reduce the total amount of data is the responsibility of a cluster leader known as the cluster head (CH). CHs will then provide the base station (BS) with the compiled data. One of the top clustering methods for achieving scalable solutions and extending network lifetime is the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol [7]. When a node's probability is less than a certain threshold and is chosen by a random number between 0 and 1 $TH(n)$ (Equation 1), it is voted as a CH in LEACH. Choosing the CHs that need the least amount of communication energy to reach, the remaining nodes join a certain cluster. A single sensor's battery should not be totally drained; in order to prevent this, CH rotates all the sensors.

$$TH(n) = \begin{cases} \dfrac{p}{1 - p\left[\left(r\ mod\ \dfrac{1}{p}\right)\right]}, if\ n \in G \\ 0, \qquad\qquad\qquad\qquad otherwise \end{cases} \tag{1}$$

In the above equation, $TH(n)$ is the threshold value of n nodes, and p denotes the probability value. Network nodes choose random numbers between 0 and 1.

Besides the advantages of LEACH, it also has some demerits, which are as follows:

- Since cluster heads in LEACH are chosen at random, it is impossible to guarantee the ideal number and distribution of CHs.
- Some nodes with low residual energy may experience an early death since they have equal priority with cluster leaders as nodes with higher residual energies.

The combination of clustering, learning automata, and optimization methods is a popular research topic in the field of WSNs and other distributed systems. In recent years, there have been many advances and new developments in this area.

Clustering algorithms for WSNs continue to be an active area of research, with new algorithms being developed to address various challenges such as energy efficiency, scalability, and data aggregation. Recent research in this area has focused on developing clustering algorithms that can handle large-scale WSNs, improve network lifetime, and minimize communication overhead [8].

Learning automata has also seen new developments in recent years, with research focusing on developing new models and algorithms that can handle large-scale and dynamic WSNs. Recent studies have focused on developing learning automata algorithms that can make real-time decisions about network behavior and improve network performance [9].

Optimization methods are an important part of the solution for improving the performance of WSNs [10]. In recent years, there have been many new developments in optimization methods, including new algorithms and techniques for handling large-scale and dynamic WSNs. The goal of this research has been to create optimization techniques that can enhance the performance of learning automata models and clustering algorithms, as well as cut down on energy usage and increase network scalability.

To solve the aforementioned problems, an enhanced energy-efficient LEACH is presented in this study. The random number of conventional LEACH is added to the COC (coverage of CHs) and CL (CH lifetime) parameters. COC makes sure the chosen CHs have more neighbors in their coverage area, and CH lifespan makes sure the chosen CHs are more energetic. Additionally, the learning automata-based routing mechanism is used to determine the best surrounding node by taking into account factors including communication cost, residual energy, distance from the BS, buffer size, and the likelihood of a prior selection. Additionally, the particle swarm optimizer (PSO) relay selection technique has been used to identify the energy-efficient routing pathways in the WSNs for dependable data transmission and the selection of energy-efficient relays.

Our contributions:

- The traditional LEACH algorithm is modified for reliable CH selection. The traditional LEACH's random number generation is stabilized by including coverage and lifetime parameters. The coverage parameter ensures the selected CHs have more neighbors in their coverage circle, and the lifetime parameter ensures that the selected CHs have higher energy.
- Using the PSO algorithm, a learning automata-based, energy-efficient, and reliable data delivery routing algorithm is designed to improve the energy efficiency and reliability of a WSN's data delivery.
- The proposed learning automata mechanism finds the best node as a successor in a routing path. So, retransmission is not necessary during packet loss, which results in improved energy efficiency.

Advantages of the proposed system:

- The modified LEACH algorithm selects stable CHs that reduce frequent re-clustering in the network. This results in reduced overhead and maximum data aggregation. Also, a considerable amount of energy can be saved by the sensor nodes.
- The learning automata scheme proposed in this study reduces the chances of retransmission by effectively

selecting the relay nodes. Hence, the data delivery rate also increased in the network.

The following is the order in which the remaining portions of the paper are presented: in Section 2, we will talk about several new research publications that deal with energy-efficient optimization routing algorithms and learning automata for WSNs. Section 3 describes the proposed technique, and the experimental results of a proposed approach with existing approaches are demonstrated in Section 4, and the conclusion of the proposed work is discussed at the end of the paper.

1.1 *Literature survey*

An analysis of learning automata and optimization methods would cover research that explores the use of optimization techniques to improve the performance of learning automata algorithms. This could include studies that investigate various optimization algorithms that optimize the parameters of learning automata models. The focus of the survey would be on the applications of this combination in various domains, such as control systems, robotics, machine learning, and more. Additionally, it would also review the strengths and limitations of different optimization techniques for improving the performance of learning automata algorithms.

He [11] proposed an energy-saving K-means algorithm to address the issues in conventional WSNs like short network cycles, restricted throughputs, and constraints in node energies. To reduce node energy consumption during data transfers, multi-hop routes are based on hop counts and transmission lengths.

Energy-Efficient Load Balancing Ant-based Routing (EBAR) algorithm was introduced by Li et al. [12]. Using updated pheromone trail updates and pseudo-random route finding, it balances the nodes' energy usage.

Shah et al. [13] developed the DBDDCA (Distance-Based Dynamic Duty-Cycle Allocation) method to address the problem of energy usage. In order to preserve energy, Cluster Head Longer Distance Nodes communicate in DBDDCA for much less time.

Singh and Malhotra's [14] fuzzy logic connection cost estimate residual energy, packet loss rate, and RSSIs (received signal strength indicators) are used in this technique. This work applies the idea of fuzzy logic-based link cost calculation. This algorithm's performance is compared to that of more established RL (reinforcement learning)-based algorithms like limited floods, real-time searches, adaptive trees, and ant-based forward flooded routing. Furthermore, the link quality is not taken into account.

Vinitha et al. [15] suggested a hybrid optimization approach for energy-efficient multi-hop routes in WSNs. They proposed the Cat and Salp Swarm Optimization Algorithm (C-SSA) for WSNs and selected optimal hops for advanced routes where CSO (cat swarm optimization) and SSO (salp swarm optimization) methods were combined. C-SSA performed several tasks. Under restrictions including energies, delays, inter- and intra-cluster distances, connection lifespan, delay, and distance, it shows superior convergence. With this approach, intrusion and assault detection are unsuccessful.

Elhoseny et al. [16] created energy-efficient clustering based on swarm intelligence with multi-hop routing protocols for long-term WSNs. Their routing strategy, based on GWO (Grey Wolf Optimization), selected optimal paths in networks. Their technique improved energy efficiency and network lifetime by combining clustering and routing procedures. It cannot carry out quick data transmissions.

Bhola et al. [17] proposed LEACH, which is a routing protocol that uses the least amount of energy, and the genetic algorithm (GA), which is an optimization algorithm. LEACH was a hierarchical protocol that turned sensor nodes into CH, which gathered and compressed data before sending it to the target node. A GA fitness function was used to find the optimal path.

Rambabu et al. [18] proposed HABC (Hybrid Artificial Bee Colony), which serves as a foundation for removing the potential for global search from the ABC algorithm. In addition, HABC reduces the potential for cluster heads to be overloaded with an excessively large number of sensor nodes, which would hasten the degradation of sensor nodes when an inadequate CH selection technique is used.

Guleria et al. [19] proposed, in order to improve the network route during data transmission, taking into account the changeability of sensor nodes, the enhanced energy proficient clustering (EEPC) protocol. The main goal was to make the sensor network last longer and make it easier to track and monitor in a WSN environment. The work created a clustering algorithm for WSNs that uses less energy and helps the network last longer and use less energy. The idea of using EEPC to find relay nodes was new. It sent sensor data to the BS using Enhanced Particle Swarm Optimization

(EPSO) and sensor data fusion to conserve energy. By adding an improved swarm optimization technique, the proposed EEPC algorithm made the sensor nodes last longer. It also fixed a common problem in which the CH itself sent event-driven data track by track to the BS. Extensive simulations showed that the proposed EEPC made tracking mobile nodes more accurate and used less energy. Simulation findings demonstrated that the suggested technique was superior to existing performance measurement methods.

Pal et al. [20] discuss a GA-based energy-efficient clustering technique by taking into account the fitness objective function. The fitness objective function makes adjustments to the steady-state phase for energy heterogeneity and uses the compactness, separation, and number of CHs optimization parameters. However, the fitness function of the protocol does not take into account the density of the nodes, and as a result, the cost of communication is excessively high.

Rani et al. [21] discuss in a protocol that can be created by integrating WSN and Internet of Things (IoT). The method results in synchronization and a transmission scheme, both of which contribute to an increase in network capacity while simultaneously reducing the amount of energy conserved. However, it does not take into account heterogeneous networks when planning network deployment.

Sahoo et al. [22] discuss an effective GA metaheuristic for maximizing area coverage in WSN for the purpose of calculating the fitness function. A population initialization, a mutation function, and a combination of Laplace Crossover method operators and Arithmetic Crossover method operators are included in the method. The paper does not participate in the process of data collection and instead only checks to see if the area has been covered.

An MFO (Moth Flame Optimization)-based clustering algorithm for increasing the network's lifetime was examined, as discussed by Mistarihi et al. [23]. The efficiency of the proposed algorithm was evaluated in comparison to that of three different clustering protocols that already exist (SSO, WOA (Whale Optimization Algorithm), and LEACH), using four distinct metrics (fitness function, network lifetime evaluation, energy evaluation and throughput). In comparison to the SSO and WOA algorithms, as well as the LEACH protocol, the MFO algorithm was able to achieve a significant performance improvement while simultaneously increasing its level of energy consumption. The proposed algorithm improved the network throughput while preserving the energy of the nodes, extending the lifetime of the sensor network, and extending the lifetime of the network overall.

The Energy-Efficient Clustering Algorithm (EECA), which is discussed by Debasis et al. [24], extends the lifetime of WSNs by minimizing the amount of energy that is consumed in sensor nodes. Within the context of EECA, the target area is conceptualized as a federation of several smaller regions. The Artificial Neural Network (ANN) is utilized by the model that has been proposed in order to determine which node in each region will serve as the CH. The sensor nodes that have a minimum energy level that has been predefined are eligible for the CH selection process. The scores of these nodes are determined by ANN based on four parameters: the amount of residual energy, the number of events that have been detected, the distance to the base station, and the number of neighboring nodes. The control node, CH, for a given region is determined to be the sensor node that has the highest score. In the model that has been proposed, a CH will perform an incoming transmission check on the medium for a very brief period of time at the beginning of each slot. In the event that the CH does not receive any signal within this allotted amount of time, it will turn off its radio. This rule reduces the amount of time spent in CHs just listening to noise. In order to evaluate EECA's effectiveness, it is benchmarked against other medium access control protocols already in use.

2. System model

2.1 *Improved LEACH based selections of CHs*

This section explains the suggested CH selection procedures and stabilizations for random number generations. The suggested approach multiplies generations of random numbers by the network's COC and CL parameters for energy dependency.

In CHs voting process, the creation of random numbers is crucial. In the conventional LEACH algorithm, the nodes first generate a random number before choosing CHs. The generated random numbers are compared with threshold values. If random values are less than threshold values, nodes become CHs for those rounds. Since CHs are chosen based on COC and CL characteristics, the proposed approach improves system performance and the longevity of networks. The proposed approach alters random number generation procedures for selecting energy-efficient CHs.

The random numbers are multiplied by node COC and CL parameter values. The method of creating random numbers is dependent on the energy of the nodes when these parameters are multiplied. The following provides an explanation of the suggested COC and CL parameters:

COC: The COC parameter measures the proportion of normal sensor nodes that are within d_0 of their respective CHs or less. The closer nodes are to their CHs, the greater the value. Normal sensor nodes will therefore use less energy to transmit data. Every sensor node in the proposed CH selection method has its COC parameter evaluated during CH selection. The nodes with a high CH coverage rate have a greater chance of becoming CHs. The computations for the same are given below:

$$COC = \frac{\left(NN\left(\mathrm{MD}_{2\mathrm{CH}}\right) \le d_0\right)}{n}$$

where d_0 can be represented as $\sqrt{\frac{\in_{fs}}{\in_{mp}}}$, while $\in_{fs}$ indicates free-space channels and $\in_{mp}$ represents multi-path channels. The values of $\in_{fs}$ and $\in_{mp}$ are $\in_{fs}$= 0.0013 pJ/bit/m and $\in_{mp}$= 10 pJ/bit/m. In the above equation, $NN(\mathrm{MD}_{2\mathrm{CH}}) \le d_0$ represents nodes with minimum distances $\le d_0$ from their respective CHs. n stands for node count.

CL: It shows the cumulative lifespan of all the chosen CHs. It outlines the period of time until CHs may resume the data collection operation. A higher score shows that CHs have a longer lifespan. This is how it is calculated:

$$CL = \frac{\sum_{i=1}^{T_{CH}} \left(E_{res}(i) / ATP\right)}{Total_{CH}}$$

where $Total_{CH}$ implies CHs counts, E_{res} (i) stands for residual energies of nodes (i), and ATP represents average transmission powers required to transmit data to BSs.

Normal random numbers are *rand* (n). The suggested method improves random number generation:

$$rand(n)' = rand(n) \times \left(COC_n + CL\right)$$

The enhanced random number value is now compared to the sensor nodes' threshold values. The threshold function plays a crucial role in the selection of CHs. The node probabilities are values used by the threshold function to choose CHs. How well threshold function nodes employ their average node energy affects network performance. To maintain the consistent use of energy, CHs duty is cycled across all network nodes. Depending on CH's selection probability, each node has a chance of being chosen as CH. The node energy determines which node is chosen to play the job of CH. The average energy of the nodes from the network's inception to its end is used by the suggested method's threshold function. The following is a representation of the suggested LEACH's threshold function:

$$TH(n) = \begin{cases} \dfrac{P_n}{1 - P_n\left[\left(r \bmod \dfrac{1}{P_n}\right)\right]} \times \left(COC + CL\right) + \dfrac{r}{P_n}, & if\ n \in G \\ 0, & otherwise \end{cases}$$

In the above equation, P_n denotes the probability of n to become CH, r denotes the round number.

The threshold function equals the modified random number's value.

$$rand(n)' \le TH(n)$$

If the random value is less than the threshold, the node becomes CH; otherwise, the operation restarts.

2.2 *A technique for energy-efficient routing based on learning automata*

This section explains the PSO-based node selection technique used to identify dependable and energy-efficient data transmission channels. For calculating the node's selection probability during route loss, learning automata are also shown.

2.3 *PSO-based relay choice method*

2.3.1 *PSO*

Fish schools and bird flocks in nature provide inspiration for PSO. These birds frequently fly in groups without running into each other as they look for food or cover. Each individual bird or group member adapts its velocity and position in accordance with the group's knowledge. Since the group shares knowledge, each bird's or member's own effort to find food and shelter decreases in a group.

PSO is made up of a set number of particles (S_n), each of which provides an answer to a particular instance of the issue. A fitness function is going to assess each particle. Every particle has the same size. In the dth dimension of hyperspace, each particle P_i possesses a location (P_{id}) and velocity (Vel_{id}). So, particle P_i exists at all times and is represented as:

$$P_i = P_{i,1}, P_{i,2}, P_{i,3}, \ldots P_{i,d}$$

Each particle P_i repeatedly updates its location and velocity in accordance with its individual best (pbest) and the global best (gbest) to arrive at the global best position. Updating continues until the gbest is identified or the maximum iteration count has been reached.

2.4 *Relay node selection using EPSO*

The sensor nodes use the relay nodes to transmit their acquired data to their respective CHs during the data transfer phase. Through multiple-hop relay nodes, sensor nodes send data to CHs. To conserve network energy, PSO is used to choose data relay nodes in the suggested method. PSO improves the fitness function for relay nodes between sensor nodes and CHs in the proposed strategy. Sensor nodes, considered particles, are assessed using the recommended fitness function. The fitness function considers residual energy and distance to CH to choose the best sensor node as a relay. Based on the fitness criteria, the proposed relay selection technique calculates a fitness value pbest for each sensor node taking part in the relay node selection procedure. The relay node that sends data to CHs is the node with the highest fitness value, gbest.

2.4.1 *Relay node selection parameters*

The node residual energy and distance to CH are employed in the PSO algorithm for picking the relay nodes. The criteria used to pick the relay node that is the most effective are very important. To conserve battery life, the relay node transfers data from member nodes to CHs. The PSO approach uses the relay selection parameters to provide fitness values for CHs nodes taking part in the relay selection process. The following are the criteria used to choose the relay:

(a) Residual energies: Relay nodes are used by all member nodes to send data to their respective CHs. Energy selection is crucial because a high-energy node can effectively execute relay duties and last for a longer duration. Insufficient energy during data transmission might cause the minimal energy node to malfunction or die, which can be stated as:

$$f_1 = \frac{1}{M} \times \sum_{i=1}^{N} E_{res}\left(N\right)$$

(b) Member to CH distance: This refers to the average distances between sensor nodes and their associated CHs. Maximum distance mandates the use of the most hops, which may result in an increase in sensor node energy consumption. To save a large amount of energy in sensor nodes, the distance to CHs should be considered while selecting the least hop nodes. It may be stated as follows:

$$f_2 = \sum_{j=1}^{m} (\sum_{i=1}^{lj} dis(S_i, CH))$$

The enhanced PSO technique gives all relay selection nodes fitness values. After calculating their respective fitness levels, the nodes send out a broadcast message to the other nodes in their range, in which they include their node identifier and fitness level. Comparing their fitness scores against those of the other sensor nodes in the cluster, the relay election nodes. The strength and conditioning relay node will send data to CH. Relay selection's fitness function:

$$\text{pbest}_i = \omega_1 \times f_1 + \omega_2 \times f_2$$

$$f_1 = \max\left\{\text{residual}_{energy}\left(n\right)\right\}, \qquad 1 \le n \le N,$$

$$\text{where } N = \text{total number of nodes}$$

$$f_2 = \text{minimize}\left\{\text{distance}\left(S_i, CH\right)\right\}$$

$$\text{pbest}_i = \omega_1 \times \frac{1}{M} \times \sum_{i=1}^{N} E_{res}\left(N\right) + \omega_2 \times \sum_{j=1}^{m} (\sum_{i=1}^{lj} dis(S_i, CH))$$

$$\text{gbest}_i = \max\left[\text{pbest}_i\right]$$

Where ω_1 and ω_2 the fitness function weight coefficient ranging between 0 and 1 ($0 < \omega < 1$).

The node with the highest fitness value wins the competition and fills the position. Before the data is transferred to the CHs, the sensor nodes communicate the data they have collected to the nearest relay node, which relays then send to the next closest relay.

Pbest is neither a minimize nor a maximize function. It denotes the particle's best value at the current round for every particle. The pbest values are compared, and the best pbest values is considered the gbest value. The above equation is nothing but the calculation of pbest value of each particle based on residual energy and distance parameters. The terms minimize and maximize mentioned in f_1 and f_2 equations denote our objective, such as that the node should have maximum residual energy and minimum distance to be selected as a relay, and have nothing to do with the parameter values.

2.5 *Learning automata approach*

In order to find the successor nodes using learning automata, this work's nodes i keep a simple "Neighbors List" with attributes shown below that hold information related to neighbors: 1) the neighbor's ID, j_{ID}, where $j = 1,..., Ni$, and Ni represents the number of neighbors of nodes i and, consequently, the lengths of the list: neighbor j's energy level $E_j(t)$ at time t, communication cost $CC_j(t)$ incurred through neighbor j at time t, and distance $d_{j2\text{BS}}$ (t) from neighbor j. 2) The buffer's size, $b_j(t)$. Note that the forwarding decisions made by learning automata-supported routing protocols are often based on the neighbors with the highest probability.

Nodes compute probabilities for their neighbors with learning automata. Selection probability (SP_j) of nodes j indicate their resourcefulness i.e., like communication cost $CC_j(t)$, residual energy E_j (t), distance from BS $d_{j2\text{BS}}$ (t), buffer size b_j (t). Based on these values stored in the Neighbor List, the automaton in i associates a selection value SV to each neighbor j, which is also stored in the Neighbor List as per the following expression:

$$SV_j = \omega_1 \times CC_j + \omega_2 \times E_j + \omega_3 \times d_{j2BS} + \omega_4 \times b_j,$$

where ω_1,ω_2, ω_3, and ω_4 are the weight coefficients ranging between 0 and 1$(0 < \omega < 1)$.

Further, selection probability (SP_j) of node j is calculated using SV_j, quality of link LQ_{ij}, and previous selection probability value SP_j^{prev} and is given by

$$SP_j = \omega_1 \times SV_j + \omega_2 \times LQ_{ij} + \omega_2 \times SP_j^{prev},$$

where ω_1, ω_2, and ω_3 are the weight coefficients ranging between 0 and 1$(0 < \omega < 1)$.

2.6 *The update strategy*

With this arrangement, node's learning automaton choose neighbors with highest chances of obtaining packages. Every learning automaton chooses next-hops from possible lists and sends packets to them depending on available information and waits for feedback. The probability set is updated to implement this feedback mechanism, which commonly rewards or punishes the automaton's behavior.

In the case of this work, the automata in node i chooses node j as the next-hop with the highest probability before sending the packets there. Node j changes the communication cost, residual energy, distance from BS, buffer size, and probability SP_j (t) reported by node i in its neighbor list when it gets the packets.

All of the other neighbors in the vicinity of i can overhear the answer, as seen on the left side of Figure 2, and perhaps carry out the same updates as j, but they will discard the packets as soon as they have been processed. As a result of being able to hear the transmission, the rest of node j's neighbors, including node i, may update when j sends the packets to node k (right side of Figure 2).

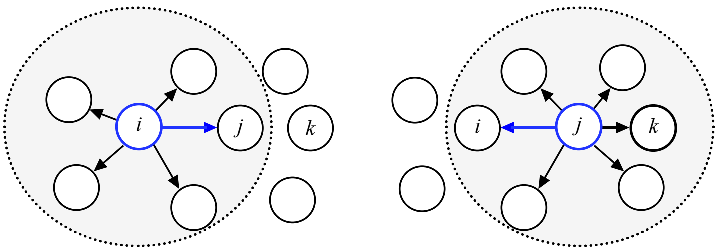

Figure 2. Update approach: (Left-side) neighbors of i update when node j passes packets, (right-side) neighbors update when node j performs updates

The learning automaton in node i will reward node j if the metrics in its feedback from node j are adequate, as shown in Figure 3. If not, j is penalized and has a lesser probability of getting picked.

2.7 *Combined routing technique*

Actually, the proposed relay selection based on PSO and LA (Learning Automata) works along with the routing protocol configured in the sensor nodes. The proposed PSO+LA technique optimizes route path selection in the routing protocol. They will act as a part of the routing protocol. Since every sensor node needs a routing protocol to select the next hop nodes for data transmission, the proposed changes do not incur any additional overhead or affect sensor node resources such as energy, etc.

In this section, we describe the combined working mechanisms of both PSO and learning automata. In WSNs, each node wants to send data to a base station. Initially, each sensor node has multiple options for the next hop based on multiple parameters. In the proposed network, the sensor nodes use PSO and learning automata together to determine the next hop nodes based on the feedback from the network. The best next-hop nodes are found using the PSO algorithm based on the selection parameters and the weights assigned to each node based on relevant factors. The learning automata is used to adjust the next hop selection based on the feedback from the network. The learning automata algorithm uses a reward-penalty mechanism to increase or decrease the probability of selecting a node as the next hop based on feedback. In short, the PSO algorithm finds the optimal next hop nodes, while the learning automata adjusts the next hop selection based on the feedback from the network. The result is more efficient and reliable routing, as the next hop selection is optimized in real-time based on the current network conditions.

Let's consider a network consisting of five sensor nodes (A, B, C, D, and E; Figure 3). Node A wants to send a packet to the base station and has multiple options for the next hop. The next hop options are the neighboring nodes B, C, D, and E. Initially, node A uses PSO to evaluate the optimal selection parameters for the next hop selection. The PSO algorithm updates the parameters based on feedback from the network and the performance of the routing. The node A uses learning automata to adjust the next hop selection based on the feedback from the network. The learning automata uses a reward-penalty mechanism to increase or decrease the probability of selecting a node as the next hop based on the feedback.

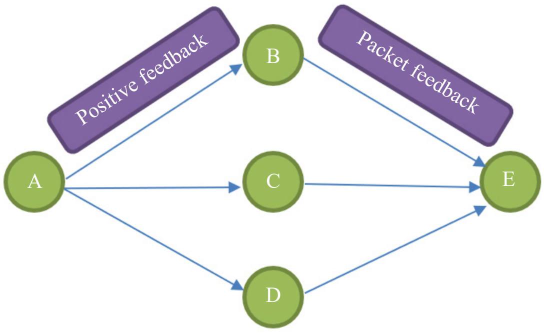

Figure 3. The proposed routing algorithm

For example, if node B consistently provides fast and reliable routes, node B is more likely to be the next hop. Let's say the first packet sent by node A is routed to node B. The network provides feedback that the packet was successfully received by the base station. Feedback helps node A choose node B as the next hop. In this way, PSO and learning automata are used together to optimize the next hop selection dynamically.

Algorithm

For all nodes 'n'
Divide the network into 'k' clusters
Cluster head selection
    Calculate $TH(n)$
    Estimate $rand(n)$
    $rand\ (n)' = rand(n)*(\mathrm{COC} + \mathrm{CL})$
        If $rand\ (n)' \leq TH(n)$
        $CH = n$;
        End if
End for
Data transmission starts
Initialize particles P_i
For all nodes 'n'
Compute fitness value of P_i
    $pbest \leftarrow P_i$
End for
    $gbest = \{pbest \mid Fitness\ (pbest) = minimum\ (fitness\ (pbest_i), \forall i,\ 1 \leq i \leq n)\}$
While (! terminate) do

For all nodes 'n'

Update position and velocity of particle P_i

Compute fitness value of P_i

if $F(Pi) > F(pbest)$ then

$pbest \leftarrow P_i$

End if

if $F(pbest) > F(gbest)$ then

$gbest \leftarrow pbest$

End if

End for

End while

Learning automata

Find Selection probability (*SP*)

Update the values in Neighbor List

Determine $Relaynode(n_i), \forall i,\ 1 \le i \le n$, (i.e., route R).

End

3. Result and discussion

3.1 *Simulation analysis and results*

NS2 simulations compared the suggested mechanism to O-LEACH (Optimized Low Energy Adaptive Clustering Hierarchy Protocol) [17], which is an improved version of the regular LEACH method, as well as an EEPC [19] algorithm. The sensor nodes are dispersed at random in a field that is 1,000 meters wide and 500 meters long, and each sensor node has a 100-joule starting energy setting. Anything between 50 and 200 nodes may be found in the network. The number of clusters will remain at its current setting of 4. It is generally accepted that CBR (Constant Bit Rate) and UDP (Indicates User Datagram) agents are traffic-generating agents. In Table 1, which includes the parameter values, the experiment's findings are reported.

Table 1. The experimental parameters

Parameter	Value
Network area	1,000 m x 500 m
Number of nodes	50 to 200
Cluster size	4
Initial energy	100 Joules
Packet size	1,024 bytes
Routing protocol	LA-PSO
Traffic source	CBR (constant bit rate)

As a packet goes through a network from source to destination, it experiences what's known as an end-to-end delay. The end-to-end delay time of the suggested technique for various network sizes is shown in Figure 4. Due to more hops in the routing route, dense networks have longer end-to-end delays. Because of the suggested method's use of efficient optimal relay selection and reliable CH selection, the end-to-end delay in the proposed scenario is lower than in the scenario with the compared protocols. The following table displays the comparative values. Compared to O-LEACH and EEPC, the suggested technique lowers latency by 31%. The average delay experienced in the proposed method was 0.32 ms, whereas it was experienced at 0.38 ms and 0.45 ms in EEPC and O-LEACH, respectively. Also, it is noticed that the time delay increases whenever the network size increases. It indicates an increase in the number of hop counts participating in the routing path. But the proposed algorithm maintains less delay by selecting the hops optimally.

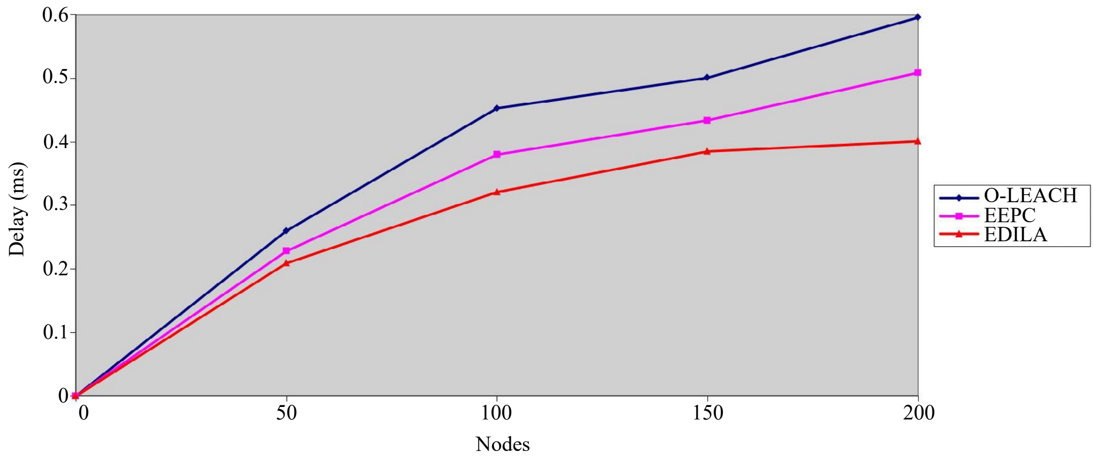

Figure 4. End-to-end delay

The sensor nodes are provided with initial energy so that they can participate in the operations of the network. Network activity decreases energy. To maintain network activity, energy efficiency should be addressed on every network. In networks that are clustered, the process of data aggregation plays an essential role in the conservation of energy. The constant CH revolution results in an unnecessary drain on available energy. Thanks to the stable CH selection that is suggested within the algorithm, the proposed method reduces the rate of energy consumption in the suggested scenario as well as the dependency of CHs on node energy rather than a random number. This is in contrast to the conventional LEACH, which uses a random number. A better PSO selects relay nodes with lower energy burdens, which reduces sensor node energy consumption. The proposed LA reduces unnecessary retransmissions in the network using optimal relay selection and adapts the strategy dynamically based on changing network conditions. This results in lower energy consumption in the network. Figure 5 illustrates energy usage. Below are energy consumption values:

Table 2. The performance evaluation of end-to-end delay

Nodes	O-LEACH	EEPC	EDILA
50	0.260	0.228	0.209
100	0.453	0.380	0.321
150	0.501	0.434	0.385
200	0.596	0.509	0.401

Note: EDILA (Energy efficient Data aggregation Improved Learning Automata Algorithm)

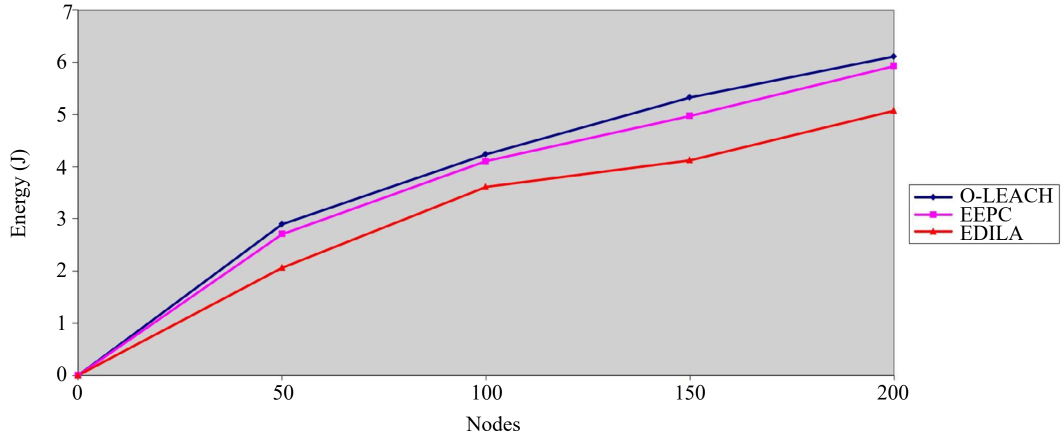

Figure 5. Energy consumption

"Packet delivery ratio" is the percentage of data packets received at the receiver end compared to the sender's total number of packets. The augmentation of the network's PDR is significantly dependent on the data gathering and relay selection processes. The optimal relay selection through the use of multi-objective PSO helped to identify the optimal pathways in the proposed protocol, which ultimately led to an increase in the PDR rate that was greater than that of the protocols that were compared. Stable CH selection by stabilizing the random number using coverage and lifetime parameters ensures stable CHs, which results in uninterrupted data transmission. The proposed learning automata technique reduces the chances of retransmission. In contrast to the existing approaches, which maintained an average PDR rate of 77 during their use, the new method attained a maximum PDR of 87, which is a much higher PDR rate. Figure 6 provides a graphical representation of the PDR, which may be found above. The PDR values are presented in the following table:

Table 3. The performance evaluation of energy consumption

Nodes	O-LEACH	EEPC	EDILA
50	2.895	2.703	2.06
100	4.234	4.105	3.61
150	5.324	4.970	4.12
200	6.110	5.925	5.07

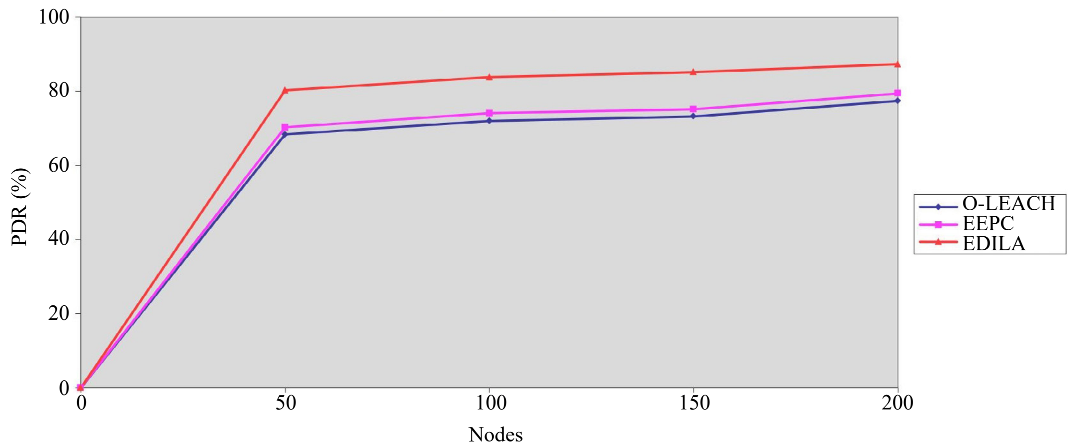

Figure 6. Packet delivery ratio (PDR)

The throughput of a node is the total number of data units that it can process in a given period of time. In order to achieve optimal data aggregation and consistent CH selection, it is helpful to select the ideal relays using multi-objective PSO and the CHs using energy-dependent random numbers. The proposed LA technique reduces the chances of retransmission by optimally selecting the relay nodes based on current network dynamics. Hence, the nodes that participate in the routing path can deliver the data in the given time, which results in a high throughput rate in the proposed network. The comparisons made in the following table show that the proposed method offers a significantly higher throughput rate than the methods that are currently being used. The recommended solution maintained an average throughput rate of 380 kbps throughout the test, whereas the conventional approaches maintained a lower rate. Figure 7 shows throughput as a graph. The following table contains the network performance values:

Table 4. The performance evaluation of PDR

Nodes	O-LEACH	EEPC	EDILA
50	68.35	70.26	80.21
100	71.96	74.08	83.81
150	73.18	75.12	85.14
200	77.38	79.37	87.30

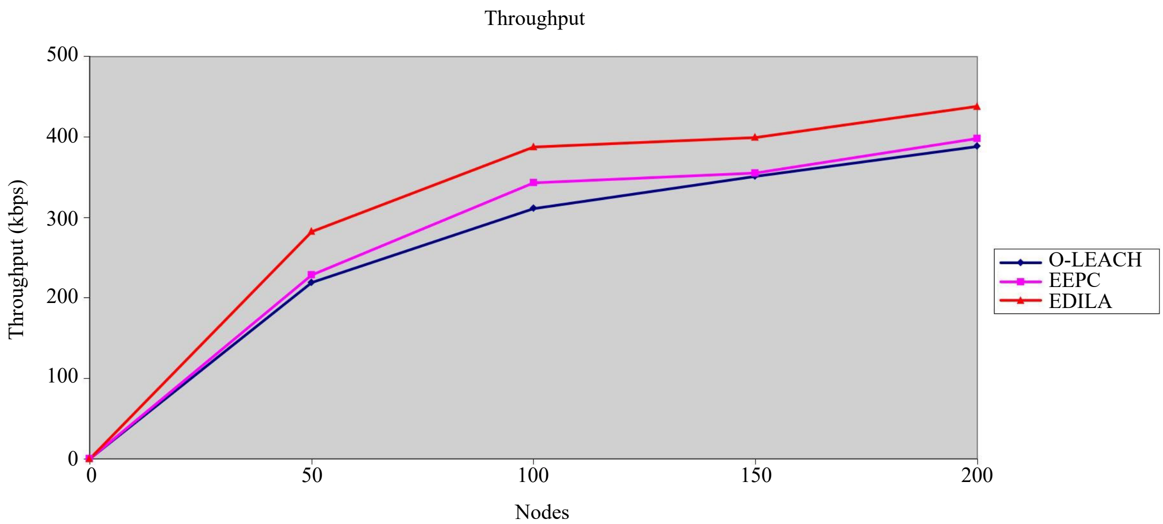

Figure 7. Network performance

The results of the simulation of the overhead that the network encounters can be seen in the preceding Figure 8, which can be seen above. The number of control packets that need to be broadcast throughout the network in order to carry out the network function is directly proportional to the overhead. Usually, in a wireless network, routing path construction requires the broadcast of control packets. The overhead increases if the number of control packets required increases. The proposed stable CH selection scheme and LA technique reduce the retransmission probability. This results in reduced control packets broadcast in the network. The proposed technique encountered an overhead of approximately 0.5%, while the O-LEACH and EEPC protocols each had an overhead of approximately 0.6% and 0.65%, respectively. Both the optimal relay selection achieved through the application of multi-objective PSO and the CH selection accomplished through the application of energy-dependent random numbers contribute to the achievement of optimal data aggregation and stable CH selection. Additionally, it lowers the likelihood of path failure, which in turn lowers the frequency of control packet broadcasting. This results in the suggested approach having a comparatively low overhead.

Table 5. The performance evaluation of throughput

Nodes	O-LEACH	EEPC	EDILA
50	219	228	282
100	310	342	387
150	351	355	399
200	388	398	438

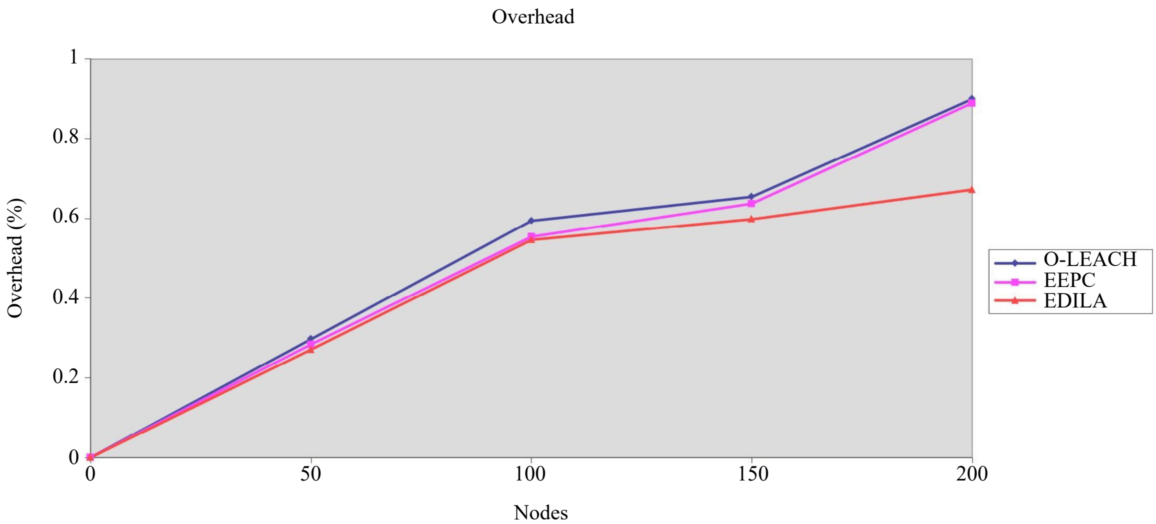

Figure 8. Routing overhead

Table 6. The performance evaluation of routing overhead

Nodes	O-LEACH	EEPC	EDILA
50	0.297	0.284	0.271
100	0.594	0.554	0.546
150	0.654	0.637	0.598
200	0.899	0.889	0.672

4. Conclusion

In WSNs, energy efficiency and reliable data delivery are the main challenges. Clustering is one of the best data aggregation strategies. But the traditional algorithms lack stable CH selection. To reduce packet loss and ensure reliable data transmission, retransmissions are required during packet loss. However, it increases the energy consumption and packet delivery delays. In order to provide energy-efficient data aggregation, a learning automata-based routing technique is proposed in this study. The coverage and lifetime parameters are included in the traditional LEACH algorithm to stabilize the generation of random numbers. The improved LEACH reduces the amount of energy required for member nodes to reach the CH by ensuring that the selected CHs have more neighbors in their coverage circle. The fitness function of the PSO has been enhanced, and a learning-automata based successor node selection strategy has been developed in order to further enhance energy efficiency and relay node selection during the data transmission phase. The simulation results show that the proposed strategy outperforms the compared techniques in terms of energy consumption, data delivery delay, data transmissions, and increased the network lifetime.

4.1 *Future scope*

It could be extended as a future research project by taking into account the network's energy harvesting and mobility of nodes.

Conflict of interest

There is no conflict of interest.

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