energies

Article

Energy Efficient Routing and Dynamic Cluster Head Selection Using Enhanced Optimization Algorithms for Wireless Sensor Networks

I. Adumbabu [1,*] and K. Selvakumar [2]

1 Department of Electronics and Communication Engineering, Annamalai University, Chidambaram 608 002, India
2 Department of Information Technology, Annamalai University, Chidambaram 608 002, India
* Correspondence: adumbabu401@gmail.com

Abstract: A large number of spatially dispersed nodes on the wireless network create Wireless Sensor Networks (WSNs) to collect and analyze the physical data from the environment. The issues that affected the network and had an impact on network energy consumption were cluster head random selection, working node redundancy, and cluster head transmission path construction. Consequently, this energy constraint also has an impact on the network lifetime and energy-efficient routing. Therefore, the primary goals of this research are to decrease energy consumption and lengthen the network's lifespan. So, using improved optimization algorithms, this paper presents a dynamic cluster head-based energy-efficient routing system. The Improved Coyote Optimization Algorithm (ICOA), in this case, consists of three phases setup, transmission, and measurement phase. The Improved Jaya Optimization Algorithm with Levy Flight (IJO-LF) then determines the route between the BS and the CH. It selects the most effective course based on the distance, node degree, and remaining energy. The proposed approach is compared with traditional methods and the routing protocols Power-Efficient Gathering in Sensor Information Systems (PEGASIS) and Threshold sensitive Energy Efficient Sensor Network protocol (TEEN) during implementation on the MATLAB platform. Performance indicators for the suggested methodology are evaluated based on data packets collected by the BS, energy usage, alive nodes, and dead nodes. The outputs of the suggested methodology performed better than the conventional plans.

Keywords: IOCA; IJO-LF; WSN; energy efficient routing

Citation: Adumbabu, I.; Selvakumar, K. Energy Efficient Routing and Dynamic Cluster Head Selection Using Enhanced Optimization Algorithms for Wireless Sensor Networks. *Energies* **2022**, *15*, 8016. https://doi.org/10.3390/en15218016

Academic Editors: R. Maheswar, M. Kathirvelu and K. Mohanasundaram

Received: 26 September 2022
Accepted: 25 October 2022
Published: 28 October 2022

1. Introduction

Hundreds of thousands of sensor nodes are deployed across the WSN to sense, analyze, and retrieve information. Such sensor nodes are less affordable and offer greater detection, computing, and communication capabilities [1]. Medical applications, defensive performance, weather prediction, and a variety of industrial and commercial uses are just a few of the applications that use WSN [2]. WSN sensors are small and run on a small battery [3]. The sensor is utilized an Analog-to-Digital Converter (ADC) to capture data, which it then processes before sending it to the primary hub, called the Base Station (BS). Across different applications, the data is evaluated at BS to make decisions. WSN sensor nodes act as a repeater, sending information to additional sinks and sensors [4]. Due to the placement of the sensor in a hostile and no-land environment, the WSN's power supply can sometimes be recharged or switched, man's it must be handled properly [5]. Various characteristics, such as energy efficiency, fault tolerance, scalability, and so on, have an impact on the construction of WSNs [6]. The energy used by the sensors in the WSN has been used in two ways: (1) environmental parameter sensing and (2) data transmission to the BS via the nodes. WSN data transmission ingests more energy than environmental sensing and data processing [7].

In the WSN, CHs are used to save energy. CH is chosen based on a set of restrictions, including the estimated distance between the receiver and fusion center, as well as residual energy [8]. For sending energy-efficient data, the CH selection of CH is significant. During the specific iterations, the CH in WSN varies to improve performance. The CH uses the Time Division Multiple Accesses (TDMA) technology to collect sensed information. This strategy eliminates redundancies by reducing and gathering information. For capturing information from multiple WSNs, dynamic clustering is the best option [9]. As a result of some aspects, such as energy-saving capability and efficient scalability, dynamic clustering has attracted the interest of various academics. Dynamic clustering is homogeneous and adapts to variations within the transmission range of the sensor. The CH operates in a variety of hop networks, in this case [10]. The periodic rearranging of clusters aids the specialist in enhancing the scalability & energy of WSNs. The spinning of CH is employed in numerous means of transport and IoT applications [11] where dynamic clustering has been used to sustain data transmission between nodes [12].

Energy constraint, in particular, is seen to be a major issue. Every one of the sensing elements requires energy to work. As a result, maximizing the network's longevity requires managing a node's energy usage [13]. One of the most well-known strategies for effectively reducing energy usage in WSNs is the hierarchical arrangement of the network in clusters.CH, the cluster's head node, is in charge of each cluster. In this regard, several unique methods have been presented, all of which have been shown to be effective [14]. Furthermore, within those processes, the direction of finding is ignored, and the heuristic function's essential choice for determining a relay node for data transmission is based solely on a single parameter [15].

Monitoring and control, surveillance systems, healthcare systems, and intelligent space have all benefited from the deployment of WSNs [16]. Furthermore, in WSNs, how to optimally employ network node energy is a worthwhile subject to investigate [17]. Cluster routing is an effective energy maintenance solution for WSNs [18], with the LEACH algorithm being the most well-known. By clustering, this algorithm splits network nodes into cluster members &cluster heads, allowing network node resources to be completely utilized and the network's life cycle to be successfully extended. To limit the number of nodes, the TEEN and PEGASIS algorithms used the clustering concept that connects directly with the base station. The energy consumption of network nodes is balanced by changing cluster heads regularly; this is utilized to extend the life cycle of the network [19].

The foremost contribution of this research work is as follows:

- For the low computational complexity and excellent stability, the ICOA is utilized in the WSN to choose the CH. Based on numerous objective values, ICOA selects the CH, such as node degree, residual energy, node centrality, distance to the BS, and distance to neighbors.
- In WSN, IT can enable the rapid discovery of solutions. By utilizing the IJLFA, the shortest route between CH and BS is discovered.
- Because of the optimal route generation and energy-efficient CH selection for the transmission of data, the network's lifetime is extended. Furthermore, by reducing the energy utilization of nodes while transferring packets, the overall packets expected by the BS are enhanced.

The research paper is organized as follows: Section 2 presents a review of recent research in the field of cluster head selection and routing algorithms. In Section 3, the proposed methodology is elaborated. The simulation results of the proposed methodology are described in Section 4. Finally, the research is concluded in Section 5.

2. Related Work

Some of the recent research works related to efficient CH selection and routing were reviewed in this section.

Moussa and El Alaoui [20] proposed an Energy-efficient Cluster-based Routing Protocol with Enhanced Ant Colony Optimization (ACO) and Unequal Clustering (ECRP-UCA).

To effectively balance the load across Cluster Heads: Based on residual energy, ECRP-UCA splits the network into uneven clusters; how far away the sink is; several nodes in the same neighborhood; and an additional factor called prior cycle's number of backward relay nodes. The next hop sensor node's energy is factored into the heuristic function, the distance between the current and the next sensor nodes.

To address these challenges, Sankar et al. [21] suggested a different cluster formation and Cluster Head (CH) selection technique. There are two stages to the procedure. Initially, by the Sailfish Optimization Algorithm (SOA),the CH is chosen to be called a Swarm Intelligence Algorithm. Next, the Euclidean distance forms the cluster. Previous clustering techniques include issues with the network's short lifespan, imbalanced load among network nodes, and end-to-end delay.

Loganathan et al. [22] introduced an Energy Enhanced Routing Protocol (EERP), which is a novel routing protocol utilizing high-efficiency data transfer rules. For creating a fault-free communication model for the WSN environment, the new EERP technique incorporates the scheme's sophisticated clustering logic. With this method, a standard routing structure concerning the base station and sensor nodes is created. The management of CH is the most significant component of a cluster-based wireless technology, as it must be chosen based on specific communication rules, including distance estimation, node capacity, positioning of the base station, and cluster region position. For analyzing the CH and improving the estimation of the pathway process, these restrictions are necessary. To provide an effective CH election process, the presented EERP method makes use of the efficient CH election algorithm Firefly.

To increase network energy, Yong et al. [23] introduced a multi-hop routing scheme depending on the path tree. To build a cluster headset, initially, several nodes that are closer to the base station and then have a lot of leftover energy are chosen. After that, the whole cluster is partitioned into smaller regions, and the nodes with higher remaining energy than the cluster's regular remaining energy are chosen as working nodes in each region. Eventually, the CHs are ordered based on how far they are from the base station.

The optimal route creation and CH selection presented by Maheshwari et al. [24] are considered tough challenges in WSNs. To improve the network's lifetime and minimize total energy usage, a mixture of ACO and BOA was employed in this study. The node centrality, neighbors' distance, nodes' residual energy, the Base Station's (BS) distance, and node degree were all used in the BOA-based CH selection. To identify the best CH, through the node groups, this fitness function was utilized. By optimizing ACO with three distinct factors, the most energy-efficient path was found. The Advanced Configuration and Power Management Interface (ACPI) and JEHDO are both independently battery- and energy-efficient, according to exploratory results by Sampathkumar et al. [25–27]. An enhanced cuckoo search algorithm is used for node localization to obtain optimal energy efficiency routing by Vaibhav Kotiyal [28].An improved version swarm intelligence approach of the whale optimization algorithm was used for node localization to improve the energy efficiency of the network by Bacanin [29].

3. Dynamic CH Selection and Energy-Efficient Routing Design

3.1. Problem Statement

The current challenges with WSNs are as follows: For WSNs to be energy efficient, an adequate selection of optimal solutions must be addressed in the network. Only when the appropriate technique is prioritized, both distance and energy, the network energy usages decrease. Both large- and small-scale WSN applications could benefit from the energy-efficient WSN. In WSN, rapid transmission of data from CH to BS uses more energy. It causes the network's hot spot problem, which results in packet loss. Because of the node's deployment in a hostile and unmanaged situation, the sensor node becomes inefficient and malfunctioning. Furthermore, while transferring data packets to their destination, the nodes' energy consumption is a major concern. As a result of the nodes' lack of energy, data transmission packets are dropped.

Because the energy consumption within every node is primarily determined by the node's distance, energy utilization is openly proportional to the node's distance. Furthermore, packet loss is prevented in WSN by taking into account each node's energy. By establishing multi-hop routing among the network, the routing challenge can be overcome. The path from the source to the BS is created using the IJLFA approach. The routing considers the nodes' residual energy, the distance between them, and the hop number in each cluster as optimal solutions. The packet loss across networks is decreased when these parameters are taken into account. As a result, an energy efficient WSN is modeled to perform well in two large and small-scale WSNs.

3.2. Network Model

Figure 1 displays the WSN schematic structure. Depending on the following conditions, the model of the network is formulated:

- In terms of processing time and initial energy, the entire nodes are the same as every other in WSN.
- Depending on the Euclidean distance, the distance of the sensor is evaluated.
- The node's position is constant after the deployment, and the nodes are casually positioned in the sensing situation.
- From the nodes, the BS obtains the distance and residual energy information. CHs are selected by an effective CH selection algorithm based on this information. Hence, the route among the CHs to the BS is obtained by the routing process.

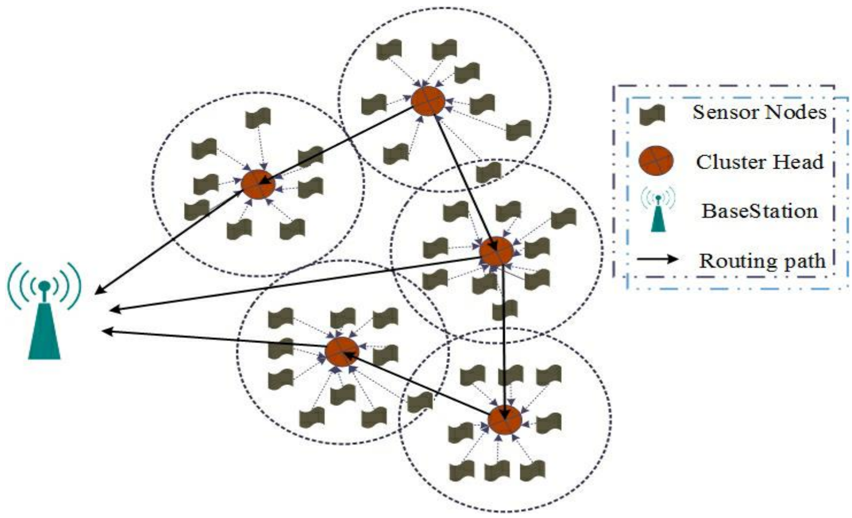

Figure 1. Structure of WSN network model.

3.3. Energy Model

A typical first-order radio paradigm is used to estimate the transmission & reception energy. Equations (1) and (2) represent the amount of energy used to broadcast and capture packets of bits at a given distance.

$$En_{txer}(\delta, d) = \begin{cases} \delta \times E_{dis} + \delta \times \varepsilon_{fs} \times d^2 & if\ d \leq d_0 \\ \delta \times E_{dis} + \delta \times \varepsilon_{mp} \times d^4 & if\ d > d_0 \end{cases} \quad (1)$$

$$En_{rxer}(\delta, d) = \delta \times E_{dis} \quad (2)$$

where the energy consumed at the receiver and transmitter is denoted as $En_{txer}\ and\ En_{rxer}$ and the threshold distance is defined by d_0, δ represents the information bits, and d is the distance between the sender and receiver. Equation (3) is used to compute the threshold distance.

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (3)$$

where ε_{fs} and ε_{mp} indicate the amplification energy in the multipath and free space models, respectively. The transmitter amplifier model was used to determine these ε_{fs} and ε_{mp}.

3.4. Proposed Methodology

The suggested method includes 2 algorithms: one for network routing and the other for selecting the CH. As IJLFO and CH select the ideal route between the BS and CH, ICOA is utilized to determine appropriate sensors. Via the IJLFO-generated channel, following that, the CHs send the data obtained to the BS. The overall process of the proposed methodology is shown in Figure 2.

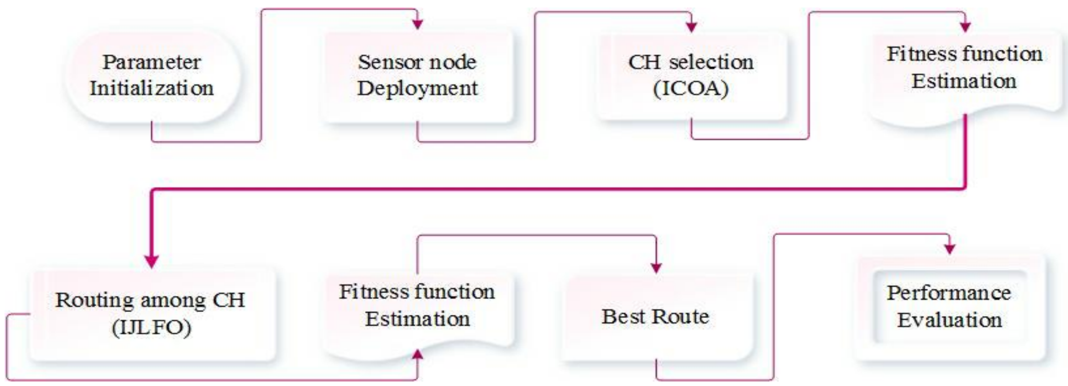

Figure 2. Schematic Block Diagram of Proposed Methodology.

3.4.1. CH Selection Using ICOA

Figure 3 represents the flow chart of selection of CH using ICOA method. The steps are as follows.

Sensor nodes parameter and random initialization: Initially, the node's global population, including Np packs, each with Ns nodes, is initialized. At a certain time, t, the pth pack population is an integer vector, and it is displayed as:

$$S_i^{p,t} = (X_1, X_2, \ldots X_d) \quad (4)$$

where the optimized problem dimension is represented as d, and the ith threshold is represented as x_i.

$$S_{i,j}^{p,t} = \mathrm{lb}_j + \mathrm{R}_j(\mathrm{ub}_j - \mathrm{lb}_j),\ j = 1, 2, \ldots, d \quad (5)$$

where lower and upper bounds are represented as ub_j and lb_j, R_j is a random value.

ICOA Fitness function: From the sensors group in the network, the optimal CH is selected by the ICOA fitness function. The residual energy is considered in the fitness function to evade a dead node as a CH. Higher centrality is used to reduce the distance of transmission among the members. The mathematical forms of fitness functions and their definitions are discussed below:

(a) CH Residual energy

CH collects data from ordinary sensor nodes and transmits it to BS in a network. Because the CH takes more energy to perform the preceding activities, the node with the most residual energy is the strongest choice to be a CH. The following Equation (6) describes residual energy (f_1)

$$\mathrm{f}_1 = \sum_{\mathrm{i}=1}^{\mathrm{m}} \frac{1}{\mathrm{E}_{\mathrm{CHi}}} \quad (6)$$

where the ith CH's residual energy is E_{CHi}

(b) Distance among sensor nodes:

It specifies the range among usual sensor nodes as well as its CH. The dissipation of energy for the node mostly depends on the transmission path distance. If the chosen node has a minimum transmitting distance near BS, then the node's energy consumption is small. Sensors to CH (f_2) the distance is displayed in Equation (7).

$$f_2 = \sum_{j=1}^{m} \sum_{i=1}^{I_j} D\left(s_i, CH_j / I_j\right) \tag{7}$$

where, $D\left(s_i, CH_j / I_j\right)$ denoted the sensor i and CHj distance and I_j is the sensor node's quantity belongs to CH.

(c) CH and BS Distance:

The energy consumption of the node is evaluated based on the distance via the transmitting track. When BS is situated away from CH, for example, data transmission will require a lot of energy. As a result, the abrupt drop in CH could be related to increased energy use. Therefore, throughout information transfer, the node that is closest to BS is selected. The optimal solution of distance among the BS (f_3) and the CH is represented by the following Equation (8).

$$f_3 = \sum_{i=1}^{m} D\left(CH_j,\ BS\right) \tag{8}$$

where $D\left(CH_j,\ BS\right)$ is the distance between BS and CH_j.

(d) Node degree

It specifies how many sensor nodes each CH has. Because CHs with more cluster members lose their energy for a shorter period, the CHs with fewer sensors are chosen. Equation (9) expresses the degree of node (f_4).

$$f_4 = \sum_{i=1}^{m} I_i \tag{9}$$

where I_i is the number of CHi sensor nodes.

(e) Node centrality

Node centrality (f_5) is an expression that expresses how far a node is from its neighbors, represented in Equation (9).

$$f_5 = \sum_{i=1}^{m} \frac{\sqrt{\frac{\left(\sum_{j\epsilon n}^{m} D^2(i,j)\right)}{n(i)}}}{L} \tag{10}$$

where $n(i)$ is the number of CHi's neighboring nodes and L is the network dimension.

Every objective value is assigned a weight value. Several objectives are combined into a single function in this situation. $S1, S2,\ S3,\ S4$, and S5 are the weighted values. Equation (10)depicts the single objective function.

$$F = S1f_1 + S2f_2 + S3f_3 + S4f_4 + S5f_5 \tag{11}$$

where, $\sum_{r=1}^{5} Sr = 1\ Sr\epsilon(0, 1)$, the values of Sr are 0.35, 0.25, 0.2, 0.1 and 0.1 correspondingly.

Updating new solutions: In each group, the alpha node is a node indicating it has the best fitness value among the groups listed below:

$$alpha(\alpha) = \min\left(S_i^{p,t}\right)\ i = 1, 2, \ldots .ni \tag{12}$$

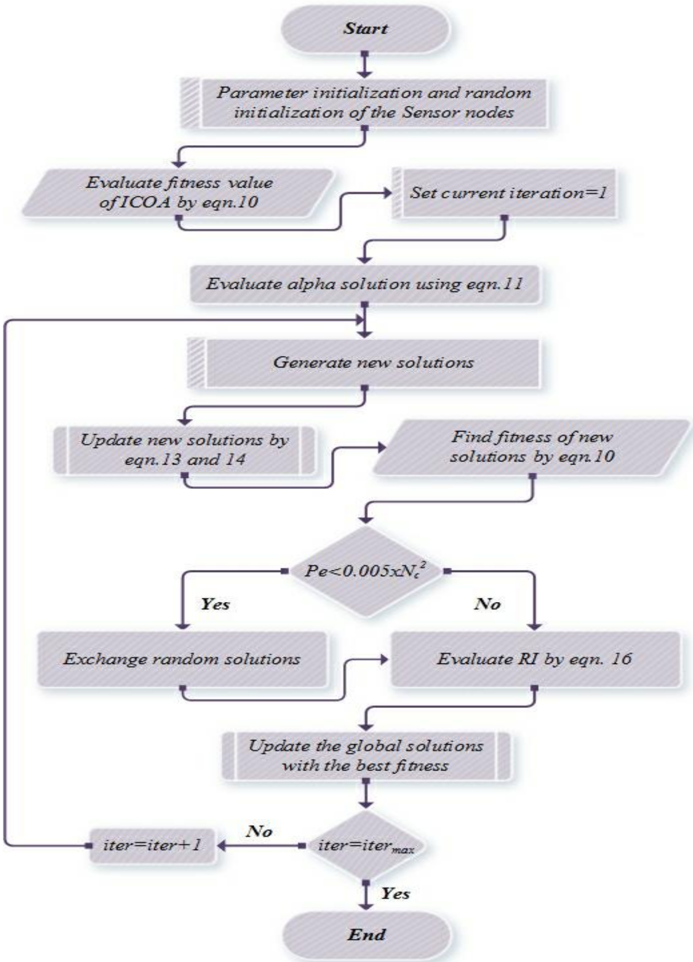

Figure 3. Flowchart for CH selection using ICOA.

The following rule is used to produce new socioeconomic problems after detecting the tendency of coyotes as well as an alpha coyote for each pack:

$$\mathrm{new}_{S_i^p} = S_i^p + R1 \times \left(\alpha - S_{r1}^p\right) + R2 \times \left(S_{gbest} - S_{r2}^p\right) \tag{13}$$

If the fitness function improves, the previous social conditions are replaced by new ones.

$$S_i^p = \left\{ \mathrm{new\_S}_i^p,\ \mathrm{ifnew\_fit}_i^p < \mathrm{fit}_i^p S_i^p,\ \mathrm{else} \right. \tag{14}$$

$$\mathrm{fit}_i^p = \left\{ \mathrm{new\_fit}_i^p,\ \mathrm{ifnew\_fit}_i^p < \mathrm{fit}_i^p \mathrm{fit}_i^p,\ \mathrm{else} \right. \tag{15}$$

Expulsion and admission: It is possible for nodes to leave packs by becoming solitary, or they might establish a pack instead, which happens with a high probability p_e.

$$p_e = 0.005 \cdot N_C^2 \tag{16}$$

Calculate RI in two iterations: The exploiting process is used to update the best solution so far by Equation (17).

$$\mathrm{RI} = \left| \frac{f\left(S_{gbest}(i-1)\right) - f\left(S_{gbest}(i)\right)}{f\left(S_{gbest}(i-1)\right)} \right| < toll \tag{17}$$

where $f\left(S_{gbest}(i-1)\right)$ and $f\left(S_{gbest}(i)\right)$ are the fitness values of the two most recent best solutions. The toll is a constant.

3.4.2. Clusters Formulation Using the Potential Function

Using the possible function indicated in Equation (18), the CHs are provided to sensor nodes once the CHs have been selected by ICOA. Sensor nodes with shorter transmission distances and more remaining energy are assigned to the CH. As a result, the quantity of energy consumed during the data transmission phase will be lower.

$$sn_p = \frac{z \times E\left(CH_j\right)}{D\left(s_i, CH_j\right)} \tag{18}$$

where z is the proportionality constant, sn_p is the potential of the sensor node and $D\left(s_i,\ CH_j\right)$ is the distance between the CH_j and sensor s_i; The sensor is assigned to a specific CH with greater potential and $E\left(CH_j\right)$ denotes the residual energy of that CH. When the distance between the two different CHs and sensor nodes is equal, the sensor node is connected to the CH with higher energy.

3.4.3. Routing Algorithm Using IJLFA

Due to the availability of local optima that can trap the search, the original Jaya method may be unable to reach the best solution. To solve this difficulty, we proposed modifying the original Jaya method by multiplying its step size by random values. Instead of using random numbers to reposition the particles, the following Equation (19) is used

$$X^{i+1}_{j,k} = X^{i}_{j,k} + |lf_1|\left(X^{i}_{j,best} - \left|X^{i}_{j,k}\right| - |lf_2|\left(X^{i}_{j,worst} - \left|X^{i}_{j,k}\right|\right)\right) \tag{19}$$

where lf_1 and lf_2 are 2-numbers chosen at random from the Lévy distribution, respectively. The power-law index β, which is required in Equation (20) to sample random numbers from the Lévy distribution, is the only added parameter compared to the original Jaya algorithm.

$$D_{lf} = \frac{U}{|V|^{1/\beta}} \tag{20}$$

where the power-law index is denoted by β, V is a random number drawn at N(0, 1), and U describes a random number drawn at N(0, σ2), and the standard deviation σ is given by Equation (21),

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{(1+\beta)}{2}\right) \times \beta \times 2^{\frac{\beta-1}{2}}}\right)^{\frac{1}{\beta}} \tag{21}$$

where Γ denotes the gamma function. Even though this new distribution is a minor change in the algorithm, it causes significant changes in the optimization procedure, which, as we will see later, results in higher actual quality to demonstrate effectiveness.

Steps convoluted in the IJO-LF algorithm are as follows:

Step 1: Population size (N) initialization: Decision variables' numbers $D(j = 1,\ 2, \ldots D)$, decision variables for upper and lower bounds of $\chi_{max,j}, \chi_{min,j}$ and maximum number of iterations it_{max} as an ending stage.

Step 2: Initialization at random: The population of N solutions $\chi_i(1, 2, \ldots N)$ inside the search space boundary. Individually jth dimension of ith solution i.e., $\chi_{j,i}$, is initialized among $\chi_{max,j}$ and $\chi_{min,j}$ as per Equation (22).

$$\chi_{j,i} = \chi_{min,\ j} + r(0,1)\left(\chi_{max,\ j} - \chi_{min,\ j}\right) \tag{22}$$

Step 3: Fitness function evaluation: F_i for each separate solution to the specific issue and determine the worst and best solutions, i.e., X_{worst} and X_{best} correspondingly. The solution with the F greatest value is considered the worst, while the solution with the slowest value is regarded as the best when minimizing the objective function.

Step 4: Random numbers consideration: r1 and r2 among 0 and 1 with uniform distribution, Equation (18) is used to update the values of choice variables with each solution.

Step 5: Evaluate the fitness F_i^{new} for comparing the fitness F_i of each formed solution to the fitness of the prior solution.

Step 6: If $F_i^{new} > F_i$ for a maximization problem and $F_i^{new} < F_i$ for a minimization problem, replace χ_i with a fresh produced solution, i.e., χ_i^{new} new for a minimization problem, otherwise preserve the prior solution, i.e., χ_i and update the relevant fitness function value.

Step 7: Sort all of the solutions according to their fitness by,

$$\chi^{new1} = F_i^{new} > F_i{}^{new} + \alpha \oplus lf(\beta) \tag{23}$$

Step 8: Evaluate the fitness F_i^{new1} of new solutions generated.

Step 9: The worst and best solutions are determined using the updated fitness function values

Step 10: Repeating steps 4–9 until reaching the termination requirement, or else report the best solution X_{best}.

3.4.4. Cluster Maintenance

For balancing the load amongst clusters, the management of clusters is one of the most critical phases in this study. For inter-cluster traffic, clusters closer to the BS consume too much energy. As a result, the management of the cluster phase is necessary to prevent the failure of the node. As a consequence, the lifetime of data transmission from the source node to the BS increases. The ICOA is re-set to cluster the network if the CH's residual energy exceeds the threshold level. The CHs are then chosen using the clustering process, and for calculating the routing path between the BS and CHs, the IFLFA is used.

In this proposed methodology the ICOA algorithm is used to achieve an effective CH selection. The CHs are chosen based on five criteria: residual energy, distance from neighbors, node degree, node centrality, and distance from the BS. Among the nodes, these factors are utilized to choose the best CH. To avoid node failure during the transmission of data, BS constantly monitors the nodes' residual energy. From the source to BS through CH, the IJLFA algorithm is used to find the best transmission path. To minimize the nodes' energy consumption, it finds the shortest path. This IJLFA and ICOA-based route generation and optimal CH selection resulted in the development of an energy-efficient WSN. During the transmission of data, an energy efficient WSN is utilized to increase the overall packets transferred to BS, extending the network lifetime.

4. Results and Discussion

4.1. Performance Metrics

The performance metrics are as follows:

Alive nodes: The number of alive nodes in a network is defined by the number of nodes that are alive. When a network contains a large number of active nodes, the network performance improves.

Average energy consumption: During each iteration, it specifies how much energy each node uses on average

Total packets transferred to BS: The overall data packets sent to BS are proportional to the number of alive nodes and their remaining energy. When there are a lot of alive nodes, BS obtains a lot of packets.

Throughput: Over WSN, the number of bits delivered to BS is referred to as throughput. Bits per second are used to measure throughput.

Packet drops ratio: It refers to the amount of data lost from the source to BS during transmission.

Routing overhead: It is described as the ratio of the total number of packets obtained by BS to the total number of packets generated.

4.2. Simulation Setup

The ease of suitable data analyses and arithmetic operations are the major reasons for choosing MATLAB. In the detecting region of 200 m $\times$ 200 m, there are between 100 and 150 sensor nodes distributed at random. The first-order radio model is used as an energy design to compare the proposed technique to different routing protocols. The simulation parameters used in the experiment are listed in Table 1. The goal of this research is to lower the entire energy usage of each network node. As a result, IJLFO-based routing between the CHs and ICOA-based CH selection is used to provide cluster-based routing. For better CH selection, distance to BS, node centrality, residual energy, node degree, and distance to neighbors are the inputs given to ICOA. Distance, node degree, and residual energy are also inputs to the IJLFO. Because these methods are commonly employed to enhance the WSNs energy efficiency, this proposed method is contrasted to several established approaches such as the Threshold ensitive Energy Efficient Sensor Network protocol (TEEN), Power-Efficient Gathering in Sensor Information Systems (PEGASIS).

Table 1. Simulation Parameters.

Parameters	Value
Number of sensor nodes	100 and 150
Sensing range	250 m $\times$ 250 m
Initial energy	0.5 J
Base station	1
Packet size	4000 bits
Number of CH	4
Number of the source node	1

4.3. Performance Analysis

A developed methodology comparison to existing schemes is shown first. The two existing techniques used to assess the introduced methodology are TEEN and PEGASIS. This assessment is carried out in two separate circumstances relating to the base station's location. The BS is located in the center of the area used to assess short-range communications, which is referred to as the first scenario. The BS is placed outside of the region where long-range transmissions are analyzed.

The following figures show the performance analyses of the proposed method with two existing routing protocols.

Figures 4 and 5 illustrate the rate of decrease of alive nodes of proposed method compared to existing methods. Figures 6 and 7 show that the proposed method has very less average energy consumption compared with TEEN, PEGASIS methods with a network size of 100 nodes and 150 nodes. Figures 8 and 9 illustrate the proposed method network lifetime in terms of rounds with conventional methods. The graph shows a good improvement in the network lifetime of the proposed method compared with existing methods of network size 100 and 150 nodes.

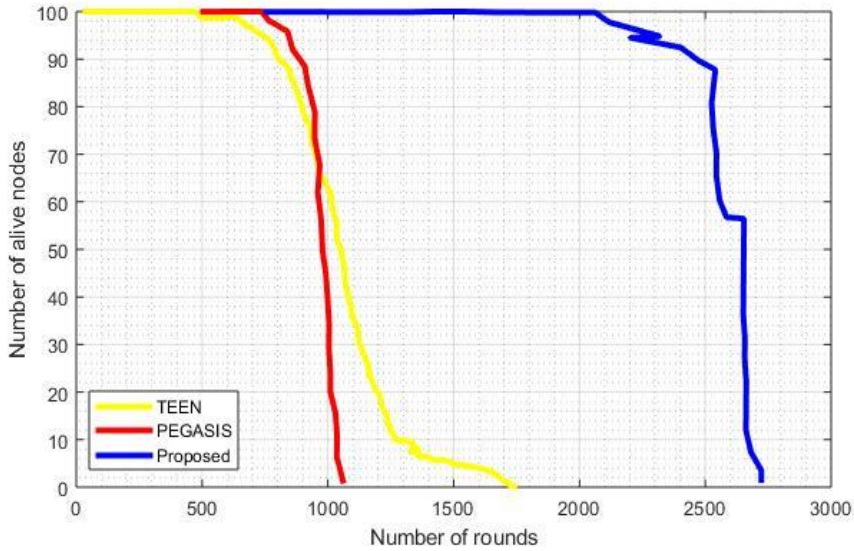

Figure 4. Number of rounds vs. number of alive nodes (100 nodes).

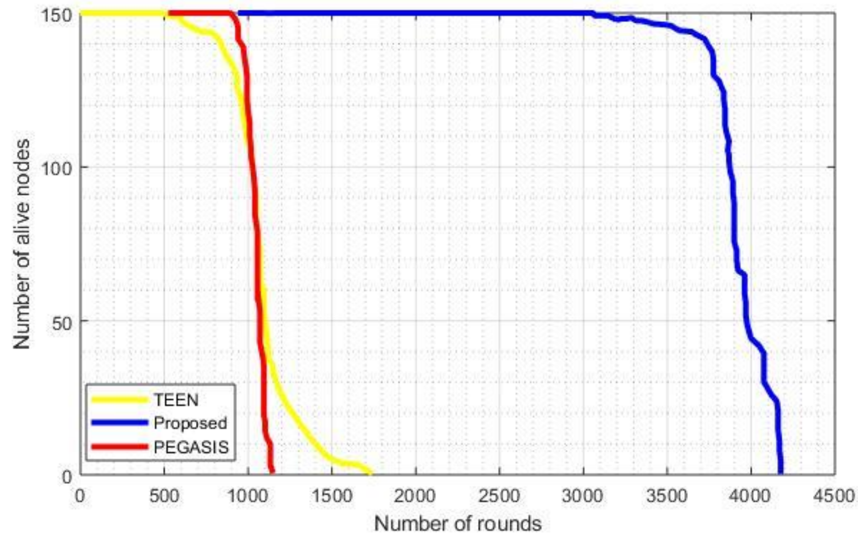

Figure 5. Number of rounds vs. number of alive nodes (150 nodes).

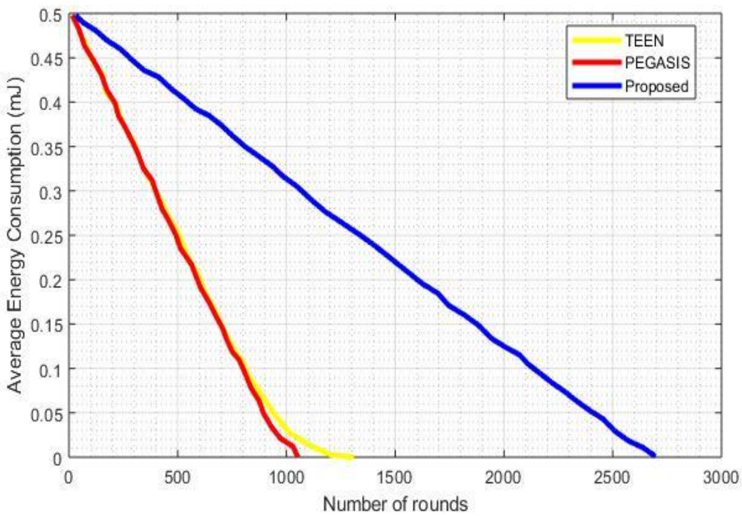

Figure 6. Energy consumption with 100 nodes.

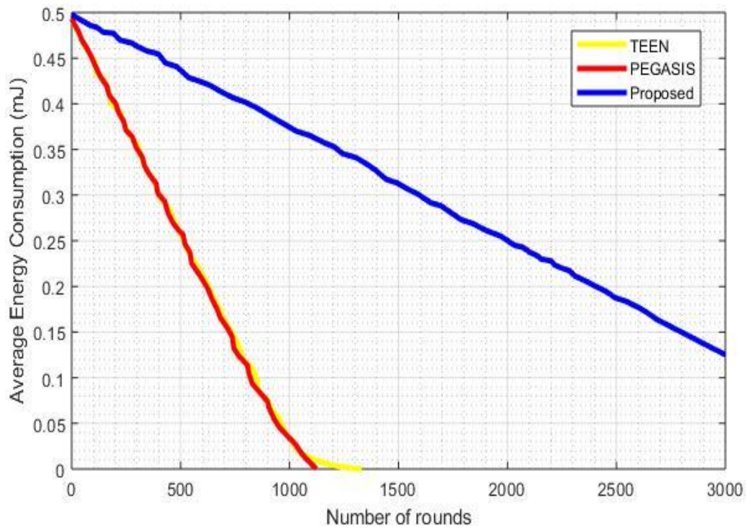

Figure 7. Energy consumption with 150 nodes.

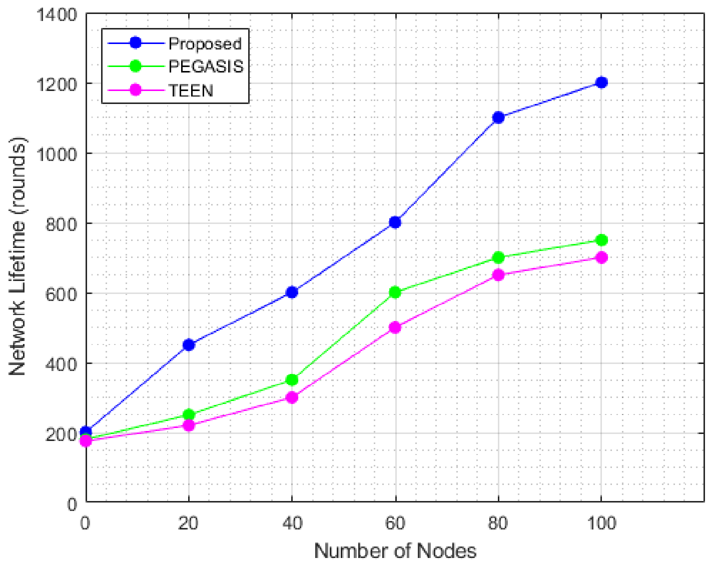

Figure 8. Number of nodes vs. network lifetime with 100 nodes.

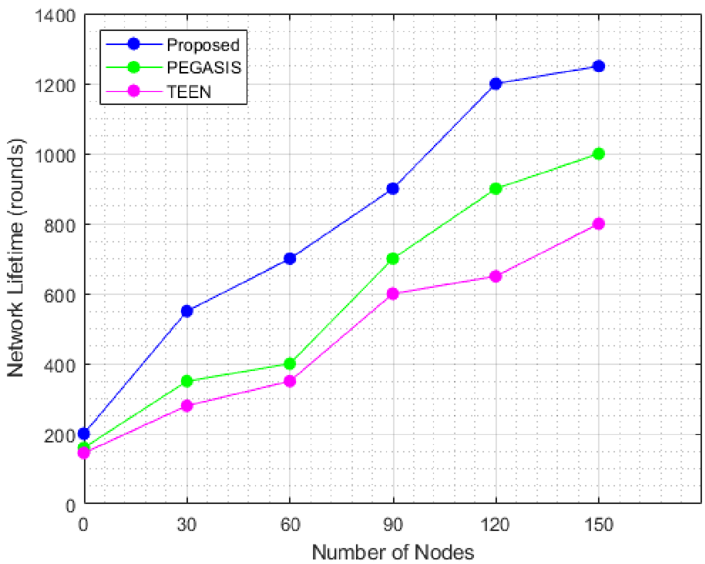

Figure 9. Number of nodes vs. network lifetime with 150 nodes.

Figures 10 and 11 illustrate the decrease in routing overhead compared to conventional methods with the proposed technique, in terms of rounds. The packet delivery ration simulation results of TEEN, PEGASIS, and proposed methods with 100 and 150 nodes are shown in Figures 12 and 13. Figures 14 and 15 depict the comparison of the proposed technique with existing techniques in terms of packet drop ratio with 100 and 150 nodes. Figures 16 and 17 show the throughput performance of the proposed method with conventional methods. The graphs show a greater improvement in throughput with the increase in sensor nodes.

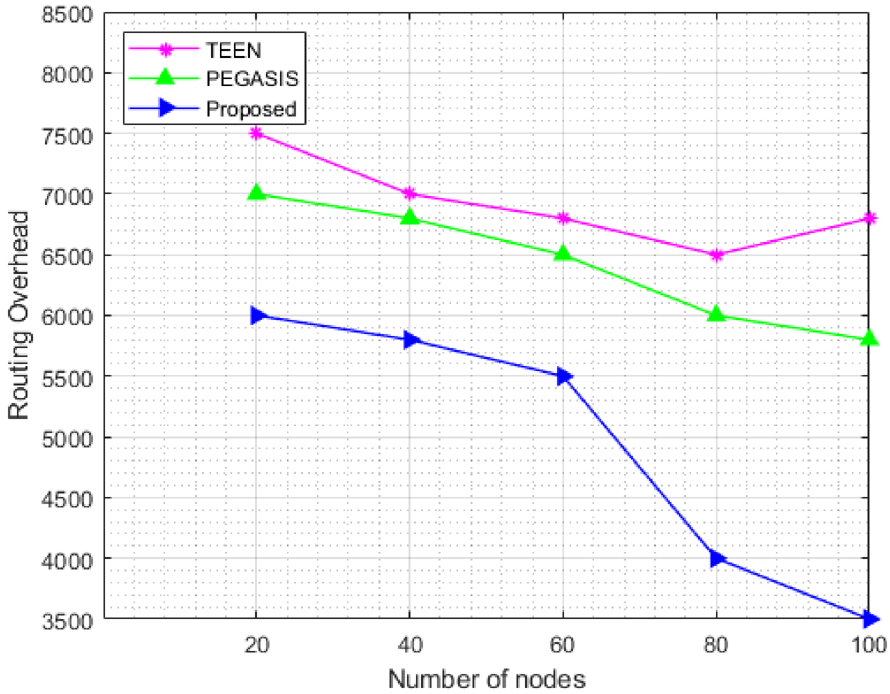

Figure 10. Number of nodes vs. Routing Overhead (100 nodes).

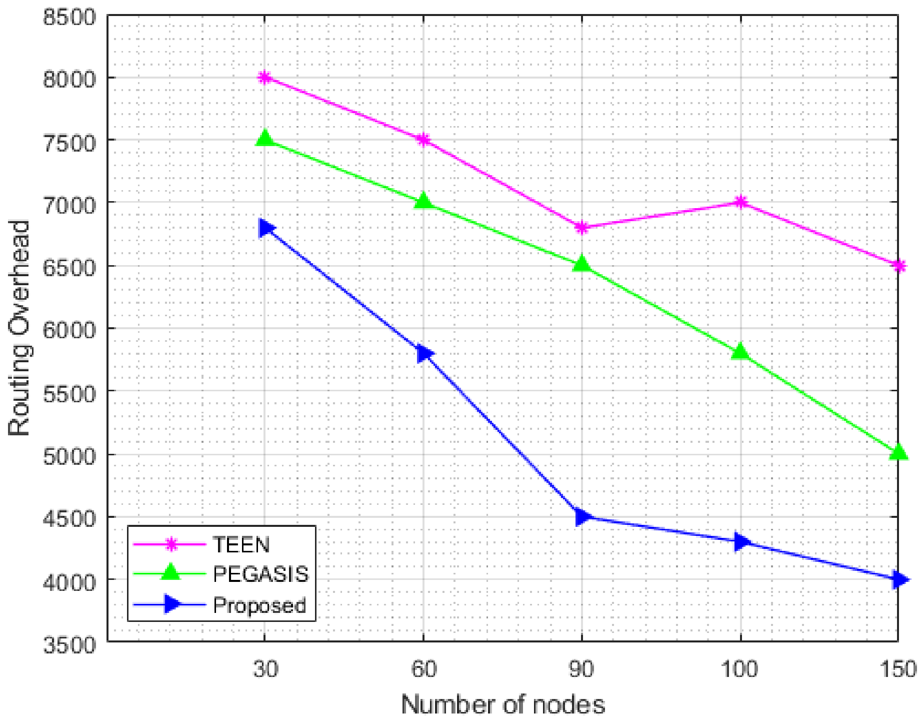

Figure 11. Number of nodes vs. Routing Overhead (150 nodes).

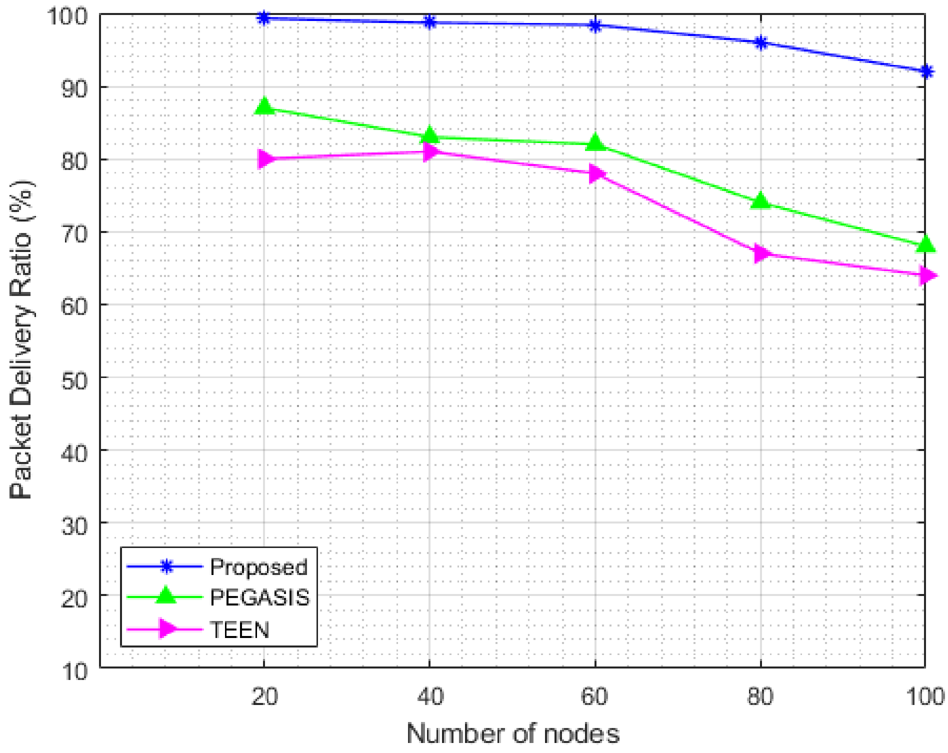

Figure 12. Number of nodes vs. packet delivery ratio (100 nodes).

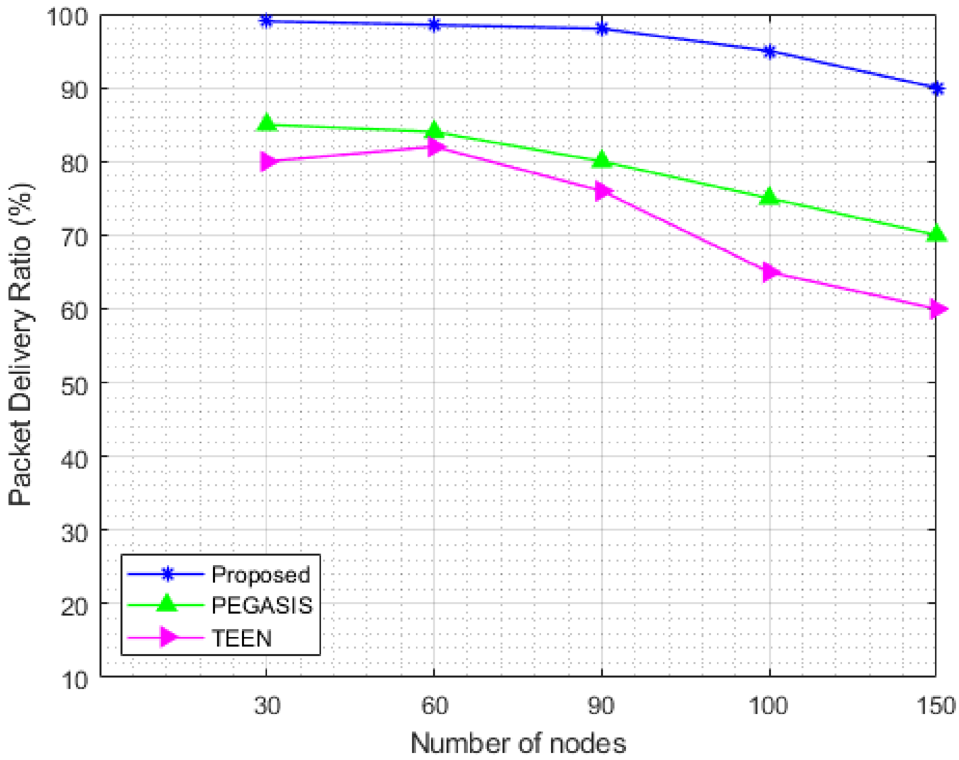

Figure 13. Number of nodes vs. Packet delivery ratio (150 nodes).

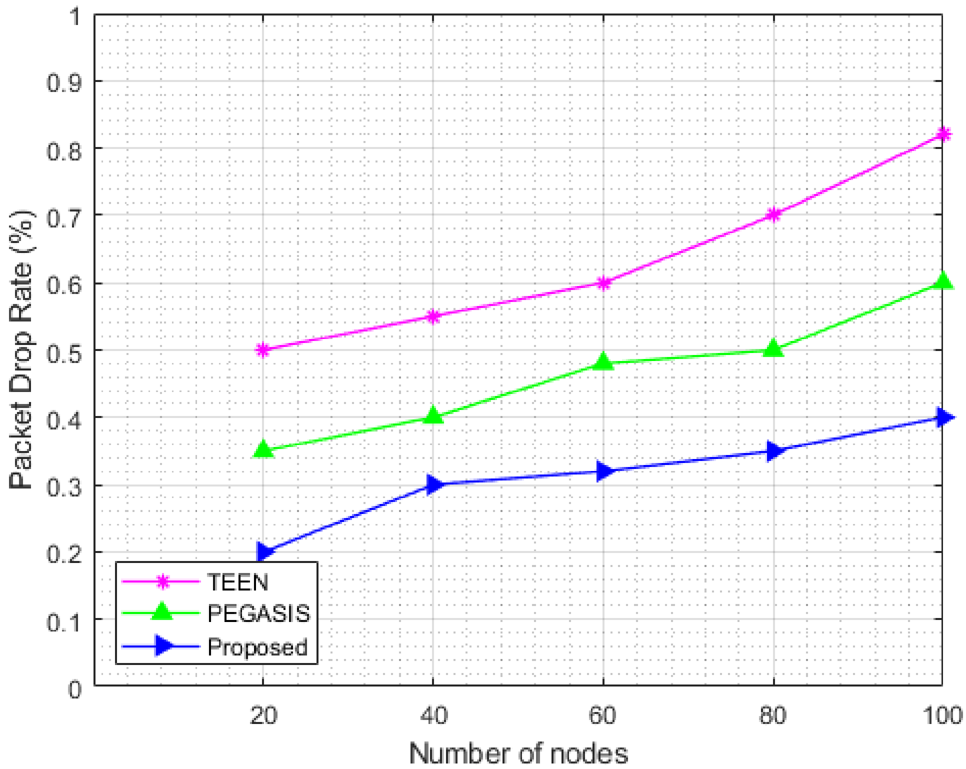

Figure 14. Number of nodes vs. packet drop ratio (100 nodes).

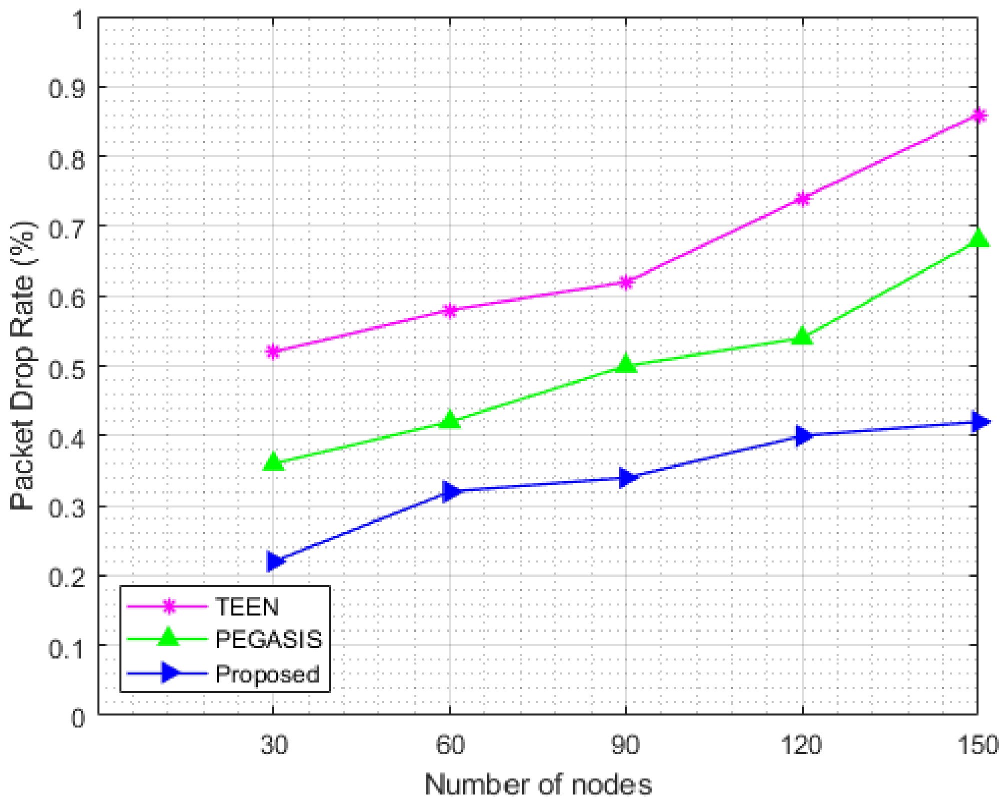

Figure 15. Number of nodes vs. packet drop ratio with 150 nodes.

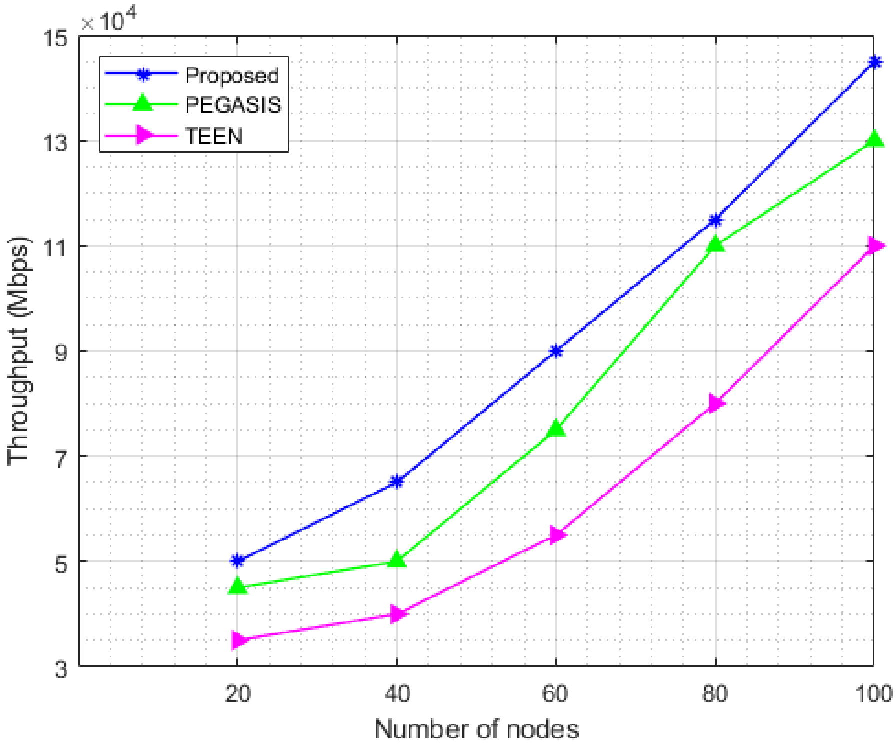

Figure 16. Number of nodes vs. Throughput (100 nodes).

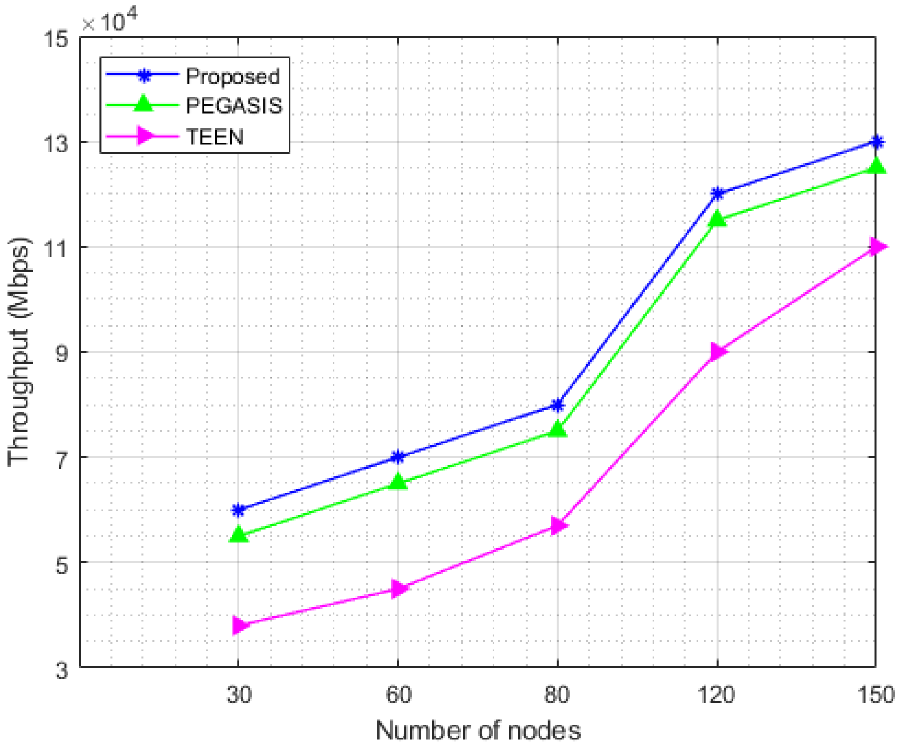

Figure 17. Number of nodes vs. throughput (150 nodes).

The simulation results indicate that the proposed strategy outperforms established methods. The average energy consumption determines the efficiency and effectiveness of the proposed method, no of alive nodes, routing overhead, packet delivery ratio, packet drop ratio, network lifetime, and throughput.

5. Conclusions

Effective route generation and CH selection are regarded as challenging problems in WSN. In this research, a combination of ICOA and IJLFA is proposed to optimize the overall energy consumption and the network lifetime is also increased. Based on five varying metrics such as node degree, base station distance, node centrality, distance to neighbors, and node residual energy. ICOA is used to choose the precise CH. With the help of the fitness values function, the best CH is selected from the cluster nodes. The energy-efficient routing is created by combining three factors such as distance, node degree, and residual energy, to improve IJLFA. Throughout the simulation of the proposed algorithms, the base station is moved from inside to outside. When compared to current methods, the proposed scheme performed better than PEGASIS and TEEN in terms of sustained network usage. Additionally, the proposed methodology is contrasted with other routing approaches. In terms of network performance, it is found that the proposed scheme performed better than PEGASIS and TEEN.

Author Contributions: Conceptualization, K.S.; Supervision; Original draft and review& editing, I.A.; validation, K.S.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data will be shared for review based on the editorial reviewer's request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. SriVenkateswaran, C.; Sivakumar, D. Secure cluster-based data aggregation in wireless sensor networks with aid of ECC. *Int. J. Bus. Inf. Syst.* **2019**, *31*, 153–169. [CrossRef]
2. Jun, Y.; Craig, A.; Shafik, W.; Sharif, L. Artificial Intelligence Application in Cybersecurity and Cyberdefense. *Wirel. Commun. Mob. Comput.* **2021**, *2021*, 3329581. [CrossRef]
3. Lee, W.K.; Schubert, M.J.; Ooi, B.Y.; Ho, S.J.Q. Multi-source energy harvesting and storage for floating wireless sensor network nodes with long range communication capability. *IEEE Trans. Ind. Appl.* **2018**, *54*, 2606–2615. [CrossRef]
4. Putra, S.A.; Trilaksono, B.R.; Riyansyah, M.; Laila, D.S.; Harsoyo, A.; Kistijantoro, A.I. Intelligent sensing in multiagent-based wireless sensor network for bridge condition monitoring system. *IEEE Internet Things J.* **2019**, *6*, 5397–5410. [CrossRef]
5. Sharma, K.; Anand, D.; Sabharwal, M.; Tiwari, P.K.; Cheikhrouhou, O.; Frikha, T. A Disaster Management Framework Using Internet of Things-Based Interconnected Devices. *Math. Probl. Eng.* **2021**, *2021*, 9916440. [CrossRef]
6. Sahu, S.; Silakari, S. Analysis of Energy, Coverage, and Fault Issues and their Impacts on Applications of Wireless Sensor Networks: A Concise Survey. *Network* **2021**, *10*, 13. [CrossRef]
7. Shu, T.; Chen, J.; Bhargava, V.K.; de Silva, C.W. An energy-efficient dual prediction scheme using LMS filter and LSTM in wireless sensor networks for environment monitoring. *IEEE Internet Things J.* **2019**, *6*, 6736–6747. [CrossRef]
8. El Khediri, S.; Fakhet, W.; Moulahi, T.; Khan, R.; Thaljaoui, A.; Kachouri, A. Improved node localization using K-means clustering for Wireless Sensor Networks. *Comput. Sci. Rev.* **2020**, *37*, 100284. [CrossRef]
9. Su, S.; Zhao, S. A hierarchical hybrid of genetic algorithm and particle swarm optimization for distributed clustering in large-scale wireless sensor networks. *J. Ambient. Intell. Humaniz. Comput.* **2017**, 1–11. [CrossRef]
10. Sangeetha, M.; Sabari, A. Genetic optimization of hybrid clustering algorithm in mobile wireless sensor networks. *Sens. Rev.* **2018**, *38*, 526–533.
11. Sennan, S.; Ramasubbareddy, S.; Balasubramaniyam, S.; Nayyar, A.; Kerrache, C.A.; Bilal, M. MADCR: Mobility aware dynamic clustering-based routing protocol in Internet of Vehicles. *China Commun.* **2021**, *18*, 69–85. [CrossRef]
12. Qureshi, K.N.; Tayyab, M.Q.; Rehman, S.U.; Jeon, G. An interference aware energy efficient data transmission approach for smart cities healthcare systems. *Sustain. Cities Soc.* **2020**, *62*, 102392. [CrossRef]
13. Arjunan, S.; Sujatha, P. Lifetime maximization of wireless sensor network using fuzzy based unequal clustering and ACO based routing hybrid protocol. *Appl. Intell.* **2018**, *48*, 2229–2246. [CrossRef]
14. Abualigah, L.M.; Khader, A.T.; Hanandeh, E.S.; Gandomi, A.H. A novel hybridization strategy for krill herd algorithm applied to clustering techniques. *Appl. Soft Comput.* **2017**, *60*, 423–435. [CrossRef]
15. Sayed, G.I.; Khoriba, G.; Haggag, M.H. A novel chaotic salp swarm algorithm for global optimization and feature selection. *Appl. Intell.* **2018**, *48*, 3462–3481. [CrossRef]
16. Venkateswarulu, B.; Subbu, N.; Ramamurthy, S. An efficient routing protocol based on polar tracing function for underwater wireless sensor networks for mobility health monitoring system application. *J. Med. Syst.* **2019**, *43*, 218. [CrossRef] [PubMed]
17. Jiang, B.; Huang, G.; Wang, T.; Gui, J.; Zhu, X. Trust based energy efficient data collection with unmanned aerial vehicle in edge network. *Trans. Emerg. Telecommun. Technol.* **2020**, *33*, e3942. [CrossRef]

18. Yuvaraj, D.; Sivaram, M.; Ahamed, A.M.U.; Nageswari, S. An efficient lion optimization based cluster formation and energy management in WSN based IoT. In Proceedings of the International Conference on Intelligent Computing & Optimization, Chongqing, China, 6–8 December 2019; Springer: Cham, Switzerland, 2019; pp. 591–607.
19. Cui, Z.; Cao, Y.; Cai, X.; Cai, J.; Chen, J. Optimal LEACH protocol with modified bat algorithm for big data sensing systems in Internet of Things. *J. Parallel Distrib. Comput.* **2019**, *132*, 217–229. [CrossRef]
20. Moussa, N.; El Alaoui, A.E.B. An energy-efficient cluster-based routing protocol using unequal clustering and improved ACO techniques for WSNs. *Peer-to-Peer Netw. Appl.* **2021**, *14*, 1334–1347. [CrossRef]
21. Sankar, S.; Ramasubbareddy, S.; Chen, F.; Gandomi, A.H. Energy-Efficient Cluster-Based Routing Protocol in Internet of Things Using Swarm Intelligence. In Proceedings of the 2020 IEEE Symposium Series on Computational Intelligence (SSCI), Canberra, ACT, Australia, 1–4 December 2020; IEEE: Manhattan, NY, USA, 2020; pp. 219–224.
22. Loganathan, G.B.; Salih, I.H.; Karthikayen, A.; Kumar, N.S.; Durairaj, U. EERP: Intelligent Cluster based Energy Enhanced Routing Protocol Design over Wireless Sensor Network Environment. *Int. J. Mod. Agric.* **2021**, *10*, 1725–1736.
23. Yong, J.; Lin, Z.; Qian, W.; Ke, B.; Chen, W.; Ji-fang, L. Tree-Based Multihop Routing Method for Energy Efficiency of Wireless Sensor Networks. *J. Sens.* **2021**, *2021*, 6671978. [CrossRef]
24. Maheshwari, P.; Sharma, A.K.; Verma, K. Energy efficient cluster based routing protocol for WSN using butterfly optimization algorithm and ant colony optimization. *Ad Hoc Netw.* **2021**, *110*, 102317. [CrossRef]
25. Sampathkumar, A.; Murugan, S.; Rastogi, R.; Mishra, M.K.; Malathy, S.; Manikandan, R. Energy Efficient ACPI and JEHDO Mechanism for IoT Device Energy Management in Healthcare. In *Internet of Things in Smart Technologies for Sustainable Urban Development*; Kanagachidambaresan, G.R., Maheswar, R., Manikandan, V., Ramakrishnan, K., Eds.; EAI/Springer Innovations in Communication and Computing; Springer: Cham, Switzerland, 2020. [CrossRef]
26. Sampathkumar, A.; Mulerikkal, J.; Sivaram, M. Glowworm swarm optimization for effectual load balancing and routing strategies in wireless sensor networks. *Wirel. Netw.* **2020**, *26*, 4227–4238. [CrossRef]
27. Sampathkumar, A.; Murugan, S.; Sivaram, M.; Sharma, V.; Venkatachalam, K.; Kalimuthu, M. Advanced Energy Management System for Smart City Application Using the IoT. In *Internet of Things in Smart Technologies for Sustainable Urban Development*; Kanagachidambaresan, G.R., Maheswar, R., Manikandan, V., Ramakrishnan, K., Eds.; EAI/Springer Innovations in Communication and Computing; Springer: Cham, Switzerland, 2020. [CrossRef]
28. Kotiyal, V.; Singh, A.; Sharma, S.; Nagar, J.; Lee, C.-C. ECS-NL: An Enhanced Cuckoo Search Algorithm for Node Localisation in Wireless Sensor Networks. *Sensors* **2021**, *21*, 3576. [CrossRef] [PubMed]
29. Bacanin, N.; Antonijevic, M.; Bezdan, T.; Zivkovic, M.; Rashid, T.A. Wireless Sensor Networks Localization by Improved Whale Optimization Algorithm. In *Proceedings of 2nd International Conference on Artificial Intelligence: Advances and Applications*; Mathur, G., Bundele, M., Lalwani, M., Paprzycki, M., Eds.; Algorithms for Intelligent Systems; Springer: Singapore, 2022. [CrossRef]