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A Hybrid Trust Based WSN protocol to Enhance Network Performance using Fuzzy Enabled Machine Learning Technique

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Abstract: This paper proposes a trust-based cluster head selection method for Wireless Sensor Networks (WSNs) using machine learning. It utilizes historical behavior and performance data of sensor nodes to establish trustworthiness. Machine learning algorithms are employed to build a trust model during the training phase, considering features like energy levels and communication quality. Real-time cluster head selection is based on trust scores calculated using the trust model. Simulations demonstrate improved network reliability, energy efficiency, and data accuracy compared to traditional methods. The approach also shows resilience against attacks and node failures. Overall, this research contributes to enhancing WSN efficiency and security.

***Keywords**: Cluster, Fuzzy Logic, Cluster Head, Clustering, Sensor Node.*

1. Introduction:

The domain of Wireless Sensor Networks (WSNs) have revolutionized the field of data collection and monitoring in various domains, including environmental monitoring, healthcare, agriculture, and industrial automation. These networks reside of a large number of tiny sensor nodes that collaborate to collect data and transmit to a central base station. One of the key challenges in WSNs is the efficient selection of cluster heads, which are accountable for aggregating and forwarding data from other sensor nodes within their respective clusters. Traditionally, cluster heads are selected based on factors such as node proximity or energy level. However, these methods do not take into account the trustworthiness of the sensor nodes, which is vital for maintaining the network's reliability and security. Trust in this context refers to the belief that a sensor node will reliably and honestly perform its duties as a cluster head. Therefore, there is a need for a trust-based approach to cluster head selection in WSNs. In recent years, machine learning techniques have shown tremendous potential in various domains, including network management and security. By leveraging machine learning models, it is possible to analyze the historical behavior and performance of sensor nodes and derive a trust model. This trust model can then be used to evaluate and select the most trustworthy sensor nodes as cluster heads. The objective of this research paper is to propose a novel approach for trust-based cluster head selection in WSNs using machine learning techniques. The proposed approach aims to enhance the reliability, efficiency, and security of WSNs by considering the trustworthiness of sensor nodes as a key factor in the cluster head selection process. By leveraging historical data and employing supervised learning techniques, we aim to build a trust model that can dynamically adapt to changing network conditions [9][10][11][12].

The organization of the rest of the paper is as follows:

- Section 2: Related Work: This section will give an overview of the existing research and literature related to cluster head selection and trust management in Wireless Sensor Networks (WSNs). It will discuss various approaches, algorithms, and techniques that have been proposed and implemented in these areas.
- Section 3: Methodology of Trust-Based Cluster Head Selection: In this section, the paper will present the methodology and details of the proposed trust-based cluster head selection approach. It will explain the steps involved in the selection process, including the trust metrics used, the evaluation criteria, and any algorithms or models employed. The section will provide a comprehensive explanation of how trust is incorporated into the cluster head selection process.
- Section 4: Experimental Setup, Results, and Analysis: Section 4 will describe the experimental setup used to validate the proposed approach. It will include details such as the simulation environment, the dataset used, and the parameters and metrics considered for evaluation. The section will then present the results obtained from the experiments and provide an in-depth analysis and discussion of these results. It may compare the proposed approach with existing methods or highlight the advantages

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and limitations of the trust-based cluster head selection approach.

- Section 5: Conclusion and Future Research Directions: Finally, in Section 5, the paper will conclude by summarizing the key findings and contributions of the study. It will discuss the implications of the proposed trust-based cluster head selection approach and its potential impact on WSNs. Additionally, this section will outline possible future research directions or areas that could benefit from further investigation in the field of cluster head selection and trust management in WSNs.

2. Literature Review

Now a days researchers are focusing on WSNs due to their wide range of uses in various fields. Effective routing protocols play a crucial role in optimizing the performance of WSNs by addressing challenges such as energy consumption, network scalability, and data aggregation. In this literature review, we will discuss several prominent routing protocols, namely LEACH, PSO, HSACP, BEE-CLUSTER, and LEACH-C, and highlight their key features and contributions.

LEACH (Low Energy Adaptive Clustering Hierarchy): LEACH, proposed by Heinzelman et al. in 2000 [1], is one of the pioneering protocols in WSNs that introduced the concept of clustering to enhance energy efficiency. It utilizes randomized rotation of cluster heads to distribute energy consumption evenly among sensor nodes. LEACH effectively reduces energy dissipation by enabling data aggregation at cluster heads before transmitting to the base station.

PSO (Particle Swarm Optimization): PSO, a metaheuristic optimization algorithm, has been applied in WSNs to optimize various aspects, including cluster head selection and data routing. Li et al. proposed a PSO-based routing protocol for WSNs in 2016 [2], which aimed to minimize energy consumption and extend network lifetime by dynamically adjusting the cluster head selection process.

HSACP (Hybrid Stable Election Protocol): HSACP, introduced by Gholizadeh et al. in 2018 [3], is a hybrid routing protocol that combines the advantages of clustering and stable election protocols. It aims to achieve load balancing, prolong network lifetime, and enhance scalability in WSNs. HSACP utilizes an adaptive energy threshold for cluster head selection, ensuring a balanced energy consumption among nodes.

BEE-CLUSTER (Bee-Inspired Cluster Formation): BEE-CLUSTER, proposed by Bhattacharjee et al. in 2017 [4], is a bio-inspired routing protocol inspired by the foraging behavior of bees. It utilizes swarm intelligence to form clusters and select cluster heads. BEE-CLUSTER aims to optimize energy consumption and extend network lifetime by dynamically adjusting the number of clusters based on network conditions.

LEACH-C (Centralized LEACH): LEACH-C, an improved version of the LEACH protocol, was proposed by Wang et al. in 2015 [5]. It introduces centralized control in cluster formation by utilizing a centralized base station for cluster head selection. LEACH-C enhances the stability and efficiency of cluster formation, resulting in better energy utilization and network longevity.

The ant colony optimization (ACO) protocol is a nature-inspired mechanism widely studied for achieving optimal routing in wireless sensor networks (WSNs). ACO is known for its dynamic nature, reliability, and support for data aggregation and routing structure collection. It effectively addresses issues like network congestion, and energy consumption, and enables multi-route data transmission, enhancing communication reliability. The primary objective of the ACO protocol is to maximize network lifetime through efficient routing methods. ACO-based techniques offer the advantages of reduced overhead and real-time computations. However, they may be subject to performance dependency on previous cycles. Nonetheless, employing ACO-based routing protocols in dynamic networks has proven suitable for mitigating link failures and improving network lifetime and load balancing through techniques like sensor node clustering [6] [7].

Fuzzy-based routing has emerged as a promising approach for enhancing the performance of wireless sensor networks (WSNs). In a study by Narayan et al. (2022), a fuzzy-based routing algorithm was proposed to optimize energy efficiency and network lifetime in WSNs. The algorithm utilized fuzzy logic to make routing decisions based on factors such as node distance, residual energy, and network congestion. The results demonstrated improved energy consumption and extended network lifetime compared to traditional routing protocols. Fuzzy-based routing in WSNs offers flexibility and adaptability to uncertain and dynamic network conditions, making it a valuable technique for achieving efficient and reliable data transmission [8].

3. Proposed Methodology

The proposed methodology used Machine Learning(ML) based CH selection and Fuzzy based route selection for data transmission in WSN named ML-FBRP (Machine Learning in Fuzzy Based Routing Protocol). The ML works for Cluster Head Selection is a critical task WSNs that aims to identify suitable nodes to serve as cluster heads for efficient data aggregation and communication. One approach to tackle this problem is by leveraging the

Random Forest technique [13] [14]. In the context of Cluster Head Selection, the Random Forest technique utilizes a dataset containing features of WSN nodes and their corresponding labels indicating their suitability as cluster heads. The algorithm starts by preparing the dataset and performing feature engineering to extract meaningful features. Next, a Random Forest classifier is trained on the dataset, learning the patterns and relationships between the features and cluster head labels. Once trained, the classifier is used to predict the cluster head candidacy for each node in the WSN. Nodes predicted as cluster head candidates are then selected, forming the final set of cluster heads. This approach offers the advantage of leveraging the collective decision-making power of multiple decision trees, resulting in robust and accurate cluster head selection in WSNs [15][16][17].

Random Forest Training*: Eq*uation 1 represents the training step of the Random Forest classifier, where X is the matrix of feature values with dimensions (n_samples, n_features) and y is the vector of target labels with dimensions (n_samples,). equation indicates that the Random Forest classifier (RF) is trained on the dataset (X, y).

RF.fit(X, y) (1)

CH Candidate Prediction: Equation 2 represents the prediction step using the trained Random Forest classifier. Given a new data point with feature values represented as x, the equation indicates that the Random Forest classifier (RF) predicts the cluster head candidacy label (y_pred) for the new data point.

y_pred = RF.predict(x) (2)

CH Selection: Equation 3 represents the selection of Cluster Head candidates from the WSN nodes based on the predicted cluster head candidacy labels (y_pred). It uses a list comprehension to iterate over each node in the WSN_nodes and selects only those nodes for which the predicted label is 1, indicating a cluster head candidate. The resulting list (CH_candidates) contains the selected Cluster Head candidates.

CH_candidates = [node for node in WSN_nodes if y_pred[node] == 1] (3)

Performance Evaluation: Equation 4 represents the evaluation of the performance of the Cluster Head Selection algorithm using a suitable evaluation metric. It compares the predicted cluster head labels (y_pred) with the true cluster head labels (y_true) and computes a performance metric (performance_metric) that quantifies the accuracy or effectiveness of the algorithm. The specific evaluation metric used depends on the requirements and objectives of the WSN application.

performance_metric = evaluation_metric(y_true, y_pred) (4)

3.1. Cluster Head Selection Based on Random Forest Technique

Dataset Collection: Collect a comprehensive dataset containing relevant network parameters, such as residual energy, node density, distance to the base station, node degree, and communication overhead. Label the dataset by designating Cluster Head (CH) nodes based on existing CH selection algorithms or simulated data. Ensure that the dataset encompasses various network scenarios and aligns with the objectives of CH selection, such as maximizing network lifetime or minimizing energy consumption [18][19].

Feature Engineering: Perform feature engineering to extract meaningful features for CH selection. Analyze the collected dataset and consider techniques such as dimensionality reduction, feature scaling, and feature encoding to improve the representation of input features. Incorporate domain-specific knowledge or network-specific metrics that may contribute to improved CH selection, such as the correlation between residual energy and CH candidacy [20][21].

Random Forest Model Selection: The multiple decision trees to make predictions, we call is random forest. Its ability to handle high-dimensional datasets, capture complex relationships, and provide feature importance makes it suitable for CH selection in WSNs [22][23].

Training and Validation: Split the dataset into training and validation sets, allocating an appropriate ratio for reliable model evaluation. Train the Random Forest model using the training dataset, adjusting hyperparameters like the number of trees and maximum depth. Validate the model using the validation set and assess its performance using metrics such as accuracy, precision, recall, or F1-score. Fine-tune the model if necessary to optimize its performance [24][25][26].

Model Deployment and Integration: Deploy the trained Random Forest model into the WSN environment. Integrate it into the CH selection process, allowing the model to make real-time decisions based on incoming data. Implement mechanisms for periodic retraining of the model to adapt to evolving network conditions and ensure its effectiveness over time [27][28][29].

Performance Evaluation: Conduct comprehensive performance evaluation of the integrated Random Forest model. Compare its performance against baseline CH selection algorithms or other machine learning models. Evaluate the model's effectiveness in terms of network lifetime, energy efficiency, load balancing, or other relevant metrics. Consider conducting experiments in various network scenarios or simulations to validate the model's robustness and generalizability [30][31][32].

Algorithm: Random Forest-based Cluster Head Selection
Input:
Dataset (D): A matrix or data structure containing the features and labels for each data point in the WSN.
Output:
Cluster Head candidates: A list or array containing the predicted Cluster Head candidates for the WSN nodes.
Dataset Preparation:
Step-1 : Collect the dataset D, where D = [X, y], and X is the matrix of feature values with dimensions (n_samples, n_features), and y is the vector of target labels with dimensions (n_samples,).
Assign labels to each node in D, designating them as Cluster Head (CH) candidates (y=1) or non-CH candidates (y=0) based on existing CH selection algorithms or simulated data.
Step-2: Feature Engineering:
Perform feature engineering on D to extract meaningful features for CH selection in WSNs.
Apply techniques such as dimensionality reduction, feature scaling, and feature encoding to enhance the representation of input features.
Incorporate domain-specific knowledge or network-specific metrics that may contribute to improved CH selection.
Step-3: Random Forest Training:
Split the dataset D into training and validation sets: D_train = [X_train, y_train], D_val = [X_val, y_val].
Train a Random Forest classifier on the training set:
RF = RandomForestClassifier()
RF.fit(X_train, y_train)
CH Candidate Prediction:
For each node in the WSN:
Compute the feature values of the node: x_node.
Predict the CH candidacy label for the node using the Random Forest classifier:
y_pred = RF.predict(x_node)
Step-4: CH Selection:
Initialize an empty list or array to store the Cluster Head candidates: CH_candidates = []
For each node in the WSN:
If the predicted CH candidacy label is positive (indicating a CH candidate):
Add the node to the list of Cluster Head candidates: CH_candidates.append(node)
Performance Evaluation:

	Evaluate the performance of the CH selection algorithm using suitable metrics such as network lifetime, energy efficiency, or load balancing.
	Compare the results of the Random Forest-based CH selection algorithm with baseline algorithms or other machine learning models.
	Conduct experiments in various network scenarios or simulations to assess the algorithm's robustness and generalizability.
Output:	
	Return the list or array of Cluster Head candidates: CH_candidates.

3.2 Fuzzy based Route Selection

The ML-FBRP model, the Fuzzy technique is employed for route selection after the completion of the Cluster Head selection process. This FSA-based approach aims to determine the optimal path for transmitting data between CHs and BS in a WSN. Which possesses the data to be transmitted, plays a crucial role in selecting the next hop for forwarding the detected data to the BS or destination [30].To facilitate the fuzzy-based route selection, several parameters and their corresponding fuzzy memberships are utilized. These parameters help in evaluating the suitability of a particular route for data transmission. The fuzzy memberships capture the degree of membership or suitability of each parameter value to a specific route. By considering these fuzzy memberships, an appropriate route can be selected based on the overall evaluation of these parameters. The specific parameters and their corresponding fuzzy memberships may vary depending on the design and requirements of the WSN. These parameters plays crucial role in determining the efficiency, reliability, and performance of the data transmission process in the WSN [33][34].

a. *Average* (AVG) *distance covered by cluster (σ1)*

In the proposed technique, distance measurements are used to compute the distances between Cluster Heads (CHs) and the sensor nodes within their clusters. The sum of these distances represents the intra-cluster distances. Reducing these distances is crucial to minimize energy consumption during communication, as sensor nodes require power to transmit data to their respective CHs. By lowering the intra-cluster distances, energy efficiency can be improved in the sensor network

$$X_1 = \sum_{s=1}^{v} \left(\frac{1}{h_s} \sum_{w=1}^{h_s} dis(SN_w, CH_s) \right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

b. *Average* (AVG) *distance from sink (σ2)*

In the proposed technique, the AVG distance to the sink is determined by multiplying the distance between a Base Station and a Cluster Head by the total number of sensor nodes (SNs) available in the cluster. This calculation provides an estimation of the average distance that data needs to travel from the CHs to the BS. By considering both the distance and the number of SNs, this approach aims to assess the overall efficiency and performance of data transmission in the network. The AVG distance to the sink is a crucial metric in evaluating the network's energy consumption, latency, and overall data transmission quality [35][36].

$$X_2 = \sum_{s=1}^{v} \left(\frac{1}{h_s} \sum_{w=1}^{h_s} dis(CH_S, BS) \right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

c. *Sensor node residual energy (σ3)*

Similarly, to extend the lifetime of a WSN, reducing energy consumption is critical. The residual energy parameter is used to optimize energy usage and balance objective functions in order to maximize available energy and network longevity.

$$X_3 = \sum_{s=1}^{v} \left(\frac{1}{\sum_{s=1}^{v} CE_{CHs_S}} \right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

d. *Fuzzy Membership Function (MF)*

The ML-FBRP utilizes fuzzy rules to determine the OPTIMAL route of data transmission from c node of cluster to the Base Station (BS). Figures 1-3 illustrate the membership functions and input range values for the parameters. Equation 8 shows representation of the membership values for the average distance within clusters.

$$\begin{pmatrix} Input \\ Membership \end{pmatrix} = \begin{cases} 1 & \text{if } Input \leq \mathrm{TH}_1 \\ \mathrm{TH}_1 - Input \big/ \mathrm{TH}_1 - \mathrm{TH}_2 & \text{if } \mathrm{TH}_1 < Input < \mathrm{TH}_2 \\ 0 & \text{if } Input \geq \mathrm{TH}_2 \end{cases} \ldots\ldots\ldots\ldots\ldots \quad (8)$$

Where, TH_2 *and* TH_1 are lower, and upper threshold

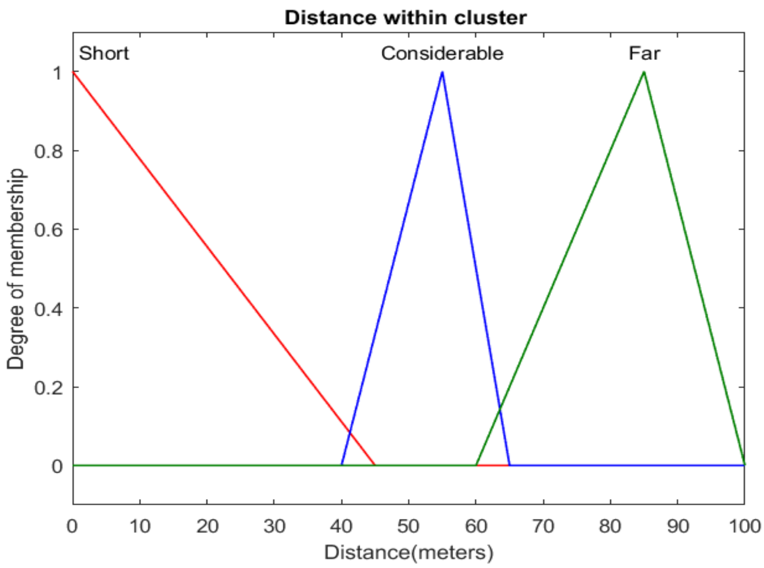

Fig.1. Fuzzification for inter-cluster node distance

The proposed ML-FBRP using fuzzy that incorporates the average distance to the sink as an input parameter for cluster head selection. Trapezoidal membership functions are used to represent the average distance within a wider range of input values, ensuring effective CH formation in high-density areas [31].

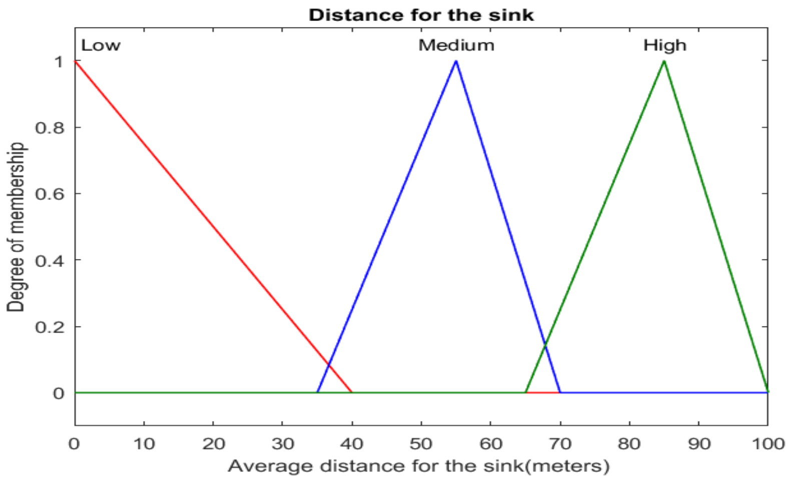

Fig.2. Fuzzification for distance to sink

In the proposed fuzzy model, Figure 2 showcases three membership functions (MFs) – {Low (lw), Medium(mm), High(hh)} representing the average distance to the sink. These MFs influence energy dissipation in data transmission, while Figure 3 illustrates four MFs - lw, mm, hh, and Very High(V-hh), representing node residual energy, which impacts available energy in sensor nodes after each transmission phase [37][38].

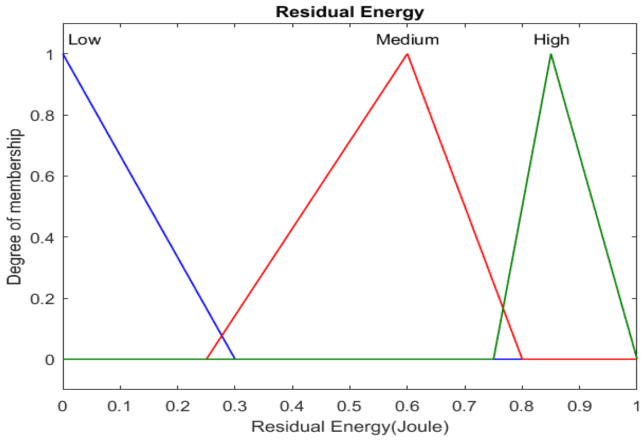

Fig.3. Fuzzification for residual energy

The proposed ML-FBRP protocol incorporates Fuzzy rules embedded in the FIS (Fuzzy Inference System) to determine the likelihood function for cluster head (CH) selection. This likelihood function is crucial for identifying the most suitable nodes for data transmission from a node to the base station (BS) in a WSN.The likelihood computation is based on fuzzy output membership, which considers three key input parameters. These parameters helps in determining the energy consumption and network lifespan. By evaluating these input parameters, the ML-FBRP protocol calculates the likelihood of CH selection, which is categorized into fuzzy membership values: lw, mm, hh, and V-hh. These fuzzy membership values reflect the probability or suitability of a node being selected as a CH for efficient data transmission [39].

The FIS in the ML-FBRP protocol applies fuzzy logic to map the input parameters to their corresponding likelihood values using fuzzy rules. These fuzzy rules define the relationship between the input parameters and the likelihood of CH selection, providing a comprehensive decision-making framework. The fuzzy-based approach employed in the ML-FBRP protocol enables intelligent decision-making for selecting CHs based on the optimal combination of input parameters. By leveraging fuzzy logic, the protocol can handle uncertainties and variations in the network environment, improving the overall performance and energy efficiency of the WSN. Figure 4 illustrates the membership functions associated with the likelihood of CH selection, providing a visual representation of the fuzzy output membership values. The different membership functions, such as lw, mm, hh, and V-hh, capture the varying degrees of suitability or likelihood for a node to be chosen as a CH.

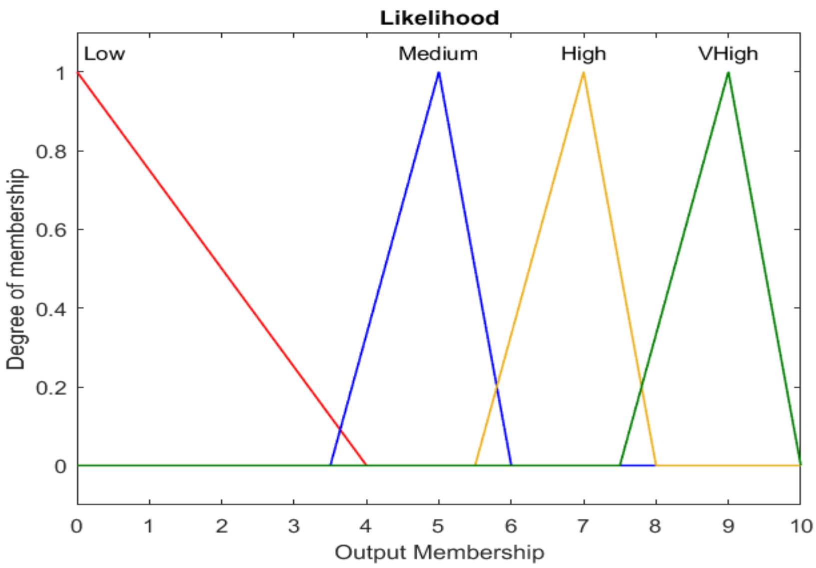

Fig.4. Fuzzy output membership

3.2.2 Fuzzy Rule Set

The Fuzzy rules are used for the Fuzzy Inference Engine(FIS) of the proposed ML-FBRP are as follows:

1. If the distance within the cluster (D_n) is categorized as Far, the distance to the sink (D_S) is classified as High, and the residual energy of nodes (R_e) is labeled as Low, then the likelihood of data transmission (Likelihood__) is determined as lw.
2. If D_n is Considerable, D_S is mm, and R_e is mm, then Likelihood__ is categorized as mm.
3. If D_n is Short, D_S is mm, and R_e is mm, then Likelihood__ is labeled as hh.
4. .
5. .
6. .

27. If D_n is Short, D_S is lw, and R_e is hh, then Likelihood__ is classified as V-hh.

These fuzzy rules provide a step-wise approach to cluster head selection, taking into account the different combinations of distance within the cluster, distance to the sink, and residual energy to determine the likelihood of data transmission.

After the cluster formation and CH selection using the ML based random forest technique, each CH predicts the optimal next hop for transmitting aggregated data to the BS. This ensures efficient and reliable data transmission, minimizing delays and maximizing network performance.

4. Simulation Results

In WSN, the position of sensor nodes (SNs) is determined during the deployment process, either by strategic placement or random scattering. Clustering is a common technique used to organize the deployed network into smaller groups, with every cluster headed by a cluster head (CH). The CH coordinates data aggregation and communication within its cluster, improving network efficiency and scalability.

In this section, the ML-FBRP technique is simulated in a simulated using MATLAB for the comparative analysis of various routing technique. Figure 5 represents the network deployment using 100 sensor nodes in a 200 x 200 m^2 monitoring area.

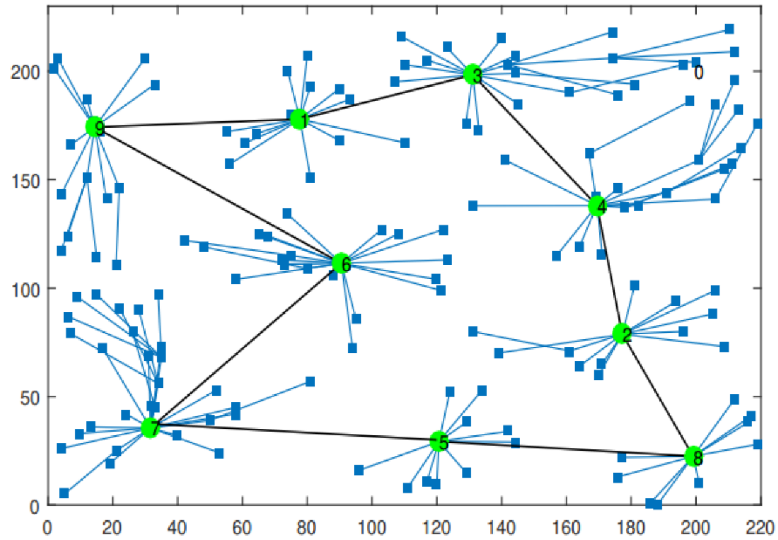

Fig.5. 100 nodes deployed in (100 x 100) m^2 area

To ensure a fair comparison with other techniques, it is important to establish consistent simulation parameters. Table 1 provides an overview of the additional simulation parameters used in the experiment or evaluation. These parameters are carefully chosen to align with the parameters used in comparative techniques mentioned in reference [25]. This ensures that the evaluation and performance analysis are conducted under similar conditions, enabling a fair and meaningful comparative analysis among the proposed and existing protocols.

Table 1. Simulation parameters

Parameter	Value
Network area	200 × 200 m^2
Total deployed nodes	100
Starting Energy of SN	0.5 J
Size of Packet	5000 bits
Base Station Position	(100,100)
Packet Header Size	25 bytes
Control Message Size	50 bytes
E_{mp}	0.0015 pJ/bit/m4
E_{Elec}	50 nJ/bit
E_{DA}	5 nJ/bit
E_{fs}	10 pJ/bit/m2

The LEACH protocol, when initially implemented, achieved a First Node Dead (FND) index of 460. This index represents the number of rounds in which the first node in the network dies due to energy depletion. However, researchers have proposed several improvements to extend the FND index and enhance the network's overall performance. By incorporating the Particle Swarm Optimization (PSO), Hybrid Swarm-based Algorithm for Clustered Protocols (HSACP), and Bee-Cluster routing protocols, the FND index was significantly increased. Table 2 shows the comparative analysis of different protocols with the proposed ML-FBRP protocol.

Table 2: Energy dissipation at various stages in different protocols

	LEACH	**PSO**	**HSACP**	**BEE-CLUSTER**	**LEACH-C**	**ML-FBRP**
First node dead	460	1000	1255	1490	1750	2535
Half node dead	550	1880	2440	3650	4300	4591
Last node dead	625	2590	3025	4250	4844	5075
Average	545	1823	2230	3130	3631	4065

The PSO-based approach extended the FND index to 1000, HSACP further improved it to 1255, and the BEE-CLUSTER protocol achieved an FND index of 1490. These enhancements were achieved by optimizing the cluster formation and data transmission processes, resulting in improved energy-efficiency and prolonging the network's-lifetime. In the case of the LEACH-C protocol, which is an enhanced version of LEACH that utilizes a clustering approach, the FND index was further elevated to 1750. This improvement was accomplished by effectively organizing the sensor nodes into clusters and employing cluster heads to coordinate data aggregation and transmission, thereby reducing energy-consumption and extending the network's operational lifespan.

Furthermore, the proposed ML-FBRP optimize the clustering process of WSN nodes. By leveraging machine learning techniques and fuzzy logic, this protocol aimed to minimize energy dissipation within the cluster and achieve a more balanced distribution of energy across the entire WSN.

As a result, the ML-FBRP protocol achieved a remarkable extension of the FND rounds to 2535 rounds, as Figure 6. This demonstrates the effectiveness, significantly prolonging the network's lifetime and improving its overall performance.

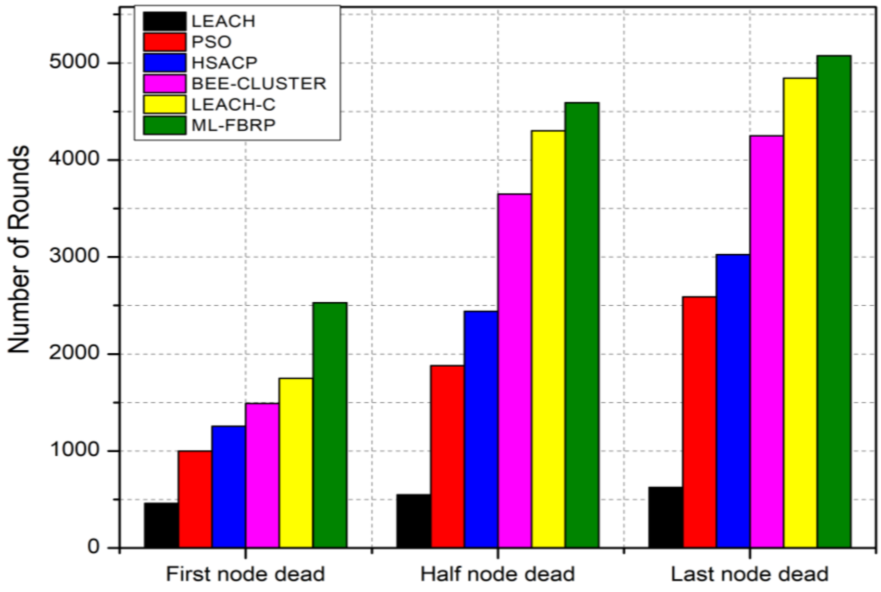

Fig.6. Energy consumption at various points

Figure 7 shows the Average Node Dead in the proposed ML-FBRP compared with the existing protocols.

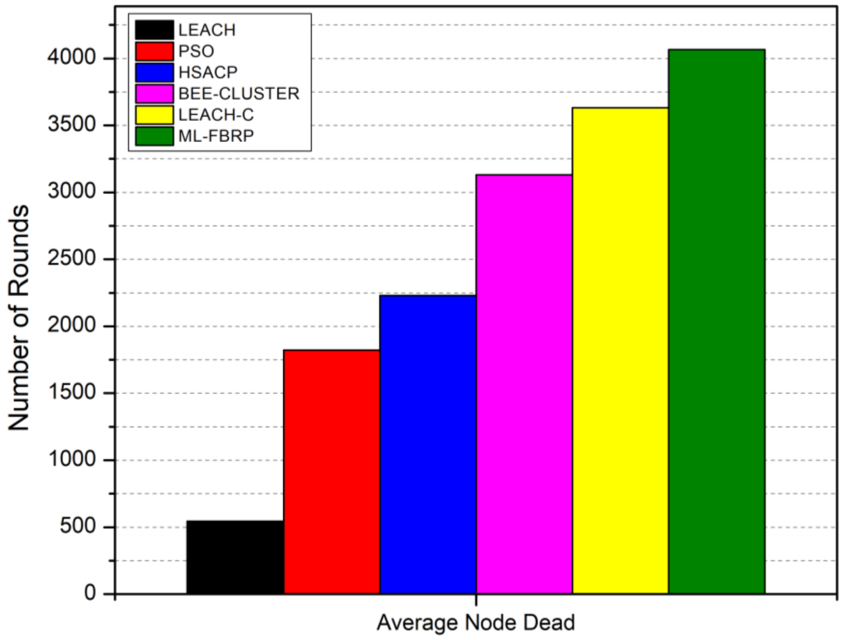

Fig.7. Energy dissipation for Average Node Dead

The average node dead rate is improved in the proposed ML-FBRP protocol as the proposed protocol survived for more number of rounds compared to LEACH, PSO, HSACP, BEE-CLUSTER , and LEACH-C protocol.

The simulation also shows the improvement in the number of dead node in the network. The total alive nodes vs the total is shown in Figure 8. It provides a comparative analysis of the number of alive nodes per round between FGWOA (Fuzzy Grey Wolf Optimization Algorithm) protocol and various existing protocols.

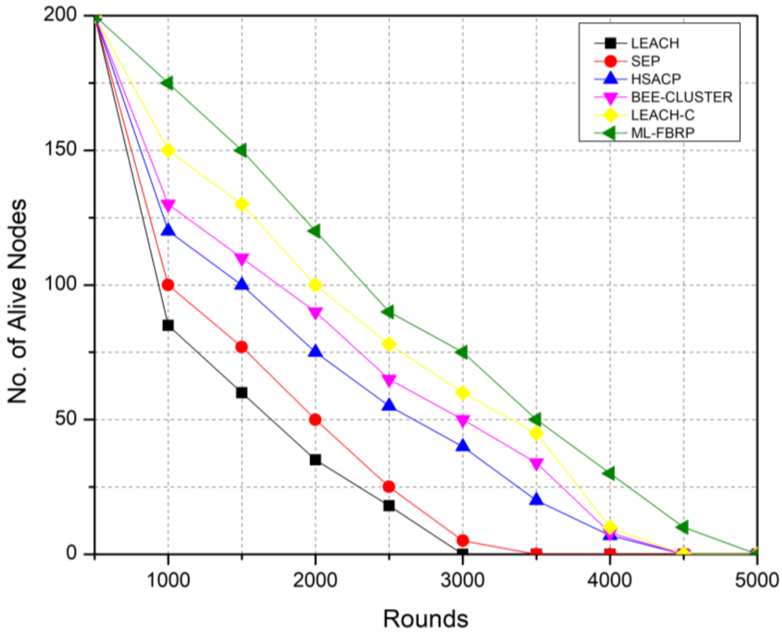

Fig.8. Total number of alive nodes

The node survivability throughout different phases of the simulation process. The Figure 8 indicate that ML-FBRP protocol consistently outperforms the existing protocols in terms of maintaining the maximum number of alive nodes at each round of the simulation. This demonstrates the robustness and efficiency of the in sustaining node activity and prolonging the network's overall lifetime. By employing the ML-FBRP, which combines fuzzy logic and the ML (Random Forest), the optimizes the cluster head selection, routing, and data transmission processes. This optimization approach ensures that the network resources are effectively utilized and that the energy consumption is minimized, resulting in an increased in total alive nodes throughout the simulation.

The different routing protocols vs rounds is shown in Figure 9.

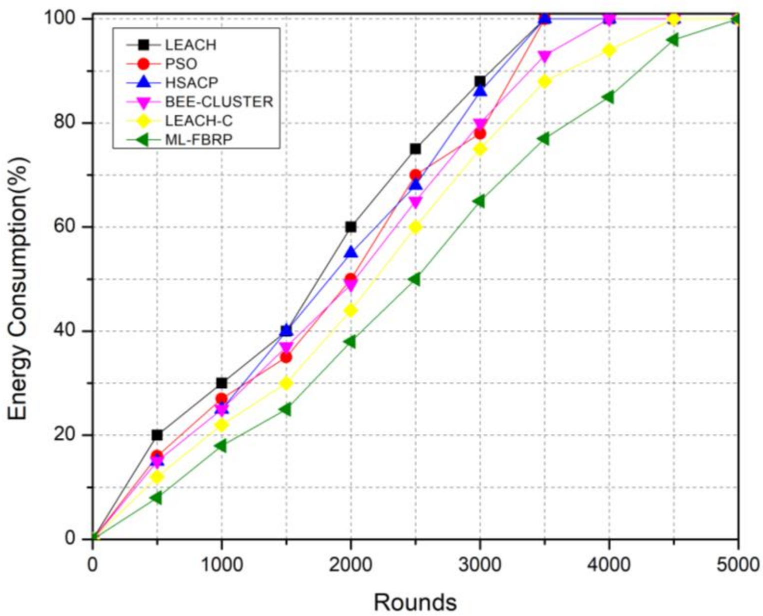

Fig. 9. The energy consumption in the network vs total number of rounds

In the comparative analysis for the simulation of ML-FBRP protocol, the energy-utilization in the network , the LEACH , PSO, and HSACP protocol survived only for 3500 rounds, BEE-CLUSTER and LEACH-C protocol survived for 4000 and 4500 rounds, while proposed ML-FBRP protocol survived upto 5000 rounds.

5. Conclusion

The proposed ML-FBRP (Machine Learning-based Fuzzy-based Routing Protocol) for WSNs that incorporates machine learning techniques and fuzzy logic. The proposed protocol was evaluated through extensive simulations using various simulation parameters to assess its performance. The simulation results showed significant improvements in energy-consumption within the network. ML-FBRP effectively reduced energy dissipation at various points in the network, such as during data transmission and clustering processes in the form of FND, HND and LND. This reduction in energy-dissipation resulted in a more balanced energy distribution and prolonged the network's overall lifetime. Furthermore, the total alive nodes in the network was consistently higher with ML-FBRP compared to existing protocols. This indicates that ML-FBRP successfully mitigated node failures and maintained a higher level of network connectivity and data transmission efficiency. The performance evaluation demonstrated the superiority of ML-FBRP in terms of network robustness, energy-efficiency and overall network performance. The effectiveness of the protocol and its potential for real-world implementations in resource-constrained environments.

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