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Addressing Rogue Nodes and Trust Management: Leveraging Deep Learning-Enhanced Hybrid Trust to Optimize Wireless Sensor Networks Management

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***Abstract*—Comprising a multiplicity of AdHoc sensors working in concert to monitor a range of environmental and physical factors for the targeted area, wireless sensor networks (WSNs). These sensors are used to provide continuous environmental status like temperature, pressure, and humidity by forwarding vital data to the internet through a base station. Aiming to greatly increase the security and performance of WSNs, this study presents a new framework that is a combination of the Deep Learning-Enhanced Hybrid Trust (DLEHT) model and the Machine Learning-Enhanced Fuzzy-Based Routing Protocol (ML-EFBRP). In this research, enhanced packet delivery, packet drop reduction, and the rogue nodes addressed in WSN from source to sink using a probabilistic approach, which depends on the experience of data with the integration of a sum-rule weight mechanism in HMM (Hidden Markov Model). Integration methodology played a major role in deep learning to observe the normal and abnormal node behavior with historic data. It enhanced the throughput and lowered latency with successful detection and addressing of rogue nodes by the integrated strategy. The proposed work, reflects an improvement in performance, both in terms of throughput and latency. The delay hyperparameters are observed, which vary from 7.48 to 26.22 ms with an average of 15.855 ms. And the packet is controlled and decreased by 7%, showcasing more improvement compared to existing work. Simulation results show considerable improvements in network accuracy, reliability, energy efficiency, and resistance during node failures and security concerns for network correctness. These findings show the combination of DLEHT and ML-EFBRP models provides stronger monitoring systems, hence enhancing operational efficiency in settings with limited resources.**

Keywords—Cluster Head Selection; WSN; Sensors; Deep Learning; Energy Optimization; Security Protocols; Network Resilience.

I. INTRODUCTION

A wireless sensor network is made up of tiny, power-efficient, and highly portable sensors or motes. These devices are deployed to work together in monitoring different targeted area environmental parameters, acquiring data, and sending it to the sink node or designated control centers. Each sensor node is very important at the sink since it deals with data encoding through a voice synthesizer and sends report data to the sink. WSNs can be deployed for diverse fields such as environmental monitoring, forest monitoring, sea monitoring, agricultural monitoring, border monitoring, and industrial monitoring due to the fact that they measure several environmental and targeted parameters [8]. The conditional random fields [1] were implemented probabilistic approach with CRF to provide data segment and segment labeling [2] for the mass public and the military. This work intends to investigate the security-related issues and challenges in wireless sensor networks. The holistic approach aims to improve wireless sensor networks' performance with respect to security, longevity, and connectivity under changing environmental conditions. It also has security concerns involving all the layers to ensure overall network security. There must be a combined effort to take a standard model to ensure security. Two models for activity recognition: "hidden Markov models (HMMs)" and "conditional random fields (CRFs)." The authors examined the performance and effect of features in the network. The result shows that CRF has high performance and is effective for a wide variety of computing features in the network [3]. The CRF is deployed in WSN intrusion detection. The outcome of this work shows effective performance compared to existing techniques in the case of relational labeling data and conditional random fields [4]. The sensor node communicates with its neighbor nodes seamlessly using transceivers, allowing for the two-way communication of information without any cabling and connectors. A well-defined communication protocol has a major role in sending, collecting, and analyzing data [9][15].

Despite Because of WSNs, there is enhanced data processing and relationship building between systems, but there are still notable challenges that are a hindrance. One of the great issues includes the constraints associated with power options, which stems from either battery usage or energy-grabbing methods. As networks of WSNs scale up in size, intricacy, and sophistication, issues like data duplicates, poorly designed routing pathways, and even energy consumption begin to arise and grow worse. This escalating predicament necessitates the formulation of more efficient solutions to boost the productivity of a network [10]. Deficiencies within communication protocols are easier to fix than WSNs that can be hacked with rogue nodes, purposeful or defective sensors that may compromise the network's data. These weaknesses must be addressed for dependable functionality and usability.

The aforementioned research goal can be achieved by deep learning, enabling more economical, productive, and security-conscious operations [11].

The ability to optimally manage resources and make decisions in real time in the Wireless Sensor Networks (WSNs) is attributed to their capacity to acquire massive amounts of data from several nodes and relay the information to a base station. As the networks grow more intricate, however, accomplishing data collection, energy usage efficiency, and general network stability becomes increasingly difficult [12][16]. One of the core elements of WSN operation is the cluster heads, which capture and relay information from the surrounding nodes to the main base station. The selection of cluster heads is one of the most sensitive parts of the process because it determines the network performance in terms of its life cycle, energy consumption, and data precision. From the traditional approaches to cluster head selection, physical features such as the remaining energy and the distance to other nodes predominate. While these selection criteria seem to be practical to some extent, and their information is provided, too often they ignore the most important characteristic of the nodes, reliability, and as a consequence encounter problems with data falsification and communication failures. It is essential to stress that, in order to settle these problems, great attention should be paid to the selection of cluster heads with the assistance of artificial intelligence that assesses nodes performance in real time [13][17]. Incorporating trust hybrid metrics—that is, combining historical records with real-time evaluations—allows WSNs to enhance their resilience toward security threats and adapt to node failures due to sensor compromise or malfunction. Recent advances in machine learning technology offer effective tools for trust modeling in which sensor nodes are evaluated based on their communication dependency, behavior history, and energy consumption behavior [14][62].

This research intends to accomplish the following:

1. Create an efficient framework aimed at the selection of cluster heads in Wireless Sensor Networks (WSNs) using deep learning and hybrid trust to improve the operation performance and secure the network from rogue nodes.
2. Formulate an energy-efficient deep learning security architecture that boosts network performance by integrating trust management models with adaptive response strategies in order to lessen the effects from malicious nodes.

A. *Summary of Findings from the Research:*

Rogue Node Detection: The primary objective of this research is to locate malefactor nodes located in the densest regions of wireless sensor networks (WSNs) using sophisticated deep learning methods so as to increase network performance while, at the same time, improving data integrity.

Hybrid Trust Metrics: A trust hybridization model is implemented using trust metrics to enhance resource management in the WSN by calculating the probabilities of service requests and forward data.

Performance Enhancement: The framework simulation shows the enhancement in WSN performance metrics due to reduced processing time and an increment in throughput.

Reduction in Packet Loss: Loss of packet rates, which is directly proportional to the reliability of WSN. It increases triple times reliability.

Trust Based Cluster Head Selection: In this research machine learning techniques focus on the node trustworthiness evaluation and pertaining to the trust metrics used in securing a reliable for Wireless Sensor Network infrastructure.

This research work addressed the energy efficiency and security research challenges of WSN using a deep learning hybrid trust model to make WSN a more robust sensor network, which can work in any target area.

II. RELATED WORK

The analysis of clustering in Wireless Sensor Networks (WSNs) has recently gained remarkable attention, indicating rapid development in research aimed at improving the efficiency and sustainability of these networks. Different protocols invariably focus on network lifetime optimization as the primary goal alongside achieving the system's optimal performance. Most protocols give particular attention to different facets of clustering and devote their clustering strategies to strengthening certain grouping features during several operations' phases. An in-depth study suggests that, at the system level, routing protocols constitute a dominant factor in the development and realization of the defined clustering approaches. These approaches include fundamental operations such as cluster construction, cluster head (CH) selection, data summary, and data delivery to sink nodes. This partitioning into functional phases makes it possible to improve network performance and energy efficiency at these levels [18]. Today, WSNs are being utilized in a variety of fields, including military surveillance, ecological monitoring, and smart city initiatives [19][61]. Each of these applications has distinct requirements concerning the routing protocols that are used. Building effective, robust, and adaptable routing schemes for WSNs is particularly difficult due to the constraints of battery-operated sensor nodes that require energy-saving solutions [20][21].

A layered approach is deployed using CRF to improve the accuracy and efficiency of WSN. The system works best with noisy data without affecting the network's performance [5][6]. In this network, user browsing behaviors are analyzed, and features or characteristics are gathered for training the CRF. After training the model, the proposed model will be deployed into the network to detect the attack. The proposed work is more potent than HMMs for intrusion detection in the wireless sensor network [7].

Important studies have tackled these problems by implementing new advanced clustering routing approaches that fit within WSN constraints [22]. The research develops the E-DSDV (Enhanced Destination Sequenced Distance Vector) routing protocol with the objective of extending the lifespan of WSNs. Each node in the proposed WSN has a routing table that contains all the information regarding neighboring nodes and the total number of nodes in the

communication between the source and the sink [59][60]. It should be mentioned that these protocols have been organized into a collection of grouping techniques based on what clustering features they possess to form a taxonomy of clustering algorithms [23]. The rapid expansion of WSNs has made the problem of efficient selection and transmission of data even more crucial. Certainly, energy issues remain central, especially given the limited life of the battery powering sensor nodes [24]. Studies have pointed out a number of approaches to energy-efficient routing of data in WSNs and divided them into many classes, such as flat and hierarchic, query, coherent and incoherent, negotiation, location, mobile agent, multipath, and quality of service (QoS) provisioning [25]. Flat protocols are best suitable in the case of a fixed sensor network, but an increasing number of nodes in the network is difficult because of processing overhead. By clustering the network into segments, we can harness its aforementioned significance for optimal scalable solutions and effective resource utilization. These clusters reduce the overall cost of transmitting messages as well as energy expenditure through message fusion and aggregation. It's also easy to use hierarchical protocols in large, heavily loaded sensor networks because of how the clusters are set up in terms of how far away they are from the cluster head and how much energy the sensors have [26][27].

The implementation of efficient routing protocols is paramount, as WSN's face many constraints such as power consumption, scalability, and data redundancy. In this overview of the literature, the principal features and contributions to the enhancement of WSNs using LEACH, PSO, HSACP, BEE-CLUSTER, LEACH-C, and many other well-known routing protocols are covered. The idea of energy-conserving clustering in WSN was revolutionized with the advent of the LEACH protocol. It employs a randomized rotation of cluster head (CH) assignments to balance energy consumption among sensor nodes. Subsequently, LEACH permits data aggregation at cluster heads prior to sending them to the base station, which dramatically reduces energy consumption in the network [29]. This remarkable innovative strategy gave rise to numerous clustering protocols designed to prolong the operation of the network while enhancing data transmission.

Research attention is increasingly shifting to the clustering of Wireless Sensor Networks (WSNs) because of the growing need to optimize the performance and lifetime of these networks. The central aim of most protocols is to achieve greater network durability alongside improving the system's overall effectiveness. Every protocol tends to focus on certain portions of the clustering procedure, and attempts to strengthen particular grouping traits during different phases of the operation cycle. Examination shows that routing protocols are of special importance to the development and realization of processes linked with clustering. These processes include crucial activities like cluster creation, cluster head (CH) election, data summarization, and data transfer to sink nodes. This division into operational steps leads to network performance and energy efficiency improvements [18]. Today, WSNs are found in military, environmental monitoring, and even smart city initiatives [19][61]. Such diversity poses new challenges for the routing protocols used. The design of WSNs is both efficient and complex due to the stringent requirement for reliability and scalability, primarily because of the limitations of power sources for the sensor nodes, which need energy-saving designs [20][21].

Recent research conducted and implemented a sophisticated cluster routing mechanism for communication in-cluster sensors and CH to CH communication. E-DSDV (Enhanced Destination Sequenced Distance Vector) routing protocol [59] is implemented in WSN to enhance and better the lifetime of the overall WSN. In this protocol, sensor nodes maintain their own routing table, which keeps neighbor node information for the next round of path creation and selection [60]. The cluster classification mechanism is implemented using a group of protocols [30], which provide effective CH selection and the creation of a cluster in WSN. Effective utilization of the sensor's hardware and other resources, especially the battery, can help to improve the lifetime of the sensor and WSN because all the sensors are powered by a tiny battery. Battery can be managed if the source analyzes the collected data, removes the redundant data, and uses optimal transmission techniques [24]. These were grouped into a number of classes, including flat, hierarchical, query-based, coherent and incoherent, negotiation-based, location-based, mobile agent-based, multipath-based, and quality of service (QoS)-based [25]. Flat protocols perform uniform stationary sensor nodes, in this realm, hierarchical protocols can be of great use since they allow dividing the network into clusters. This segmentation reduces the energy portion spent on transmitting messages because of data fusion and aggregation. In addition, the clusters are arranged in terms of the sensor's remaining energy and distance to the cluster head, which makes hierarchical protocols suitable for high utilization and large-scale sensor networks [26][27].

As WSNs address critical issues such as energy efficiency, scalability of the network, and data summarization, the implementation of effective routing protocols is essential to harness their full benefits. This review of the literature provides the main features and contributions to WSN performance of several popular routing protocols: LEACH, PSO, HSACP, BEE-CLUSTER, and LEACH-C. WSNs are well equipped in energy-efficient clustering because of the protocol LEACH (Low Energy Adaptive Clustering Hierarchy), which the astonishing author Heinzelman and colleagues first presented in 2000. It uses a random rotation of cluster heads (CHs) towards achieving balanced energy consumption throughout the sensor nodes. LEACH greatly increases the energy efficiency of the WSNs by enabling data aggregation at CHs before it is transmitted to the base station [28]. This novel method has paved the way for numerous clustering protocols that seek to maximize the life of the networks while delivering the data. To identify malicious nodes, a trust evaluation model and encryption method are used with the help of a blockchain, whereas the blockchain identifies sensor nodes and aggregator nodes [71][72][73].

III. Proposed Methodology

A. Development and Optimization of a Deep Learning-Enhanced Hybrid Trust (DLEHT) Model for Wireless Sensor Networks

The Deep Learning-Enhanced Hybrid Trust (DLEHT) model was designed and implemented to monitor abnormal activity of nodes in a wireless sensor network (WSAN). This model is simulated with Network Simulator 3 (NS-3), which is an advanced tool for simulating and analyzing WSANs model's performance. The configuration consists of a WSAN model where all nodes implement the DLEHT model, which combines energy-saving measures with complex security measures based on deep learning. This novel approach solves the glaring weaknesses of most traditional WSANs. The network performance is closely analyzed under different circumstances with respect to energy dissipation, throughput, latency, and the number of attacks captured. These metrics are crucial for determining the efficacy of the framework in enhancing security at the same time energy conservation. The publicly available dataset from the Intel Berkeley Research Lab provides the needed data for the training and evaluation along with simulated data from NS-3. This mixture offers different sensor readings and network activities that are fundamental for validating the DLEHT model in terms of effective energy and security.

The DLEHT model design integrates Convolutional Neural Networks (CNNs) and blends them with Long Short-Term Memory (LSTM) Networks for reducing the energy footprint and enhancing the security of wireless sensor and actor networks (WSANs). LSTMs capture important temporal components to detect security anomalies, while CNNs analyze the spatial aspects of the sensor data. The model is composed of five convolutional layers using ReLU functions and is followed by max-pooling layers to lower the dimensionality of the data. The sequential data is processed by three LSTM layers with 128 units each, followed by a dense layer that is activated by softmax functions for classification. Important hyperparameters are learning rate = 0.001, batch size = 128 and training through 100 epochs. In the model, the dropout layers are placed with a rate of 0.6 to avoid overfitting while increasing the robustness of the model. The effective management of energy in devices improves their performance and increases their life span which helps in reducing the operating cost due to the high amount of energy consumed. The odds for various network activities that include, but are not limited to, query servicing and data transfer is determined using a sum-rule weighted method. This approach aggregates individual probabilities from distinct evaluation criteria, assigning particular weights to them according to their importance. The probability score assists in decision making accuracy, throughput maximization, and processing time minimization. Furthermore, the secure middleware of the wireless sensor network incorporates deep neural networks as a fundamental element, providing the network with the capability to address multiple scenarios by combining logical inference with reinforcement learning and other underlying layers. Certain features are activated at the start of the data transmission process after estimating the detrimental device behaviors and adaptive characteristics of the network. Such features comprise data loss monitoring and delay management, which help to strengthen the operational integrity of the network.

The integration of IoT technologies with secure sensor features in WSANs has improved network reliability and data integrity. This strategy optimizes energy efficiency and allows for better security, which enables sustainable communication in more complex ecosystems. Further improvements in these strategies will enhance the effectiveness and reliability of WSANs, in the long term. The routing framework based on a Connected Dominating Set (CDS) as depicted in Fig. 1, starts with the Cover Set Detection process to create a cover set. CDS plays a crucial role in this research to enhance security with optimal path creation and selection. The main aim is to provide a security framework that can detect normal and abnormal behavior of the nodes during the data transmission from the source node to the sink.

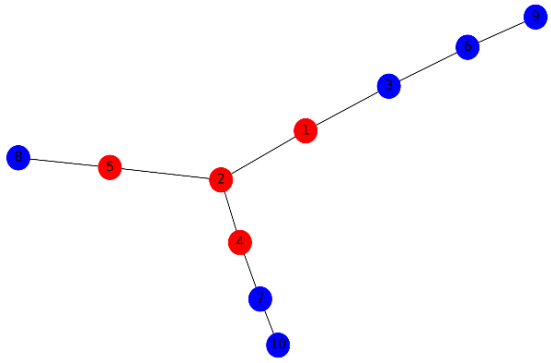

Fig. 1. Integration of CDS in WSN

B. DLEHT Security Mathematical Model:

It is the integration of HMM, CDS, polynomial neurons, and Gaussian distribution. It will track the transition of the sensors, the creation and selection of the optimal path for communication between source and sink, and checking security metrics with evaluation and detection of abnormal sensors.

1) Optimal path creation and selection: CDS

$$Pt = \{ Pt1, Pt2, - - - - - Ptn) \quad (1)$$

2) State transition: HMM

$$Pr(S\ i + 1 \mid Si) = A \quad (2)$$

3) Polynomial Equation: Calculate the security or trust score of sensors Ss(t).

$$Ss(t) = Co + C1.R(t) + C2.PT(t) + C3.PL(t) + C4.\sum P(t) \quad (3)$$

C0 to n: coefficient values for reliability R, transmission power PT, packet loss PL and other parameters P at any given time t.

4) Neural methodology for abnormal behaviour

$$f(x) = \partial(Wx + b) \quad (4)$$

C. Algorithm for Assessing Sensor Security/Trust Values

Step 1: Initialize sensor nodes and set up network trust security parameters

Set `sensor_trust_value` to `0.5`

```
Set sensor_anomaly_value to 0
Set sensor_energy_percentage to 100
Create an empty list for sensor_history
Create an empty list for sensor_comm_metrics
Execute anomaly_detection_train
(sensor_history)
```

Step 2: Observe the behavior of sensor nodes within the network

```
Calculate sensor_packet_delivery_ratio using co
llect_sensor_packet_delivery_ratio(sensor)
Calculate sensor_jitter using collect_sensor_ji
tter(sensor)
Calculate sensor_delay using collect_sensor_del
ay(sensor)
Calculate sensor_energy_consumption using colle
ct_sensor_energy_consumption(sensor)
Append the values of
sensor_packet_delivery_ration,sensor_jitte,
sensor_delay and sensor_energy_consumption to
sensor_history
```

Step 3: Compute trust values for the sensor: both indirect and direct

```
Determine sensor.indirect_trust(sensor,
neighbours)
Determine sensor.direct_trust(sensor)
Calculate the combined trust_value using the
formula:
trust_value = (sensor.indirect_trust * 0.7)
+ (sensor.direct_trust * 0.3)
```

Patterns of behavior are set using the average values of the metrics prior to anomaly detection. The difference between benign and malicious nodes is advanced from the variance and standard deviation of the trained input parameters. The parameters that are provided serve as inputs to the neurons, which, using the data that other allocating neurons have gathered, compute the metrics and assign probabilities to them. The model has four hidden layer neurons, which consist of both active and inactive ones. A random matrix is generated using a transfer function which is integrated with a random vector. The sigmoid function and SoftMax function are employed as polynomial arithmetic operations when setting the bias. The difference in the position of the introduced neuron and the training data is used to determine the distance with the error for training data to be refined in error. State and parameter functions are used to model behavior and misuse functionality, respectively. In the activation phase, the threshold for neuron matching is determined at the start of each epoch for every hidden layer with outputs being a determinant of the preceding layer.

The canonical fragment for a probability distribution function in the hidden layer is represented as:

$$PD = Sum(e^{-\frac{\epsilon}{K*T}}) \quad (5)$$

$\in$ is the Dissemination Continual using Boltzmann, K is the Erudition factor, and T is the Knowledge Time Part.

Validation of the hypothesis is necessary to diagnose the steps marked by behaviors in a hypothetical context with the intention of distinguishing various behavioral types factoring characteristics. In the accompanying Fig. 2, the second depicts the deep learning architecture proposed in this study. Normal behavior is established with defender actions, and the attacker's intentions are inferred from the behaviors. When the malicious nodes are within reach, detector nodes send out an "attacker announcement" to the rest of the network and hence disable the attacker nodes from the system.

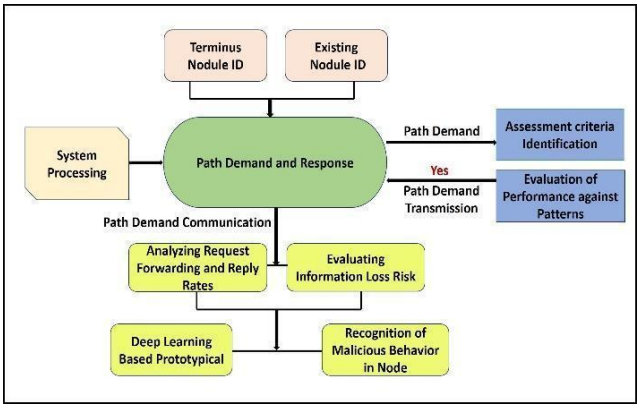

Fig. 2. DLEHT model architecture

The below algorithm is aimed at implementing a Wireless Sensor Network (WSN) and monitoring its activities for any deviations through a Neural Network framework. The process is initiated by defining the normal and abnormal sensor nodes, which in turn leads to the initializing of the feature matrix and label for the nodes. The network is appropriate to perform training so as to provide for the classification of nodes, and this promotes the efficiency of anomaly detection within the network.

Step 1: Generate and deploy sensor nodes

```
Create (S): Construct 100 sensor nodes
that are location defined so as to form
the WSN.
Label the nodes: Implement a labeling
algorithm to denote the normal sensor
nodes that have the value of zero.
```

Step 2: Generate and deploy abnormal nodes

```
Create abnormal sensor nodes (AS): Create
5 abnormal nodes randomly.
Label the abnormal sensor nodes: Set the
marking for these sensors using the
labeling algorithm to 1.
```

Step 3: Construct the feature matrix

```
Develop a feature matrix for which each
sensor node represents a row and
corresponding features are included in
that row.
```

Step 4: Construct the label vector

```
Construct a label vector that classifies
nodes as normal and abnormal.
```

Step 5: Segment the dataset into training and testing sets

```
Implement a Hold Out cross-validation
method with an 80:20 split to allocate
portions of the dataset as training and
testing data.
```

Step 6: Create the structure of the Neural Network

Input Layer:

```
Add 2 neurons for the (x) and (y) positions of the sensors.
```

Hidden Layer:

```
Create a single hidden layer containing 10 neurons which is fully connected and uses the Rectified Linear Unit (ReLU) as the activation function.
```

Output Layer:

```
Create a fully connected output layer with one neuron and an activation function for binary classification.
```

Step 7: Educate the Neural Network

```
Optimize with Adam and train the network for 100 epochs with a mini-batch size of 16.
```

Step 8: Conduct analyses to predict and appraise the output.

```
Make predictions to detect if any attacks took place and evaluate the model's accuracy.
```

D. ML-EFBRP (Machine Learning-Enhanced Fuzzy-Based Routing Protocol)

As With the increasing use of Wireless Sensor Networks (WSNs) in interconnected systems, a number of issues arise, especially regarding security gaps and energy constraints, which endanger the overall efficiency of the system. To mediate these primary concerns, we propose a new hybrid security approach that integrates traditional security methods with sophisticated deep learning models. In our framework, Convolutional Neural Networks (CNNs) are employed in feature extraction and anomaly detection in sensor data, while Long Short-Term Memory (LSTM) networks are used to capture temporal behaviors of features. This allows the system to maximize security combined with dynamically responding to emerging threats. Our model also seeks to minimize energy expenditure to maintain sufficient performance levels in low-capability environments. This model is aimed at practically applying it in the real world, hence, the performance evaluation is done using important metrics such as energy efficiency, data throughput, latency, and incidence of security breaches, which in turn provide a comprehensive view of its effectiveness. We made the following modifications to raise the performance of our deep learning improved hybrid security model for Wireless Sensor Networks (WSNs):

1) Using Reinforcement Learning Techniques:

Reinforcement learning elements in the model have been fitted to enable it to change with newly discovered security concerns. This helps to strategically modify the security measures by enabling continuous learning depending on the interactions of the network users and the conditions of the network. By use of reinforcement learning, the system may make decisions depending on environmental feedback to react to different security issues. It therefore can more successfully handle certain security issues.

2) Evaluation of Performance and Scalability of Real-Life Use Case

We tested the scalability and operational performance of the model from many node densities as well as shifting nodes, testing it. We investigated the capacity of the model to withstand real-life practical situations and obtained relevant knowledge enabling the fine adjustment of parameters to attain desired performance in several operating environments. This evaluation guarantees the model's realistic and strong enough nature to meet the difficulties presented by actual WSN implementations.

3) Head Selection in Clusters Applied in Machine Learning Methodologies

The general operation of WSNs and data transfer depends on the choice of the suitable nodes acting as cluster chiefs. We apply Random Forest, one of the most potent ensemble learning methods with great accuracy for classification issues, for this aim. Among the basic procedures in our work are the following:

4) Creation of Datasets

Initially we try to obtain values that are representative of a variety of metrics like communication overhead, node density, distance (from base station), node degree, residual energy, etc. Each record, depending on existing selection methodologies or simulated methodologies, is marked categorically to flag potential cluster heads. This multifarious dataset captures a number of network conditions, which is required for CH selection optimization, and is very useful to our work.

5) Feature Engineering

To make the selection procedure of cluster heads more efficient, the selection feature engineering techniques are performed. In order to improve the representation of input features, this procedure employs the techniques of dimensionality reduction, feature scaling, and encoding. We also apply domain-specific measures and give importance to residual energy with regard to its impact on the cluster head candidate.

6) Training Random Forest Model

The prepared dataset is used to train the Random Forest classifier. Cluster head candidacy for each node is predicted during the training cycle using a model from a previous dissertation [62]. Random Forest, a type of ensemble learning, combines results from multiple trees to make accurate predictions. The following is a mathematical representation of the training process:

a. Random Forest Classifier Training:

$$RF.fit(X, y) \tag{5}$$

b. CH Candidacy Prediction:

$$y\_pred = RF.predict(x) \tag{6}$$

c. Choosing CH Prospects:

$$If\ y\_pred[node] == 1, then\ CH\_candidates = [node\ for\ node\ in\ WSN\_nodes] \tag{7}$$

7) Assessment of Performance

Using a selected performance metric, we compare the predicted labels to the real CH labels in order to determine how effective our CH selection method is:

$$evaluation\_metric(y\_true, y\_pred) = performance\ metric \quad (8)$$

We make sure the Random Forest model is strong and dependable in choosing appropriate cluster heads by using this multi-step procedure.

E. Data Transmission Using Fuzzy-Based Routing

Subsequently, after selecting CH, a routing strategy using fuzzy logic is implemented to account for the changing nature of WSNs. The fuzzy logic system has multiple rules to consider while making routing decisions including the delivery success, energy, and reliability of the node. Designing Fuzzy Logic Systems and the fuzzy routing protocol uses fuzzy logic to generate rules based on variables extracted from the state of the network. This allows for better flexibility and adaptability because it allows for decision-making granularity during uncertain situations.

1) ML-EFBRP Integration

For real-time adaptive decision-making in response to changes, the trained Random Forest model is incorporated into the fuzzy routing protocol in a seamless manner. By ensuring that the routing decisions are directed by predictive analytics, this integration helps to improve the efficiency of data transmission and the depletion of energy resources [59][60].

2) Adaptation of the Model

Retraining intervals for the model are set in order to maintain the system performance efficacy which causes this model to be more sustainable and flexible in the long term to better respond to the network environment over time.

Algorithm: Cluster Head Selection Using Random Forests

Input:

Dataset (D): A table that holds the attributes of WSN nodes and their class labels.

Output:

A list containing the prepared and identified Cluster Head candidates: Cluster Head candidates.

Steps:

Dataset Preparation:

Collect dataset `((data = [features, labels]))`, where `((features))` contains node characteristics and ((labels)) shows whether nodes are suitable as Cluster Heads `(CH candidate: ((labels = 1)), non-CH candidate: ((labels = 0)))`.

Feature Engineering:

Perform feature engineering on `((data))`, apply some form of dimensionality reduction, feature scaling and encoding, and domain metric CH enhancement metrics are added in the requisite areas.

Random Forest Training:

Partition the dataset into training and validation sets: `((data_train= [features_train, labels_train])),((data_val= [features_val, labels_val])).`

Train the Random Forest classifier: `((model = RandomForestClssifier()))` `((model.fit(features_train, labels_train)))`

CH Candidate Prediction:

For each node, calculate the feature values of the node: `((node_features))`, and estimate candidacy: `((predicted_label = model.predict(node_features)))`

CH Candidate Selection:

Prepare an empty list or array for storing the Cluster Head candidates: `((CH_candidates=[ ]))`

Performance Evaluation:

Evaluate algorithm performance using the network lifetime and the energy efficiency, comparing with baseline methods.

Output:

The final step is to provide the resultant list or array of cluster head candidates: `((CH_candidate)).`

The algorithm contributes towards an optimal identification of the suitable cluster heads in WSNs using an automatic machine learning technique, which improves data aggregation and communication effectiveness.

3) Fuzzy Based Route selection

After the completion of Cluster Head (CH) selection, the ML-EFBRP model employs fuzzy logic for route selection. In a Wireless Sensor Network (WSN), this approach attempts to find the most appropriate route for the flow of information between Cluster Heads and the Base Station (BS) [39]. In order to send the detected information to the BS or its final destination, the CH has to decide on the next hop [40]. Several constraints along with their respective fuzzy membership functions make fuzzy-based route selection possible. These criteria are helpful to determine whether or not given routes can facilitate data transmission, and fuzzy memberships depict the degree of acceptability of each route-related parameter [41]. The route is determined using fuzzy logic after a thorough consideration of all parameters that influence the route. Fuzzy logic parameters and the associated memberships may vary [42] which greatly affects the performance, reliability, and efficiency of data transmission within the network. Apart from that, the implementation of deep learning and machine learning models answers the complex problems quite well, which is greatly in line with the purpose of our research works [49].

F. Important Factors in Route Selection

The prior considerations for the selection of a route are critiqued on the following measures:

1) Mean Distance Overall Covered by Cluster:

It is the distance between nodes and their CH, CH to CH, and CH to sink. Sensor nodes require PTX (transmission power) to send data to their near CH to reach the sink. Distance is directly proportional to the PTX in radio management conditions.

2) Mean Distance from Sink:

It indicates the distance between sensor nodes to sink. Majorly CH communicates with the sink, and each node can become CH according to the available residual energy. The mean distance of any participating node should be measured from the CHs to the sink. It has a major role in measuring the required transmission power and impacts on energy use, latency, data transmission quality, and overall network performance [45].

3) Sensor Node Residual Energy:

Residual energy can be enhanced if the sensor lowers energy expenditures, which directly increases the lifetime of the WSN. The importance of the residual energy of sensor nodes, which have the ability to balance the network's objective to maximize energy availability and increase the network's longevity while optimizing energy consumption, is extended, shown in Fig. 4.

4) Fuzzy Membership Function:

The ML-EFBRP applies fuzzy criteria to ascertain the optimal route to transfer data from the nodes to the Base Station. The approach involves constructing membership functions demonstrating the relevance of each parameter towards route selection [48]. The ML-EFBRP model utilizes fuzzy logic in the route selection process to evaluate a number of factors that impact data transmission, which is done very efficiently with the model. Improving the reliability and efficiency of data flow in wireless sensor networks assists in the overall achievement of network performance with this tactical approach. The parametric input boundaries and ranges for the membership functions are illustrated in Fig. 3 to Fig. 5, which show how these functions impact the route selection process.

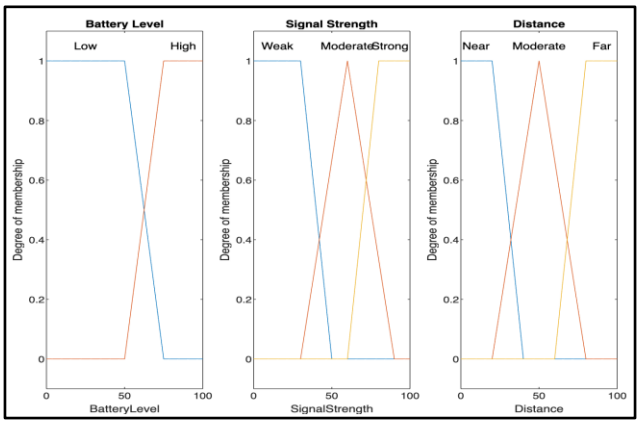

Fig. 3. Fuzzification for Battery level, Signal Strength and Distance of sensor nodes

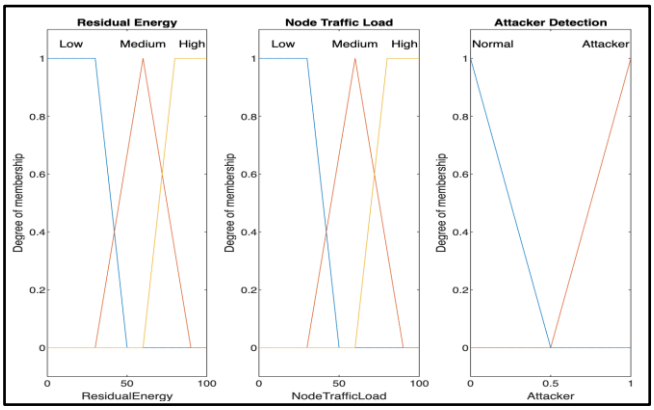

Fig. 4. Fuzzification for Residual Energy, Node Traffic Load and Attacker

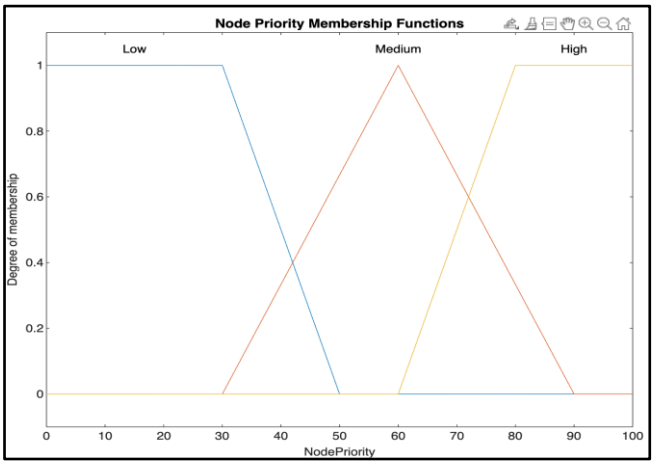

Fig. 5. Fuzzification for node priority while creation path from source to sink

The average distance to the sink is also an important input parameter for the cluster head selection in the proposed ML-EFBRP model with fuzzy logic. The model uses trapezoidal membership functions and thus accurately represents the average distance for a wide range of input values. This approach allows for optimal CH selection based on distance criteria by aiding the formation of cluster heads in high density areas, shown in Fig. 6. The ML-EFBRP combines fuzzy logic to make more sophisticated decisions, which leads to improved network performance and data transmission. The suggested fuzzy model features three membership functions (MFs) corresponding to the average distance to the sink: Low (lw), Medium (mm), and High (hh). These MFs significantly impact energy dissipation during data transmission. Fig. 3 depicts the four MFs that represent the nodes' residual energy: Low (lw), Medium (mm), High (hh), and Very High (V-hh) MFs. These MFs impact the amount of energy within the sensor nodes after every transmission round, enabling network energy management optimization.

The fuzzy logic, The Fuzzy Inference System (FIS) assigned the probability values for the Cluster Head (CH) selection parameters M1 and M2 within the ML-EFBRP protocol's scope. The fuzzy rules assigned to the framework enable a structured form of decision-making by defining correlations between several input criteria and the probability of a specified node being assigned as a CH. The ML-EFBRP protocol's fuzzy logic approach makes an appropriate

inductive reasoning process to define the most suitable combination of input values for CH selection. After applying fuzzy logic, the protocol improves the performance and energy efficiency of the Wireless Sensor Network (WSN) by resolving the ambiguities and dynamics existing in the network environment.

Fig. 5 shows the node priority. If a node has a priority score of 82.6338, that means it's a normal node; if a node has a priority score of 20.106, it indicates an attacker node.

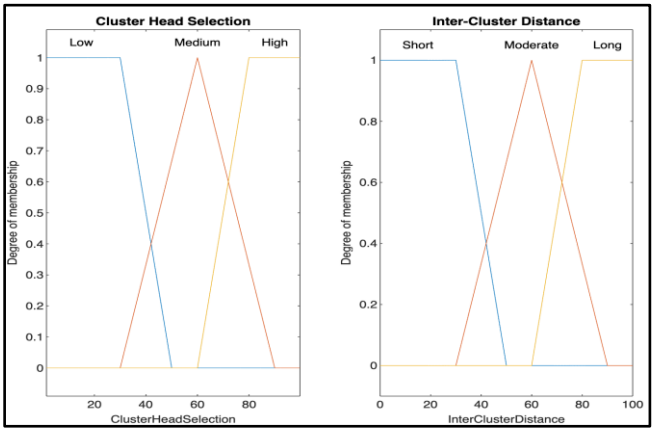

Fig. 6. Fuzzification for CH selection and intercluster distance

Fig. 7 depicts the fuzzy output membership values along with the functions correlated to the probability of choosing a CH. These functions demonstrate different degrees of suitability for a specific node to be chosen as a CH. The functions representing membership—Low (lw), Medium (mm), High (hh), and Very High (V-hh)—indicate the node's appropriateness level, which subsequently improves the CH selection process and the network's efficiency as a whole.

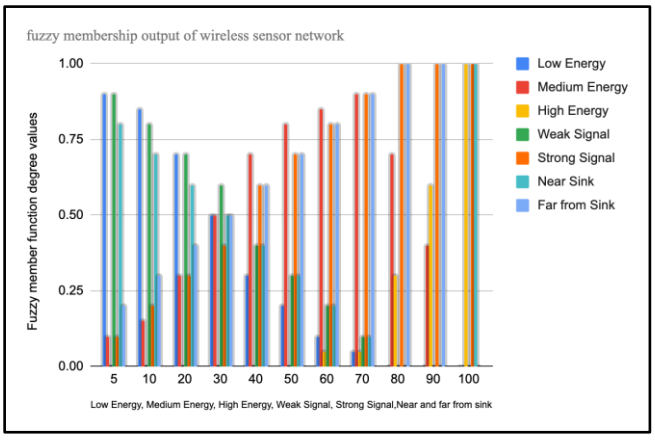

Fig. 7. Fuzzy output membership

5) *Fuzzy Rule Set*

The suggested ML-EFBRP protocol employs a fuzzy inference system (FIS) for a particular type of fuzzy logic. Designed for the protocol, the system makes decisions with regard to Cluster Head (CH) selection and the probability of data transmission with the aid of previously defined fuzzy logic rules [61]. The fuzzy rules listed below describe the most important relations between the parameters inside the cluster and at the sink node, as well as the node energy level remaining:

Rule 1: *For the case when D_S is evaluated to be High, D_n is Far, and R_e is Low, the associate probability of data transmission marked a chance is Low (lw).*

Rule 2: *When the distance between the sensor and its cluster (D_n) is Considerable, the distance to the sink (D_S) is considered Medium (mm) and residual energy (R_e) is also considered Medium (mm), then the probability is considered Medium (mm).*

Rule 3*: When (D_n) is Short, the distance to the sink (D_S) is Medium (mm) and the nodes residual energy (R_e) is Medium (mm), then the probability is considered High (hh).*

Rule 4: *When the distance to the cluster (D_n) is Far, the distance to the sink (D_S) is Low (lw) and the residual energy (R_e) is Low (lw), then the probability is Very Low (V-lw).*

Rule 5: *When (D_n) is Considerable, the distance to the sink (D_S) is High, and the remaining energy (R_e) is High (hh), then the likelihood becomes Medium – High (mh).*

Rule 6: *When the distance within the cluster (D_n) is Short, the distance to the sink (D_S) is High, and the residual energy (R_e) is Low, then the likelihood is High (hh).*

….

Rule 27: *If the distance within the cluster (D_n) is Short, distance to the sink (D_S) is Low (lw), and remaining energy (R_e) is High (hh), the likelyhood is categorized as Very High (V-hh).*

These fuzzy rules represent the core of the FIS which incorporates an assessment of the chosen parameters toward their overall contribution of failure or success to data transmission in the network. Its operation is self-driven to different degrees of the WSN's environment, thus improving the reliability and efficiency for data routing.

IV. RESULTS AND DISCUSSIONS

A. *Deep Learning-Enhanced Hybrid Trust (DLEHT) Model*

This model is designed to improve mobility and security of Wireless Local Area Networks (WLANs) through the use of deep learning technology. This model features a specialized application that monitors and evaluates the network's performance and offers valuable information that will aid administrators in making decisions. With deep learning, the DLEHT Model continuously monitors critical performance metrics, including reliability, service downtime, and security weaknesses. The hybrid trust system keeps track of nodes based on their historical behaviour and assigns them trust levels concerning data and resource allocation for enabling or disabling information forwarding. In this way, the DLEHT model is able to strengthen the management of security and service reliability in WLANs by making use of deep learning technologies, which allows networks to be more flexible and better integrated.

The proposed DLEHT model undergoes validation through an evaluation approach that considers various performance indicators. The settings utilized in the runtime environment are detailed in Table I.

TABLE I. IMITATION ARRANGEMENT

Constraint	Assessment
Sensor Quantity	550 nodes
MAC Protocol	Sensor MAC (IEEE 802.11)
Data Category	Priority Queue
Coverage Radius	85 m
Area Dimension	600 × 600 m
Antenna Type	Omnidirectional
Packet Size	600 bytes
Communication Protocol	UDP
Packet Generation Interval	0.05–0.25 seconds
Throughput Rate	4 Mbps
Simulation Time	30–120 seconds
Attacker Quantity	4 DDoS attackers
Initial Energy Level	600 Joules

Synthetic Minority Oversampling Technique The Tomek Link (SMOTE-TomekLink) technique [74] deployed the best features of scaling, training, and detection on 374,661 records of the WSN dataset. The outcome shows 99.78% accuracy using binary classification. Efficient Key Distribution for Secure and Energy-Optimized Communication using Bioinspired Algorithms (EKD-SOCBA) [75] is designed to enhance the security and energy in WSN. The EKD-SOCBA technique improved the minimal attack by 7.2896 and brute force attack by 15.1000 compared to the existing techniques such as CA, AOA, ARCHOA, DHO, and CUBA-LSS (Coot upgraded butterfly algorithm with logistic solution space). Distance having the major factor in any WSN for reliable and long lifetime of WSN, If the distance increases between the sensor and CH, it requires more transmission power for communication. If it is not provided with sufficient transmission power, it will lead to packet drops, increases in jitter and delay, and the path will become faulty.

1) Analysis of Packet Delivery Ratio

Table II presents an analysis of the packet delivery ratios, packet drop ratios, jitter duration during packet delivery, delay during packet transmission, and throughput of the overall WSN. These are the major parameters that are affected if protocols/models are not energy efficient and secure. Proposed work simulated various time durations with increasing density of the nodes, which shows better results compared to the SMOTE-TomekLink, EKD-SOCBA, and other optimal and ML-based algorithms used in WSN. This study offers a comparative analysis between the existing work and the proposed Deep Learning Enhanced Hybrid Trust (DLEHT) model. The purpose is to assess whether the DLEHT model can improve network performance, especially in the packet delivery ratio and network reliability and security with the increasing node density. The goal of this analysis is to validate the claim about the DLEHT model's effectiveness in tackling issues related to modern WSN implementations. Table III outlines a comparison made in the network packet delivery ratio, when distance increases, packet delivery will radio because transmission power may not be enough to transmit the packet at long distances, as illustrated in Fig. 9.

2) Network Delay Comparison Analysis

Table II outlines a comparison made in the network latency for the current simulation phase and the previous phase within a defined short period of time. As illustrated in Fig. 7, while metrics on the whole improve as deep learning techniques are applied, the DLEHT model shows the smallest network latency when the number of nodes is large. This result emphasizes the effectiveness of the DLEHT protocol in network delay reduction; therefore, useful communication can be made in the network without much delay.

3) Jitter Measurement Analysis

Table II summarizes the observed jitter in the experimental network for a period under abuse as well as the measurements taken in the previous phase. In Fig. 7, it can be seen that the DLEHT model, compared to most conventional network models, exhibits the lowest amount of jitter. With the anticipated increase in the size of the network, it is expected to reduce the jitter and delay during packet transmission. The decrease is an indication of greater network stability leading to better performance and quality of data transmission. Table III outlines a comparison made in the jitter measurement at different distances d, as illustrated in Fig. 9.

TABLE II. NETWORK PERFORMANCE ANALYSIS

Sl. No	Intervals (s)	Jitter in ms	Delay in ms	PDR %	Throughput
1	100	94	40	94	41
2	150	93.7	40.5	93.7	41.3
3	180	93.4	41	93.4	41.6
4	200	93	39.8	93	42
5	250	92	38	92.5	42.3
6	300	91.8	34.5	92.75	42.6

TABLE III. WSN PERFORMANCE METRICS OF JITTER, DELAY, PACKET DROP, PACKET DELIVERY AND THROUGHPUT OF DLEHT MODEL WITH DISTANCE

Sl. No	Distance	Jitter	Packet Drop	Packet Delivery	Throughput	Residual Energy	Delay	Predicted Delivery
1	50	5.20	7.04	92.97	93.74	93.85	7.48	83.96
2	100	10.28	8.76	91.25	87.74	91.94	8.63	83.33
3	150	7.69	12.75	87.26	78.98	87.73	11.01	83.73
4	200	10.93	16.79	83.22	72.93	79.24	11.81	81.09
5	250	3.42	19.65	80.36	63.33	78.72	12.51	80.21
6	300	10.64	23.53	76.48	55.08	75.39	15.41	77.34
7	350	4.29	26.52	73.49	49.99	69.54	20.75	76.39
8	400	12.41	28.71	71.3	44.22	64.15	21.45	74.29
9	450	11.51	33.83	66.18	37.23	62.66	23.28	73.87
10	500	8.71	35.78	64.23	25.14	59.10	26.22	74.37
AVG		8.508	21.336	78.674	60.838	76.232	15.855	78.858

4) Throughput Assessment

The throughput measures from the experimental network done over a short period of time are shown alongside the other models in comparison in Table III. The DLEHT model has much better performance when compared to traditional network models in overall throughput, as shown in Fig. 7. Furthermore, the throughput values are nearly double, illustrating the scalability of the DLEHT protocol in addition to its effectiveness in data traffic management as the number of nodes increases. Table IV outlines a comparison made in the throughput measurement at different distances d, and it's inversely proportional to the distance, as illustrated in Fig. 9.

5) Average Energy Consumption

Table III displays the average energy consumption values over a short period of time compared to previous values. In this case, the DLEHT model shows the most significant energy consumption decrease, up to 52%, as the number of nodes increases, which is shown in Fig. 8. This answer shows how much more efficient the DLEHT protocol can get in terms of energy expenditure. Table IV outlines a comparison made in the residual energy measurement at different distances d, and it's inversely proportional to the distance, as illustrated in Fig. 9.

The results from the proposed work reflect an improvement in performance, both in terms of throughput and latency. The delay hyperparameters are observed, which vary from 7.48 to 26.22 ms with an average of 15.855 ms. And the packet is controlled and decreased by 7%, showcasing more improvement compared to existing work. The use of deep learning algorithms has also improved the dependence of the DLEHT protocol by mitigating the chances of network failures due to malicious node actions.

B. ML-EFBRP Model

In Wireless Sensor Networks (WSNs), the location of sensor nodes (SN) is fixed at the time of deployment, which can either be through random scattering or through predefined placement. Cluster-based techniques are one of the most common approaches, which subdivide the larger network into smaller, manageable groups in which each group is led by a cluster head (CH). The cluster head, who is responsible for the cluster, controls the communication and data aggregation within his cluster to enhance the scalability of the network. An ML-EFBRP routing strategy simulation is described in this section with the implementation done in MATLAB. The set-up consists of 100 sensor nodes spread randomly in a square field of 180×180 m, as illustrated in Fig. 8. Fig. 9 shows the normal and attacker nodes in the WSN simulation using MATLAB, simulation results in Fig. 10 visualize the distance of all nodes from the sink, which can help prevent attacks.

In order to ensure fairness while comparing alternative routing strategies, it is fundamental to maintain simulation parameters. The additional parameters utilized in the trials are consolidated in Table III. In order to ensure that the evaluation and performance analysis are done under similar conditions, these parameters are selected in accordance with those employed in the comparative methodologies outlined in earlier studies. This approach enables proper comparison of the proposed ML-EFBRP technique with existing methods.

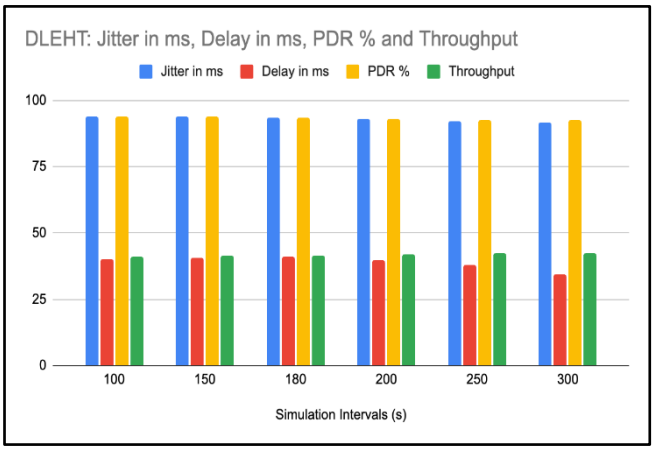

Fig. 8. Statistical Analysis visualization of jitter, delay, PDR and throughput of DLEHT model

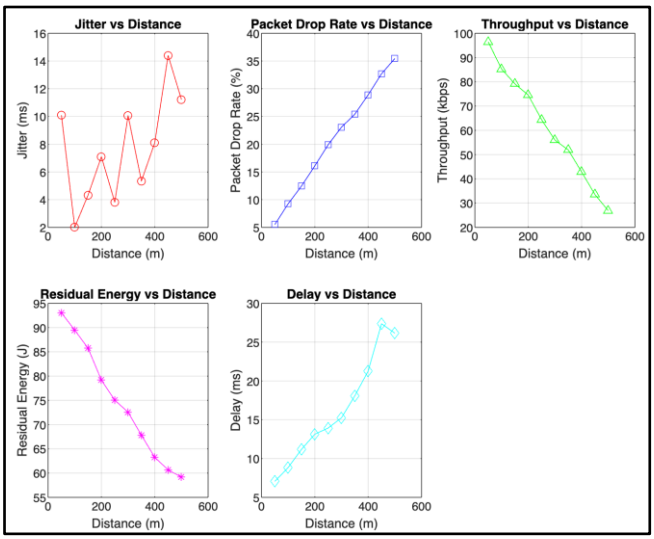

Fig. 9. Statistical Analysis visualization of jitter, delay, packet drop, packet delivery and throughput of DLEHT model with distance

The proposed model of WSN is simulated in MATLAB, as shown in Fig. 10. It shows the number of normal and attacker nodes detected by research work in Fig. 11. Distance is the major factor, as shown in Table III; research work calculates the distance of all nodes from the sink in Fig. 12.

When the LEACH protocol was first introduced, it reported a First Node Dead (FND) index of 483, which is the number of rounds to the first node death in the network due to energy exhaustion. Since then, other researchers have tried to improve the FND index as well as the network performance. The implementation of methodologies, such as Particle Swarm Optimization (PSO), Hybrid Swarm-based Algorithm for Clustered Protocols (HSACP), and Bee-Cluster routing protocols, earned remarkable improvements to the FND index. A comparative study of some routing protocols with the proposed ML-EFBRP protocol is done in Table V.

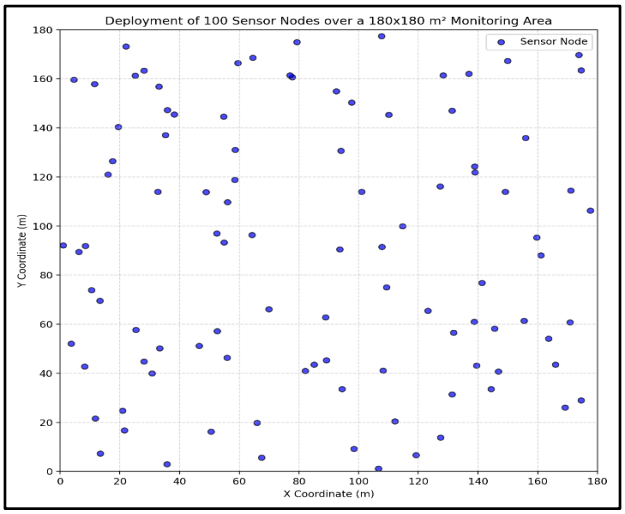

Fig. 10. Deployment of Nodes

Fig. 11. Detection of attacker node in WSN

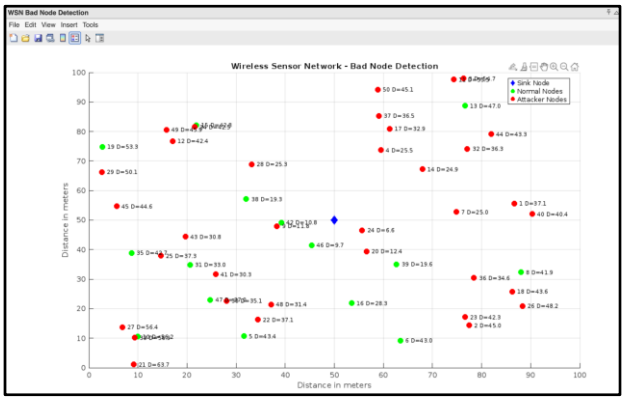

Fig. 12. Distance of attacker nodes from sink

TABLE IV. KEY SIMULATION ATTRIBUTES

Parameter	Value
Total Nodes Deployed	100
Initial Energy of Sensor Nodes	0.5 J
Packet Size	5000 bits
Base Station Coordinates	(100, 100)
Packet Header Size	25 bytes
Control Message Size	50 bytes
Energy Consumption for Data Transmission ($\boldsymbol{Emp}$)	0.0015 pJ/bit/m²
Energy for Electronics ($\boldsymbol{EElec}$)	50 nJ/bit
Energy for Data Aggregation ($\boldsymbol{EDA}$)	5 nJ/bit
Energy per Transmission Surface ($\boldsymbol{Efs}$)	10 pJ/bit/m²
Total Nodes Deployed	100

TABLE V. ENERGY LOSS PATTERNS AT DIFFERENT STAGES IN DIVERSE PROTOCOLS

Protocol	First Node Dead (FND)	Half Node Dead	Last Node Dead	Average
LEACH	483	578	656	573
PSO	1050	1974	2725	1914
HSACP	1318	2562	3176	2331
BEE-CLUSTER	1565	3832	4463	3286
LEACH-C	1837	4515	5086	3813
ML-FBRP	**2662**	**4820**	**5329**	**4268**

PSO increased the FND index to 1050, and it was subsequently raised to 1318 by HSACP. An FND index of 1565 was registered by the BEE-CLUSTER protocol. These changes are due to imCloud and iCloud protocol enhancements that have increased the efficiency of data transmission and improved cluster formation optimization, which further reduces energy consumption and increases the lifetime of the network. The value of 1837 as an FND index corresponding to the LEACH-C protocol was observed from an improved version of the original LEACH where clustering is employed. This enhancement stems from the effective partitioning of sensor nodes into clusters and the employment of cluster heads to facilitate the transmission and aggregation of data, thereby saving energy. The proposed ML_EFBRP protocol is designed to optimize the clustering processes among WSN nodes. This protocol aims at achieving a more balanced energy distribution across the network and minimizing energy wastage in the clusters by deploying Fuzzy logic and Machine Learning algorithms. Therefore, ML EFBRP was able to increase the FND cycles to 2662, thus improving the sustainability of the network. The effectiveness of the provided protocol was compared with the existing ones in terms of energy consumption, which is shown in Fig. 13. Fig. 14 shows the Performance Evaluation of Energy Efficient Protocols in Dynamic Conditions [57][58].

The ML-EFBRP method beats the averages of node dead rates for the LEACH, PSO, HSACP, BEE-CLUSTER and LEACH-C protocols because it continues to operate over a larger number of rounds and simulations further proof the improvement of active nodes in the network for the duration of its lifespan. The following figure illustrates the comparison of the total alive nodes as well as the total nodes in the network over various rounds. It presents an extensive analysis of alive nodes by rounds, emphasizing the ML-EFBRP protocol's performance against the Fuzzy Grey Wolf Optimization Algorithm (FGWOA) and other protocols. The Fig. 15 highlights how efficient the ML-EFBRP protocol is when it comes to maintaining node activity, energy efficiency, and adding to the strength of the network.

The node survivability was studied through a specific set of phases of the simulations. The figure provided proves that the ML-EFBRP protocol is superior to all other existing protocols given that it maintains the maximum number of alive nodes through every simulation round which portrays the efficiency of the ML-EFBRP protocol in sustaining node activity and extending the longevity of the network. The ML-EFBRP smartly combines fuzzy logic with Random Forest machine learning, which allows for the best cluster head

selection, rerouting, and data transmission optimization [51]. This optimization guarantees effective resource deployment across the network while minimizing energy usage which leads to more alive nodes during the span of simulation.

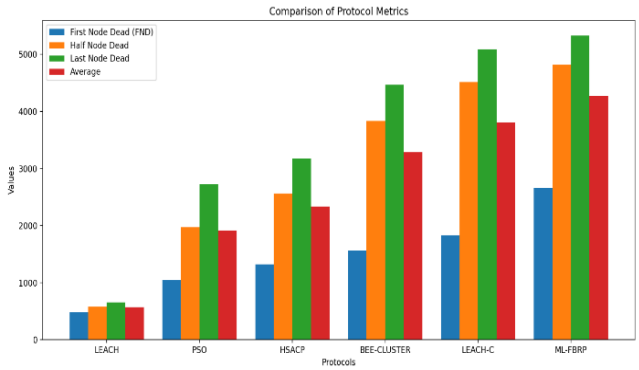

Fig. 13. Comparison Metrics for Energy consumption at various points

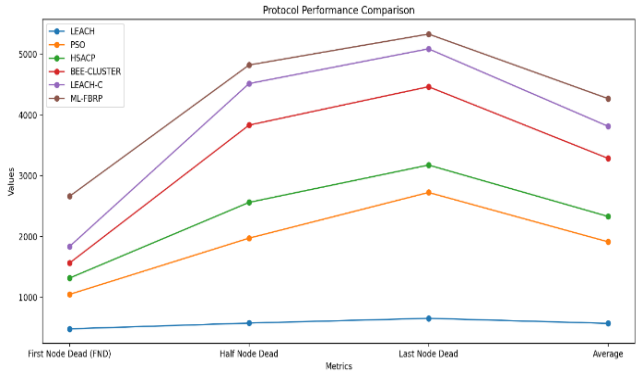

Fig. 14. Comparison of Protocol Performance Under Varying Node Conditions

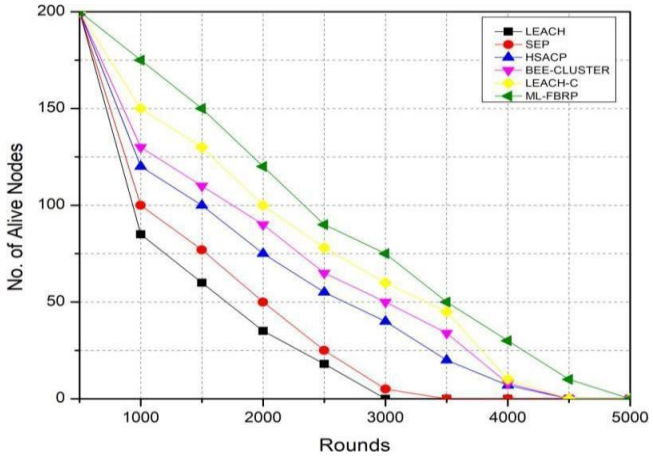

Fig. 15. Total Count of Active Nodes in the Network

Moreover, in Fig. 16, a comparison of various routing protocols as a function of rounds is included, which illustrates once more how well the ML-EFBRP protocol accomplishes network vitality maintenance over time. While analyzing the simulation for the ML-EFBRP protocol, it was evident that there were notable differences with regards to energy consumption in the different routing protocols within the network. The LEACH, PSO, and HSACP protocols remained functional for merely 3500 rounds. However, the BEE-CLUSTER and LEACH-C protocols showed better results by surviving 4000 and 4500 rounds, respectively.

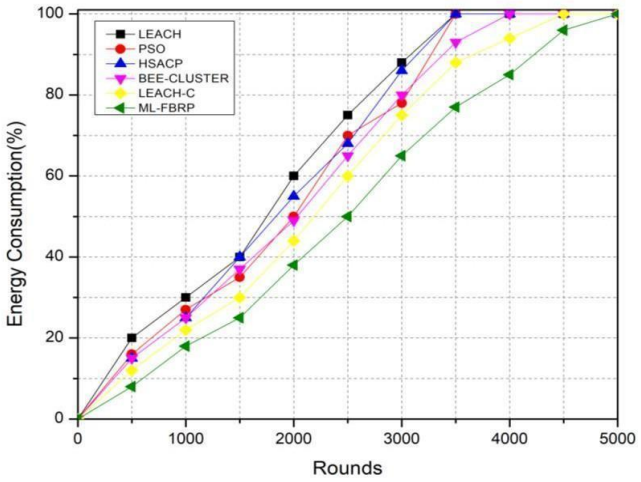

Fig. 16. Total Rounds Impact on Network Energy Consumption

Importantly, the proposed protocol ML-EFBRP showed the longest endurance as it remained functional for up to 5000 rounds. This prolonged survival certainly stresses how the ML-EFBRP protocol is efficient in energy optimization and the general performance of the network.

C. Integration of DLEHT and ML-EFBRP Models

The combination of the Deep Learning Enhanced Hybrid Trust (DLEHT) model and the Machine Learning Enhanced Fuzzy Based Routing Protocol, in contrast, constitute an all-inclusive model that improves security and performance of Wireless Sensor Networks (WSNs). This integration aims to mix both models in order to improve network security, lower data transmission's dependability, and improve decision making.

1) Trust Management Mechanism

The DLEHT models assess nodes according on their prior performance, energy levels, and communication dependability. Built within the DLEHT concept is a dynamic trust evaluation system. Trustable node identification in the network depends on the trust score generated with deep learning methods. Including this trust evaluation into the ML-EFBRP proactively node trustworthiness by adding more factors into the choosing process of Cluster Heads (CHs) and data routing pathways. This method assures that essential network functions are performed by the most trustable nodes which increases the level of data communication assurance.

2) Enhanced Routing Policy Decisions

Fuzzy logic is used in the ML-EFBRP to assist the routing decision making at different levels using multiple parameters, including node reliability, energy expenditure, and distance. Incorporating the trust score from the DLEHT model enables the fuzzy logic set to make routing decisions that consider both efficiency of resources and the security of the information being transmitted. This ensures an all-encompassing routing policy that achieves the performance goals and security objectives.

3) Elevated Performance Indicators

The DLEHT and ML-EFBRP integration yields considerable improvements in essential network performance indicators. In the first part of the proposed DLEHT model,

the sensor consumed less transmission power for transmitting data to its CH. This HMM model is a key player for tracking normal and abnormal nodes in WSN. If any node suddenly consumes more transmission power compared to threshold values, dropping more packets and reducing throughput, nodes will be declared as abnormal nodes and removed from the WSN. So WSN becomes more secure and energy efficient. The second part of the proposed work, the ML-EFBRP model, has a significant role in achieving the objectives of WSN for the effective utilization of all the sensor nodes and communication link. The result of the integration shows better throughput, improvement in packet delivery, reduction in packet drop, latency and jitter. Trust/security score allows only reliable and authorized nodes for communication to the CH or sink based on the score collected.

4) Adaptability to Network Dynamics

The combination of the real-time trust assessment of the DLEHT model and the flexible routing strategies of ML-EFBRP creates a framework that has the capability to respond dynamically to changing network conditions. The framework is able to respond to node failures, changes in node density, and other environmental changes, enabling real-time decision-making that improves the responsiveness and robustness of the WSN.

5) Security Enhancements

The application of these models enhances the security posture for the WSN. The Trust Evaluation Mechanism in DLEHT assists in the detection of possible malicious nodes and those nodes trust reputation influences the routing decisions in ML-EFBRP, thereby allowing only trusted nodes to participate in data transmissions. This combination of proactive security measures is imperative to mitigating the problems posed by malicious nodes to information security.

Table VI underscores the improvements noticed prior to and subsequent to the model integration, which include trust evaluation, data transmission, and network efficiency. These results depict the success of the contention in improving network performance and security as displayed in Fig. 17.

TABLE VI. ENHANCED NETWORK PERFORMANCE: A COMPARATIVE ANALYSIS BEFORE AND AFTER INTEGRATION

Performance Metrics	Before Integration	After Integration
Average Trust Score	0.55	0.78
Packet Delivery Ratio (%)	82%	95%
Network Throughput (Mbps)	3.5	7.2
Average Latency (ms)	120	75
Energy Consumption per Transmission (Joules)	0.45	0.32

Combining the models DLEHT and ML-EFBRP has shown several satisfying improvements with regards to many performance metrics. The nodes' trustworthiness, or Average Trust Score, increased from 0.55 to 0.78, which sinks to the average range. This implies that there is sufficient capability to discriminate trustworthy nodes in the network. Similarly, the Packet Delivery Ratio increased with a wide margin from 82% to 95%, which means the effectiveness of transmission processes has improved. There was also a remarkable increase in Network Throughput from 3.5 Mbps to 7.2 Mbps with the implementation of the integrated models. Average Latency also improved from 120 ms to 75 ms, which indicates the responsiveness for data communication has improved. Finally, Energy Consumption per Transmission fell from 0.45 Joules to 0.32 Joules, which shows the operational success with regard to the energy management integrated into the framework.

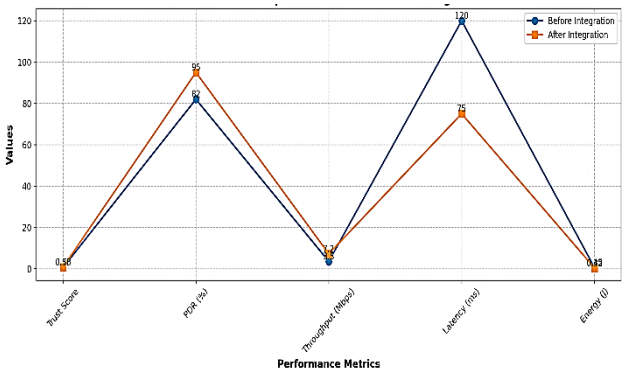

Fig. 17. Performance Comparison Before and After Integration

V. CONCLUSIONS

This study highlights the importance of several Quality of Service (QoS) parameters, such as delay and network lifetime, in the functionality of Wireless Sensor Networks (WSNs). There is serious attention towards the packet loss ratio which may be made worse with the presence of Distributed Denial of Service (DDoS) attacks, which lowers network quality. The suggested integrated protocols attempt to reduce packet loss as well as the network lifespan extension expenses. These protocols cope with node Malicious activities which are much more sophisticated than those of earlier models by partitioning the nodes into reliable nodes which are needed for normal communication and overly active nodes which are suspected to be harmful.

Considerable advancements in operational metrics have been realized due to the collaboration of the DLEHT model with the ML-EFBRP protocol. The ML-EFBRP approach, which utilizes fuzzy logic and machine learning, has shown a remarkable reduction in energy consumption across the network. This integration improves the network's dependability as seen from the increase in the number of active nodes relative to other routing methodologies, and therefore, increases the network's resilience towards node failures. Moreover, the results show a significant reduction in packet loss from 23% to 8%, while latency has also improved by reducing delays from 70 ms to 42 ms. These results confirm the claim of the DLEHT and ML-EFBRP models of improving network strength, reducing energy consumption, and enhancing the performance of WSNs in general, particularly in environments with scarce resources.

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