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Efficient Neuro-Fuzzy Based Energy-aware Relay Selection in IoT-enabled SDWSN

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Abstract: The Internet of Things comprises wireless sensor devices (nodes) that work together to create a dynamic network without central management or continuous assistance. Due to their high mobility, sensor nodes cause periodic topological changes in the network that cause link failures, frequently forcing nodes to rediscover new routes for efficient data transmission in the IoT. This process consumes more energy, which makes the network's lifetime shorter. This brings attention to energy management and network lifetime issues. A single artificial intelligence technique is insufficient to solve these issues. A relay selection is one way to reduce node energy while routing the data in an IoT network. The proposed work aims to develop an efficient energy-aware relay node selection during the routing process using an adaptive neuro-fuzzy model (ANFIS).
The proposed work utilizes a centralized controller architecture called software-defined network which minimizes the overhead of sensor nodes by managing the topology control and routing decisions through intelligent algorithms. This paper presents an energy-aware relay selection technique (ERST) using an ANFIS to optimize the overall energy usage and improve the span of the network. The relay node is selected based on the remaining energy, signal strength, mobility, and the expected transmission ratio of the nodes, which is given to the fuzzy inference system to make intelligent decisions based on the fuzzy rules and neural network used to fine-tune the fuzzy system to select the optimal relay node. The proposed work is evaluated using MATLAB and NS3 simulators. The obtained results of the suggested work outperform the previous protocols by minimizing 5% of end-to-end delay and 4% of energy usage and maximizing 8% of average throughput, packet delivery, and overall network lifetime. The proposed ERST achieves efficiency, reliability, and scalability in IoT.

Keywords: Relay Node Selection, Software-Defined Network, Energy Efficiency, Fuzzy Logic, Neural-networks.

1. Introduction

The IoT (Internet of Things) makes it possible for physically existing objects or devices to connect, exchange crucial information for decision-making, and do critical tasks without human intervention. Over the past ten years, energy utilization has risen alarmingly, leading to a growing number of digital users and gadgets. There are estimated to be 50 billion IoT-connected devices by 2030 [1]. The WSN (Wireless Sensor Network) is an eminent element of the IoT. It quickly spreads into many new fields, like smart cities, innovative healthcare, intelligent transportation, smart agriculture, smart homes, and other areas. It includes 5G connectivity, enabling technologies, and heterogeneous intelligent sensors. These applications generate vast volumes of data, and it is essential to transport this data via the network. Some unpredictably dynamic pauses during data transmission, such as mobility, connection quality, remaining energy, and scalability, may suffer in time-varying network topology aspects [2]. The sensors of dynamic IoT are resource-constrained (resources like battery, memory, and processor); the battery is one of the major resources because it is irreplaceable.

To keep the network alive, the wise utilization of these resources is essential for IoT devices because frequent communication can quickly deplete the battery. One such solution for minimizing energy utilization is to select an efficient relay node that extends the lifetime of the network and reliable operations. For example, consider healthcare applications in which all the sensors or devices gather medical data related to patient health and medical conditions, then transmit these data to the sink. While transferring the data, optimal route selection is essential, and this can be achieved by choosing an efficient relay node that plays a significant role.

The primary challenge of relay selection is the heterogeneity of devices, which includes devices with different energy

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sources, communication capabilities, and processing power; furthermore, various devices may use different communication protocols, making it difficult for relay selection. The other one is dynamic network topology, which deals with mobility, especially in applications like smart cities and transportation. Mobile nodes and the node's movement can lead to frequent changes in IoT network topology, and physical and environmental factors can affect signal strength. Network connectivity requires dynamic and adaptive relay selection strategies [3].

Achieving energy efficiency through an energy-aware relay selection in IoT involves dynamic adaption, which adapts to changing network conditions, such as the location of devices, energy level, and communication link parameters. This ensures the relay selection is optimal. Developing energy-aware routing strategies for dynamic WSNs to meet QoS (Quality-of-Service) objectives, such as network longevity, link reliability, and scalability, is still difficult, particularly in situations with limited resources in real-time applications [4]. An SDN is also the ideal design for applications with few resources. The application plane, the data plane, and the control plane are its three layers. The central controller makes all decisions, and sensor nodes are deployed in the data plane. These sensor nodes relay the perceived data to the controller [5]. A versatile network structure known as SDWSN was created by combining the SDN and WSN to satisfy the application requirements in IoT networks [6].

Many researchers have concentrated on developing optimal link stability and reliability routing solutions using artificial intelligence algorithms for good decisions; the fuzzy logic technique is efficient for making decisions. In addition, the neural network also helps train the data through the learning process. Combining both techniques to make more efficient decisions in routing problems, especially in relay selection [7].

Motivation: Energy management plays a significant role in IoT networks since sensors/devices have limited battery life and must be used effectively to maintain network connectivity. The devices are communicated through routing protocols to transmit the data to the destination. In the routing process, relay node selection is crucial to lowering sensor node energy usage. The path that uses the least energy from source to sink has the best relay. Energy optimization is required to reduce the cost-effectiveness and sustainability of the network. This motivates the authors to propose an energy-aware relay selection technique for dynamic networks to maximize the energy efficiency of the network.

The prominent objectives of the proposed study are as follows:

- To improve the ratio of packet delivery.
- To optimize network energy usage.
- To reduce the delay during data transmission.
- To increase network throughput and lifetime.

Contributions: The key contributions of the suggested paper are as follows:

- Proposed an energy-aware relay node selection algorithm by considering various network performance factors such as remaining energy, link condition, traffic pattern, and mobility.
- The proposed work considers input parameters such as residual energy, path loss, and ETX to choose the next relay node to select a reliable, energy-aware path.
- The proposed algorithm uses a fuzzy inference system that selects an optimal relay node by applying fuzzy rules and uses a neural network to fine-tune the input parameters based on the feedback over a dynamic network.
- Comparing the proposed work with existing protocols by simulating various scenarios using MATLAB and NS-3.37 simulators.

The remaining paper structure is as follows: Section 2 explains the existing survey, and Section 3 explains SDN approach. Section 4 describes the proposed ERST algorithms and ANFIS, followed by 5 explains the implementation part, Section 6 discusses the results, and finally, the conclusion and future enhancement in 7.

2. Literature Study

This section explains the recent literature reviews on relay selection to optimize energy in IoT and WSN, as shown in the Table. I.

A. Context and Background

Wireless Sensor Networks (WSNs) have become integral in many applications, including environmental monitoring, industrial automation, healthcare, and innovative city implementations. These networks consist of numerous sensor devices that monitor and collect data from their surroundings, transmitting it to a central gateway for processing. Despite their wide range of applications, WSNs face a significant challenge, such as the limited energy resources of sensor nodes, which are typically battery-powered. Efficient energy management is paramount to extending the network's operational lifespan, reducing maintenance costs, and ensuring reliable data transmission.

In WSNs, relay nodes are crucial in forwarding data from sensor nodes to the central gateway, especially in multi-hop communication scenarios. However, relay nodes consume considerable energy during data transmission and reception, making their efficient selection essential for the network's sustainability. Hence, software-defined networking (SDN) has emerged as a promising paradigm for enhancing the management and efficiency of dynamic WSNs. Therefore, relay selection is made through the routing protocol. Designing an efficient and reliable routing protocol for dynamic networks is a big challenge in IoT. In recent years so, many studies have been proposed based on these problems. Still, it is a challenge to select the best relay for communication.

Krzysztof Grochla et al. [8] proposed a power-aware algorithm for relay selection over low-power WAN. The relay node is chosen based only on the current battery capacity of the nodes. The simulation results prove that the proposed algorithm achieves energy efficiency and network life compared to existing algorithms. The energy parameter is not enough to select the best relay to enhance the network span, which is the main drawback of this algorithm.

Wenli Lei et al. [9] suggested a relay-chosen algorithm based on the predetermined olive-shaped area for relay node selection to the destination. The single hop, transmission, and radius of each node were considered for the selection. The simulation outcome shows that the olive forwarding method provides energy efficiency for static networks, but for nodes with dynamic networks, this algorithm is not suitable.

Samia Allaoua Chelloug et al. [10] presented a dual-phase blockchain-oriented relay selection mechanism to select the best relay over the UAV network. This protocol considered the channel capacity, distance, and bandwidth parameters to choose the following trusted relay nodes using the blockchain concept. The simulation results show that the proposed optimal UAV provides reliable-secure communication over data transmission. However, this algorithm is unsuitable for the dynamic network due to its dynamic nature, blockchain overhead, and interoperability.

Mangang Xie et al. [11] proposed an Lth relay selection policy in a two-hop-cooperative system with ARQ updates through decoder and forwarder relays to solve the age of information and energy consumption problems in IoT systems. This policy outperforms the existing systems in terms of energy efficiency. Still, it applies only to single-source and designation networks and not to multi-source and multi-destination networks.

Abdullah M. Almasoud et al. [12] suggested a hybrid-energy-efficient approach to solving the relay placement problem in which energy harvested with buffered relays is used, and the BPSO algorithm is adapted for selecting the energy-efficient relays. The proposed approach outperforms the existing search algorithms regarding delay and energy, but it does not consider other parameters.

Sina Shaham et al. [13] suggested a relay selection method using transfer learning in industrial IoT. This reduces the communication overhead and computational complexity. The suggested framework is evaluated and tested using the dataset and proved suitable for large-scale networks. The dynamic time-varying nature creates more challenges for relay selection, so the work can adapt different energy optimization algorithms to reduce energy in the future.

Kamal Das et al. [14] suggested optimal relay methodology for two-hop star topology in which fuzzy inference was used to choose the optimal node as the next forwarder by considering link quality parameters. The simulation results proved that the suggested OR-TH outperforms the existing protocols, but it suffers from scalability problems due to its being applicable only to star topology.

Feng-Wen Lo et al. (2023) [15] proposed a best relay selection method using a two-hop relay model in cognitive radio wireless networks. Apply the proper buffer size rules to select the best relay to reach the destination. The suggested model performs better than the existing one and provides average throughput. Because of the buffer at the node, the energy consumption is higher at the CH.

Yufeng Han et al. [16] proposed a dynamic relay selection method to choose a relay node using a drift-plus-penalty optimization algorithm for autonomous underwater surface vehicles. This method reduces energy consumption and latency but suffers from complexity due to the calculation of drift and penalty for each selection.

Table. I outlines the advantages and disadvantages of previous studies, demonstrating that most studies employed static network types, with only a few publications considering dynamic situations. Mobility and inadequate relay selection are the two main issues. Furthermore, the link is unreliable because of the weak selection of routing parameters. To solve this problem, a neural network that uses trustworthy parameters and fuzzy logic to make decisions based on fuzzy rules is employed to decide which relay is optimal for transmission via an IoT network.

3. Proposed System Design

The proposed work considered an SDN architecture scenario for environment monitoring shown in Figure. 1, which consists of three layers, namely the upper layer, the middle layer, and the lower layer. All the network applications, such as traffic engineering, load balance, network monitoring, and analytics are executed on the upper layer (application plane). The Northbound APIs are interfaced between the upper layer and the middle layer. The lower layer (data plane) consists of source nodes (S), relay nodes (R), and a sink for monitoring the environment. The sensed data is sent through relay nodes using the data path (solid arrow) from source to sink, and control information is sent back to the source through the control path (dotted arrow), as shown in Figure. 1.

The SDN controller is placed in the middle layer (control plane), which controls the upper and lower layers. The Southbound APIs provide the OpenFlow interface between the middle layer and the lower layer. The SDN controller takes the routing decisions based on the neuro-fuzzy logic concept, manages the flow table, and adopts the topology dynamically according to the information obtained by the data plane. The proposed work assumed that the network consists of a group of M sensors or nodes and one BS (base station) placed at the center of the network, in which some nodes are considered source nodes that gather information from the environment and the rest of the nodes are moving relay nodes. The set of nodes is represented by $M = n1, n2, n3, ..., n_M$, where n_k represents the k^{th} node in the network. Consider a graph representing an IoT-based sensor network in which sensors are denoted as vertices and connections between vertices are represented as edges.

TABLE I. Existing literature review on energy-efficient relay selection in IoT

Reference	Protocol	Methodology	Network Type	Strengths	Weaknesses
Aljawharah Alnasser et al. (2021) [17]	V2X	Analytic Hierarchy Process	Dynamic	Improved PDR	Not energy-efficient due to packet collisions
Abdullah M. Almasoud et al. (2022) [12]	MILP	BPSO algorithm	Static	Less energy consumption and delays.	It is applicable for only delay-constrained applications.
Sina Shaham et al. (2022) [13]	Relay framework	Transfer learning technique	Static	Achieve moderate accuracy	Consume energy and increased delay.
Ali Reza Heidarpour et al. (2022) [18]	DDQN-MRS	DDQN double deep Q network	Static	Improve overall network lifetime	It reduces the average-success rate.
Qian Yang et al. (2022) [19]	ACPSO	Adaptive chaotic particle swarm	Static	Maximum Throughput	Does not support mobility and dynamic factors.
Samia Allaoua Chelloug et al. (2023) [10]	Optimal UAV	Dual-Phase and Blockchain technique	Static	Enhanced efficiency and security	Blockchain overhead and difficult to adapt in a dynamic environment.
Mangang Xie et al. (2023) [11]	PRS (lth best relay)	Decode-and-forward relays	Static	Energy efficiency.	Not applicable for multi-source and destination networks.
Saad Haseeb et al. (2023) [20]	ED-CARP	Channel state information	Static	Less energy dissipation, high PDR	Not suitable for the dense network.
Feng-Wen Lo et al. (2023) [15]	MTTRs	Two-hop relay model	Static	High throughput	Increased latency and consumes more energy.
Kamal Das et al. (2023) [14]	OR-TH	Fuzzy algorithm	Static	Achieve good PDR and throughput	Apply only for star topology, scalability problem
Yufeng Han et al. (2024) [16]	DA (dynamic access scheme)	Dynamic optimization using drift-plus-penalty	Dynamic	Energy efficiency and average latency	Increased complexity.
Safiu A. Gbadamosi et al. (2024) [21]	Max-SINR	Interference-aware and coverage-analysis	Static	Efficiency, inference minimization	Applicable only for D2D communication.
Wenli Lei et al. (2024) [9]	OFA-RSA	Olive Forwarding Area	Static	Energy efficiency and network lifetime.	Not suitable for dynamic networks.
Jaeyoung Song et al. (2024) [22]	DQN-policy	Optimal scheduling policy	Static	Obtain high accuracy	More training cost while training the data.
Ting Lyu, Haitao Xu et al. (2024) [23]	ADP	Adaptive dynamic programming-based	Dynamic	Reduce transmission power and delay	Efficient optimization algorithm can be applied to achieve efficiency
Manju Bargavi et al. (2024) [24]	SEERS	Energy and bandwidth-based relay selection	Static	Reduce energy consumption and enhance network life	Consider delay parameters to select the best relay
Proposed work	ERST	Adaptive neuro-fuzzy model	Dynamic network with node mobility	Energy efficiency, low delay, high PDR, and throughput.	Future study: Clustering architecture can be considered with heterogeneous devices.

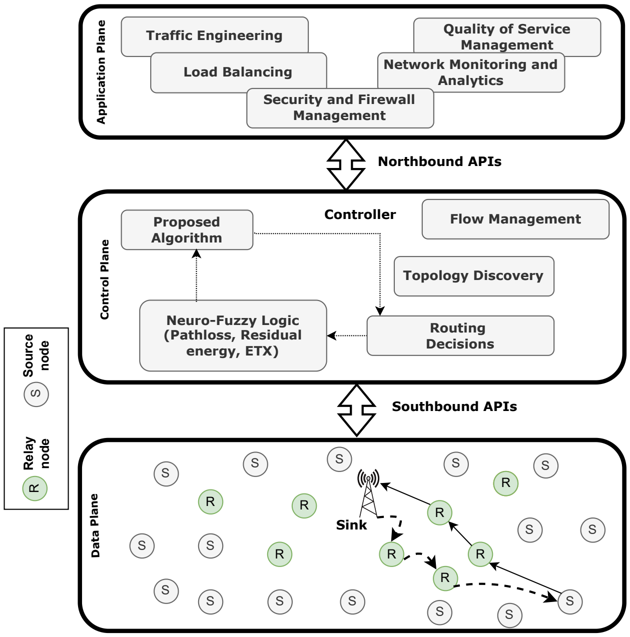


Figure 1. SDN architecture

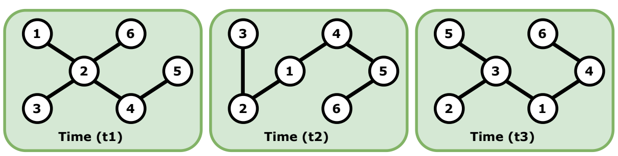


Figure 2. Network Graph in Different Time Instance

A sensor node pair (n_k, n_j) is connected when the distance of the pair is less than the transmission range TR_r, and distance is calculated based on Euclidean distance (ξ_{ij}). Consider an edge $e(n_k, n_j)$ between sensor pairs, which is represented by Eq. 1 [5].

$$e(n_k, n_j) = \begin{cases} 1 & if \quad \| d_i - d_j \| \ \leq TR_r \\ 0 & \quad otherwise \end{cases} \tag{1}$$

Where the distance between sensor pairs (n_k, n_j) is calculated. IoT network is dynamic and consists of both stationary and moving nodes. In this network, the relay node moves randomly at different occurrences of time (t1, t2, and t3), which is presented in Figure. 2.

A. Network Energy Model

The proposed work implements a basic energy model based on [25] in which Eq. 2 displays the energy model, where T_E indicates the required amount of energy for transmitting p bits of data from the source to the destination. It depends on the energy consumed by their electric components E_{elec} and energy required for amplification such as rs and ε_{amp}. This approach considers both the signal sensitivity and noise disturbance levels of the node-received signals. The distance between the nodes is denoted di, compared with the threshold distance (d_0).

$$T_E = \begin{cases} p * E_{elec} + p * \varepsilon_{rs} * di^2, & if\ di < d_0 \\ p * E_{elec} + p * \varepsilon_{amp} * di^4, & if\ di \geq d_0 \end{cases} \tag{2}$$

$$d_0 = \sqrt{(\varepsilon_{rs}/\varepsilon_{amp})} \tag{3}$$

The energy required for transmission is proportional to two if the transmission distance is shorter than the threshold value; otherwise, it is four. Where d_0 is represented by Eq. 3.

B. Node Mobility

In the IoT network node movement is unpredictable. The proposed study uses a random way-point movement technique to create the nodes' mobility as a consequence. To demonstrate the randomness in node location, stochastic geometry, an investigation of random spatial organization, is used [26]. The placement of the mobile devices is based on random point patterns using the Poisson point technique.

The mobile nodes (devices) move randomly over a dynamic network, which results in an unstable network connection between two devices (d_i,d_j) at time T_n^{th} instance is represented using Eq. (4),

$$e(d_i, d_j, T_n) = \begin{cases} C_{ij}^{T_n} & \xi_{ij} \leq T_r\ at\ \ time\ T_n \\ 0 & otherwise \end{cases} \tag{4}$$

where $C_{ij}^{T_n}$ represents the duration of connectivity between two devices (d_i,d_j) at time T_n.

C. Parameters for Relay Selection

The term path loss (PL) describes the decrease in signal strength when a wireless signal travels between a transmitter and a receiver over a distance through the propagation medium. That can be calculated by using Eq. 5.

$$PL(Di)_{dB} = PL(Di_0) + 10_{nlog_{10}}(Di/Di_0) + M_\sigma \tag{5}$$

The distance between the source and destination is denoted by Di, where Di_0 is the reference distance, and M_σ is a variable with zero mean and variance of σ^2. The ETX (Expected Transmission Count) is a metric used to estimate the successful data transmission that can be calculated by Eq. 6.

$$ETX = (1/df * dr) \tag{6}$$

where df represents the probability of a packet being received by a neighbor, while dr represents the probability of a successful acknowledgment packet receipt.
The RE is calculated using Eq. 7

$$RE = I_e - E_{p,Total} \tag{7}$$

The energy level at the relay node is computed by subtracting the amount of energy needed to transmit p bits of data from the initial energy (I_e).

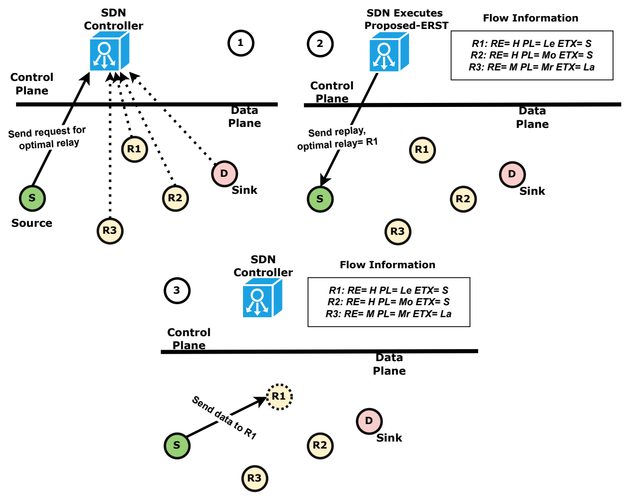


Figure 3. Relay Selection Process in Proposed ERST

4. Methodology

This section contains the proposed algorithm, fuzzy inference system, and neural network training process to select the optimal relay node.

A. Proposed ERST Approach

The design and function of the proposed ERST are shown in Figure. 3. To select the best relay for data communication, the source node first requests the SDN controller for the optimal relay. Meanwhile, other nodes exchange their routing table information with the SDN controller, shown by the dotted line. The SDN controller then accepts the request from the source (S) and searches for the optimal relay in the flow table, which consists of relay node information such as RE, PL, and ETX of all the nodes. The controller then executes the proposed ERST algorithm that gives the best optimal relay node, which is R1, because it has high residual energy, low path loss, and a small ETX value, and then sends a replay back to S. Finally, the source sends the data to Relay (R1), and then R1 sends that data to the sink or search for next relay.

B. Fuzzy-logic Inference System (FIS)

The FIS generates fuzzy rules based on the membership function states. The Fuzzy Logic Designer used to design the proposed three inputs (RE, PL, and ETX) membership functions, in which degrees of membership and truthfulness of the input value to each linguistic term are shown in Figure 4. It shows the fuzzy membership functions for RE, PL, and ETX. The membership degrees indicate the level of relevance or similarity between the input value and the fuzzy set. The input variable RE ranges from 0 to 100. That is divided into three fuzzy membership states: Low, Medium, and High, denoted as L, M, and H, as shown in Figure. 4(a). Similarly, the path loss of the input variable PL (range 0 to 60) is split into Less (Le), Moderate (Mo), and More (Mr) in Figure. 4(b). The ETX (range from 0 to 10) is divided into Short, Avg, and Long (S, A, La), as shown in Figure. 4 (c). Figure. 5a demonstrates that the node has a high RE with less ETX and has the highest degree. Consequently, Figure. 5b explains the degree of residual energy and path loss. The node with a high RE and less path loss has a high degree of membership.

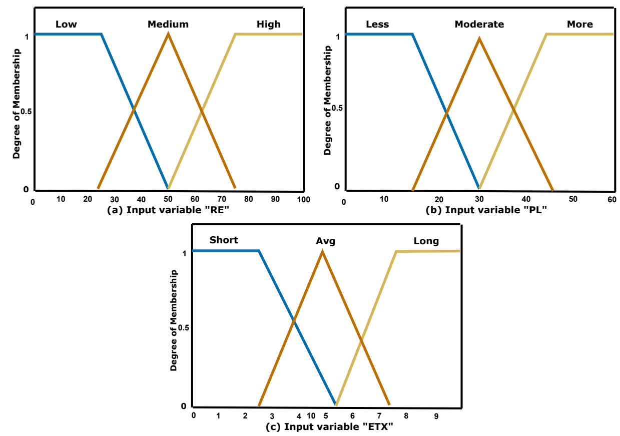


Figure 4. Membership Functions

The proposed inference rules are shown in Table II, which is used for fuzzification. In the fuzzification stage, the linguistic variable is converted into its corresponding fuzzy set. The linguistic values used are I_{RE}={L, M, H}, I_{PL}={Le, Mo, Mr}, and I_{ETX}={S, A, La}. The values are subsequently mapped onto the output set y = {First, Second, Third, Fourth, Fifth, Sixth, Seventh} using the function (I_{RE}, I_{PL}, I_{ETX}). The mapping process employed IF-THEN rules. The Eq. 8 shows a trapezoidal function known as *trape* is used to define the linguistic values. The function uses the variables E and F to represent support and c1 and c2 to define the trapezoidal membership function's kernel. It is assumed that the values of c1 and c2 are between E and F, with c1 being less than or equal to c2.

$$trape(y; E, c1, c2, F) = \begin{cases} (y-E)/(c1-E), \; if y \in [E, c1] \\ 1, \; if y \in [c1, c2] \\ (F-y)/(F-c2), if y \in [c2, F] \\ 0, \; otherwise \end{cases} \tag{8}$$

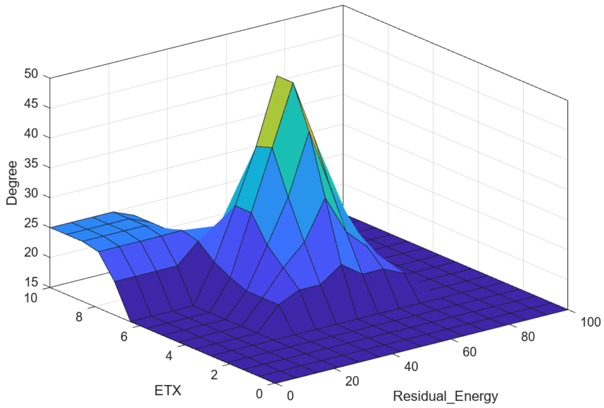
To define the fuzzification value for path loss I_{PL}, we utilize the trapezoidal function.

$$Le = trape(I_{PL}; 0, 0, 15, 30)$$

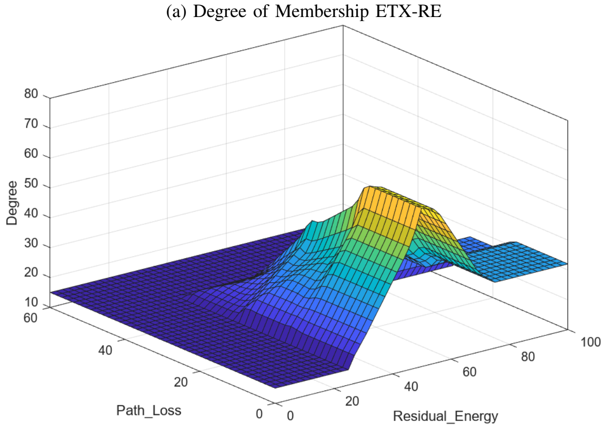
$$Mo = trape(I_{PL}; 15, 30, 30, 45)$$

$$Mr = trape(I_{PL}; 30, 45, 60, 60)$$

The I_{RE} is defined as a function of the relay node's residual



(a) Degree of Membership ETX-RE



(b) Degree of Membership RE-PL

Figure 5. Degree of Membership Function

energy, with 50% being the midway point.

$$L = trape(I_{RE}; 0, 0, 25, 50)$$

$$M = trape(I_{RE}; 25, 50, 50, 75)$$

$$H = trape(I_{RE}; 50, 75, 100, 100)$$

The I_{ETX} is the average number of transmissions needed to deliver a packet from the source node to the destination node, ranging from 0 to 10.

$$S = trape(I_{ETX}; 0, 0, 3, 5.5)$$

$$A = trape(I_{ETX}; 2.5, 5, 5, 7.5)$$

$$La = trape(I_{ETX}; 5.5, 7.5, 7.5, 10)$$

The output degree of membership $\mu(y)$ for

$$f(I_{PL}, I_{RE}, I_{ETX})$$

is defined as a value between 0 and 100, determined by the combination of I_{PL}, I_{RE}, and I_{ETX}.

C. ANFIS Model

The ANFIS (adaptive neuro-fuzzy inference system) utilizes the Takagi-Sugeno fuzzy inference method with supervised learning, as shown in Figure.6 [27]. The ANFIS is composed of five Layers. The beginning layer is the fuzzification layer, which generates the membership function (MF). The second layer, the rules layer, calculates the strength of a rule's fringes. MF are quantified in the third layer based on the fringed rules. The fourth layer, the aggregation layer, aggregates and generates new MF for old MF. Lastly, the final layer, the defuzzification layer, converts the resultant MF into crisp values. Compared to a fuzzy logic inference system (FIS), ANFIS is significantly superior; it has higher functionality to adapt to dynamic learning practice, updates the membership function weight, and reduces the error rate while determining the guidelines for "fuzzy". Consider a system with three inputs, X, Y, and Z, and a single output, d. The first-order Takagi-Sugeno rules can be defined as follows: Rule 1: If X is X1 and Y is Y1 and Z is Z1, then d1 = p1X1 + q1Y1 + r1Z1 + C1 Rule 2: If X is X2 and Y is Y2 and Z is Z2 then d2 = p2X2 + q2Y2 + r2Z2+ C2. Where p1, q1, r1, p2, q2, and r2 are learning parameters. C1 and C2 are constants used to adjust the MF.

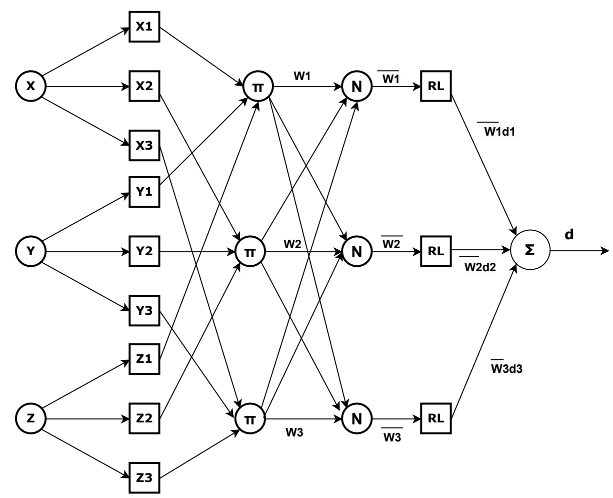


Figure 6. ANFIS Model

D. Neural network training process in ANFIS

The training process of ANFIS involves optimizing the parameters of the FIS using the learning ability of artificial neural networks (ANN). ANFIS combines fuzzy logic and ANN to leverage the strengths of these methods. There are two main phases during the training process: Forward pass (evaluate the function): It evaluates all the layers of ANFIS from layer 2 to layer 5 and calculates the error between the predicted output and the actual target.
Backward pass: The backward pass involves updating the parameters to minimize errors. ANFIS typically uses a hybrid learning algorithm combining gradient descent and least squares estimation (LSE).

E. Proposed-ERST with ANFIS

Initially, in the proposed ERST, the routing node metrics such as RE, PL, and ETX of the sensor nodes are assumed to be used to select the next reliable, energy-efficient relay node from the FIS. Consider NR (next relay), which is used to choose the next relay from the FIS, determined by ANFIS. The proposed three input structural designs of ANFIS can be seen in Figure. 7. It takes three inputs RE, PL, and ETX, and the corresponding linguistic variables of the relay selection metrics, such as residual energy RE= L, M, H and is defined as RE1, RE2, RE3, path loss = Le, Mo, Mr that is represented by PL1, PL2, PL3, and the ETX=S, A, La denoted by ETX1, ETX2, ETX3, and finally, output parameter degree is based on the rules layer (Rl) = First, Second, Third, Fourth, Fifth, Sixth, Seventh as Rl1, Rl2, Rl3, Rl4, Rl5, Rl6, Rl7, and Rl stands for Rules layer, which consists of 27 if-then rules generated by Takagi-Sugeno fuzzy inference system takes three linguistic variables of three input variables as shown in the Table. II.

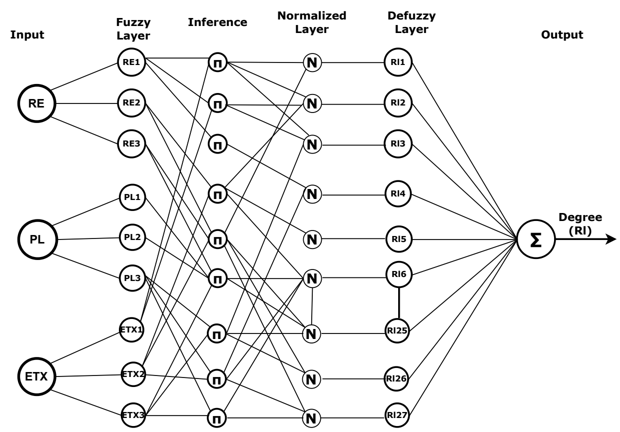


Figure 7. Proposed ERST using ANFIS

In the neuro-fuzzy inference system, the first layer, the fuzzy layer (membership function layer), consists of several nodes. This layer generates a membership ranging from 0 to 1 and applies different membership functions, like triangular, trapezoidal, and Gaussian. The proposed work uses the trapezoidal membership function. The outcome of the first layer was calculated using Eq. 9, Eq.10, and Eq. 11.

$$O_{1,j} = \mu_{X_j(X)} \quad for \quad j = 1, 2, 3 \tag{9}$$

$$O_{1,j} = \mu_{Y_{j-2}(Y)} for j = 3, 4, 5 \tag{10}$$

$$O_{1,j} = \mu_{Z_{j-3}(Z)} \quad for \quad j = 4, 5, 6 \tag{11}$$

Likewise, the membership functions μ_{RE_j}, μ_{PL_j}, and, μ_{ETX_j} can be determined. The second layer called the inference layer (T-Norm Layer) contains several nodes that are labeled with π (firing strength) (Figure 7). This layer takes the input from the fuzzy layer and applies inference rules to perform the AND operation. Each node in this layer calculates the antecedents based on the Eq. 12. In this layer, the parameters X, Y, and Z are adjusted using ANN (artificial neural network).

$$O_{2,j} = \mu_{RE_j}(X) \times \mu_{PL_j}(Y) \times \mu_{ETX_j}(Z) \ where, j = 1, 2, 3 \tag{12}$$

The following layer is called the normalized layer, it is non-adaptive and is represented by N in figure (Figure 7). Every node in this layer generates the output by taking the ratio of the i^{th} rule produced by the inference layer. The output of this layer can be obtained by using Eq.13. Where Wj represents weights.

$$O_{3,j} = \overline{W_j} = \frac{W_j}{W_1 + W_2 + W_3} \quad j = 1, 2, 3 \tag{13}$$

A fourth layer is called the adaptive defuzzification layer. This gives the output as a product of the normalized layer firing strength and out of individual rule. The outcome of the normalized layer is as follows Eq. 14.

$$O_{4,j} = \overline{W_j} d_j = O_{4,j}(p_j X + q_j Y + r_j Z + C_j) \tag{14}$$

Where p_j, q_j, r_j, C_j are tuning parameters used to update when an error occurs. Finally, the last layer is called the non-adaptive Output Layer. The single aggregated output is generated at this layer by using Eq. 15.

$$O_{5,1} = \sum_j \overline{W_j} d_j = \frac{\sum_j W_j d_j}{\sum_j W_j} \tag{15}$$

F. Proposed-ERST algorithm and flowchart

The comprehensive flowchart is presented in Figure. 8 illustrates the suggested relay selection procedure. When the source node (Si) needs to deliver data to the sink, it requests the SDN controller for the best relay. The controller then looks through the flow table for the best relay. If not, use the ERST approach to choose the optimal relay. To choose the best relay node among the group of relays, the proposed ERST method makes use of the ANFIS model. The fuzzy and neural network concepts are the foundation of the ANFIS model's operation. Initially, the FIS receives the RE, PL, and ETX routing parameters as crisp inputs. It then creates fuzzy membership functions like RE, PL, and ETX, and the firing strength is then calculated using the fuzzy AND operation, and the parameters are adjusted using an artificial neural network. The firing strength is then normalized, and the overall output is then calculated to obtain the optimal relay node with a higher degree of output.

The proposed optimal relay nodes in a dynamic network are selected using the Algorithm 1. Every sensor node in the network must exchange its routing information, which contains neighbor node details and source and destination addresses, with its neighbors. The Network Controller (NC) manages all sensor nodes and their applications within the SDN architecture. The sensor nodes exchange routing and flow details with the NC. When there is data

Rule	RE	PL	ETX	Rl	Rule	RE	PL	ETX	Rl
1	RE1	PL1	ETX1	Rl1	15	RE2	PL2	ETX3	Rl4
2	RE1	PL1	ETX2	Rl2	16	RE2	PL3	ETX1	Rl1
3	RE1	PL1	ETX3	Rl3	17	RE2	PL3	ETX2	Rl2
4	RE1	PL2	ETX1	Rl1	18	RE2	PL3	ETX3	Rl2
5	RE1	PL2	ETX2	Rl1	19	RE3	PL1	ETX1	Rl5
6	RE1	PL2	ETX3	Rl2	20	RE3	PL1	ETX2	Rl6
7	RE1	PL3	ETX1	Rl2	21	RE3	PL1	ETX3	Rl7
8	RE1	PL3	ETX2	Rl1	22	RE3	PL2	ETX1	Rl4
9	RE1	PL3	ETX3	Rl1	23	RE3	PL2	ETX2	Rl5
10	RE2	PL1	ETX1	Rl3	24	RE3	PL2	ETX3	Rl6
11	RE2	PL1	ETX2	Rl4	25	RE3	PL3	ETX1	Rl5
12	RE2	PL1	ETX3	Rl5	26	RE3	PL3	ETX2	Rl7
13	RE2	PL2	ETX1	Rl3	27	RE3	PL3	ETX3	Rl7
14	RE2	PL2	ETX2	Rl3					

TABLE II. Inference Rules

to transmit from the source node (S), it reaches out to the NC for guidance on which relay to use. The NC then uses neuro-fuzzy rules to choose a high-degree node as the next forwarder, considering RE, PL, and ETX. Finally, the source (Si) sends data to the selected relay or goes into sleep mode.

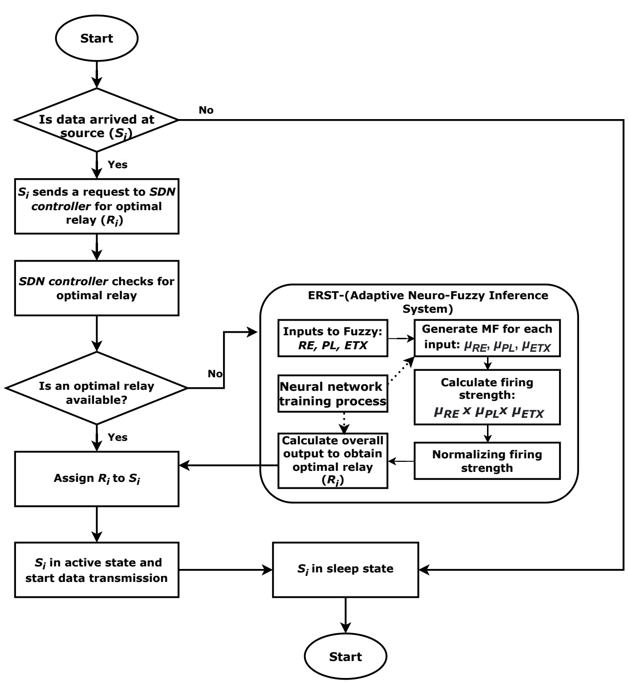


Figure 8. Flowchart for Relay Selection Process

The proposed Algorithm 2 utilizes a neuro-fuzzy model of ANFIS to select Rl (relay). This model consists of two passes: a forward pass and a backward pass. To train the premise and consequent parameters of these passes, the model uses gradient descent and the least mean squares hybrid algorithm. During the forward pass, the static input parameters *(RE, PL, ETX)* are given to the fuzzy layer. The information then passes through the hidden layers and reaches the defuzzy layer, where the output is analyzed for errors. In the backward pass, these errors are sent back to the fuzzy layer to adjust the parameters. This allows us to update the membership function using the gradient descent method. This process continues until N_{epoch} (one round of execution, including both passes).

Algorithm 2 RL selection using Neuro-fuzzy

Input: *RE, PL, ETX, and N*
Output: *Rl*
for $n=1$ to N_{epoch} **do**
    Input *RE, PL, ETX* to fuzzy inference engine
    Generate membership functions (μ_{RE_j} μ_{PL_j} and μ_{ETX_j}) for each node by fuzzy layer using Eq.(12)
    Calculate the normalized firing strength of each node based on Eq.(13)
    Defuzzification process done based on Eq.(14) for each node
    Calculate the final output *Rl* using Eq. (15)
end for

5. Implementation

This section evaluated the proposed work with simulation tools MATLAB and NS-3.37 to analyze the performance of the proposed protocol ERST. A sensor network of 200 nodes is simulated in a 300 x 300 area. Nodes selected at random are considered source nodes. Each simulation is run for at least 300 seconds and repeated 20 times. To evaluate the performance measures, average values from the findings are extracted and considered as input datasets to ANFIS. Table III summarizes the simulation parameters used to evaluate the proposed algorithm packet de-

Algorithm 1 Optimized Energy-aware RS

```
Input data: source (S), Sink (D) relay ( R1, R2, R3,....Rn)
Outcome: Ri optimal (relay-node)
Initialization: Ie (Initial-Energy), TRr (Range of Transmission), ET (Energy threshold), S=idle
 Sensors Si and relays Ri exchange their flow table and neighboring information to NC
while data arrival at Si do
    Si request the NC for optimal relay within its expected TRr
    The NC executes neuro-fuzzy function /* Selecting the best relay based on PL(5), ETX (6), and RE(7) value*/
    for i=0 to n do
        if Ri.RE=High && Ri.ETX=Short && Ri.PL=Less then
            NC assign Ri to Si
            Si=active;
            Si starts data transmission to Ri
        else
            NC recursively executes the fuzzy function
            if next optimal relay is available then
                NC assign Ri to Si
            end if
        end if
    end for
    S=idle;
end while
```

livery ratio, end-to-end delays, average throughput, energy consumption, and network lifetimes for a comprehensive analysis. The simulation's outcomes are compared with the earlier routing protocols like MRE and RRS [28], [29].

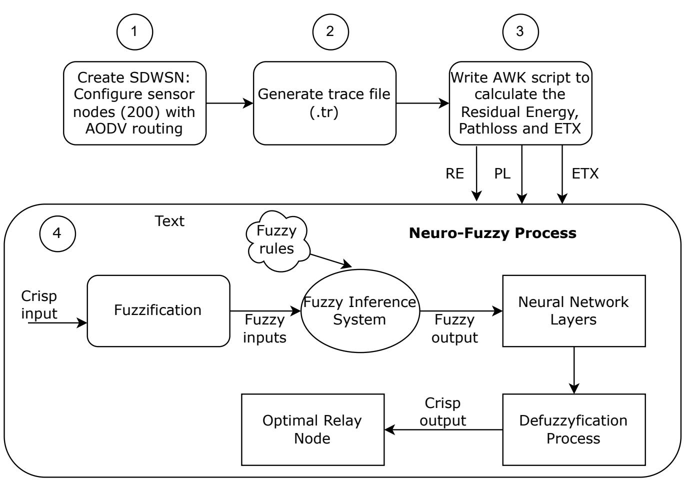


Figure 9. Proposed Simulation Process

The hybrid simulation process is explained in Figure. 9. During the simulation process, the first step involves creating a simulation environment with 200 sensor nodes and using the AODV routing protocol for data transmission. Step 2 generates a trace file, which calculates the RE, PL, and ETX values based on an AWK script in step 3. The optimal relay node is then determined in step 4 using the Neuro-Fuzzy Process, which performs fuzzy and neural network operations.

TABLE III. Simulation Parameters

Parameters	**Symbol**	**Values**
Network Size	Sq.mt	300*300
Transmission Range	TR	50m
Sink Node	D	(0,0)
Position of source	S	(200,200)
Channel	ch	Nakagami-m fading channel
Energy Threshold	ET	0.001J
Power Dissipation	elec	50 nJ/bit
Packet size (k bits)	L	512 bytes
Initial energy	IE	2J

A. Validation of ERST

The proposed ERST is validated through performance metrics, namely packet delivery ratio, energy consumption, E-to-E delay, and throughput.

- Data collection phase: extract ETX, PL, and RE values from the trace file of the proposed ERST simulated by NS3.
- Design the membership function: design the MF as mentioned in Section 4.B using FIS.
- Train the ANFIS: Give the collected data to ANFIS to train the model. During the training process, adjust the parameters of FIS using backpropagation.
- Evaluate the algorithm: The obtained output is compared with the existing MRE and RSS protocols.

B. Simulation details

- The packet-delivery ratio (PDR) is a metric used in computer networking to measure the success rate of transmitting packets in a network.
- The node's energy consumption is the amount of energy used over time.
- The end-to-end Delay (E-to-E) defines the time taken for a data packet transmission from the source node to the destination within a computer network.
- The average throughput indicates the average data transfer rate or the amount of data successfully transmitted over a network during a given time period.
- Network lifetime refers to the duration or lifespan of an IoT network before its nodes become unable to communicate or exhaust their energy resources.

6. Results And Discussions

This section presents the obtained results, tables, graphs, and an explanation of the proposed work efficiency with the baseline protocols.

TABLE IV. PDR

Successful packet delivery ratio (%)						
Nodes	100	120	140	160	180	200
Proposed-ERST	97	97.89	97.90	98	98.34	99
MRE	94	94.79	94.80	95	95.45	95.89
RRS	93	94	94.39	94.60	94.75	94.86

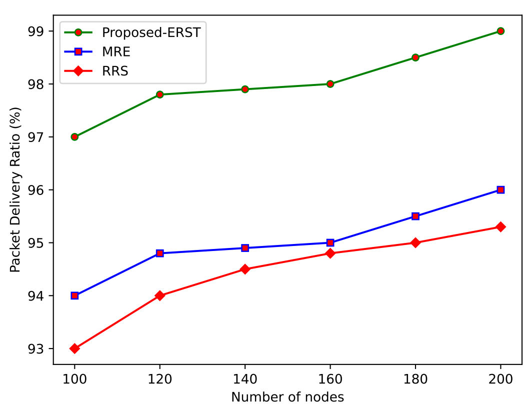


Figure 10. Packet Delivery Rate

Figure. 10 shows the packet delivery ratio of the proposed work. The ERST algorithm demonstrates an 8% increase in successful packet delivery rate compared to existing MRE and RRS protocols. This is achieved by selecting an optimal relay node using a neuro-fuzzy model, which applies various fuzzy rules and fine-tunes the membership functions for selecting the energy-efficient, robust, and reliable relay node. As the number of nodes in the network is inserted, the number of potentially available relay nodes also increases, increasing the packet reception ratio at the sink. This indicates that the proposed algorithm is highly scalable. This can also be suitable for mobility-based dynamic networks. In contrast, the previous MRE protocol only selects the next relay based on the residual energy of a node without considering link quality, which is unsuitable for a dynamic nature network. Similarly, the RRS protocol chooses a random node as the next relay, which may result in reduced packet delivery if the node fails as data is retransmitted through the same relay node. The existing MRE and RRS provide less packet delivery percentage due to congestion and unstable links, leading to network sinkhole problems. The proposed ERST overcomes these problems efficiently. Table IV represents the obtained values of PDR.

TABLE V. E-to-E delay

End-to-End delay (ms)						
Rounds	20	40	60	80	100	120
Proposed-ERST	14	19	23	26	29	34
MRE	16	22	25	28	33	38
RRS	25	34	40	43	55	59

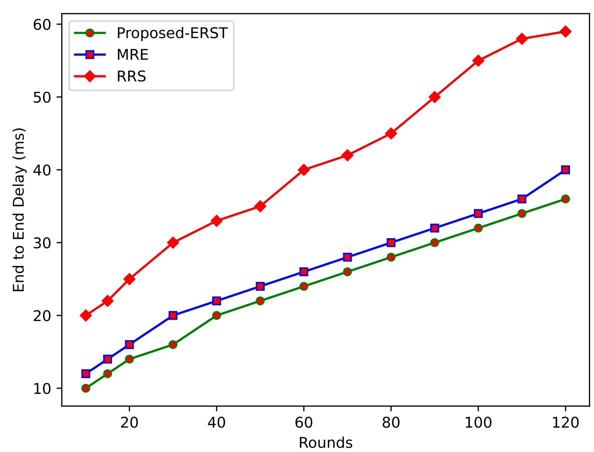


Figure 11. Delay (End-to-End)

The proposed ERST reduces End-to-End delay by 5% by considering path loss rate and ETX for data transmission. This results in selecting a less congested and more reliable relay node over the network, as shown in Figure. 11. The existing MRE protocol was causing delays due to its selection of unreliable links for data transmission. It even selects high ETX links as the next forwarder, which leads to further delays. In contrast, the previous RRS protocol only selected nodes randomly based on distance without considering robust link parameters such as ETX and RE, resulting in additional transmission delays. The proposed ERST uses different fuzzy rules to select the best relay using the neural network learning process. This builds a robust, non-congested path from source to sink to provide energy-aware and reliable transmission with minimum delay. Table V represents the obtained results for delay.

TABLE VI. Energy Consumption

Total energy consumption (J)						
Nodes	100	120	140	160	180	200
Proposed-ERST	1.0	1.7	0.8	0.7	0.69	0.6
MRE	1.239	1.182	1.176	1.020	1.0	0.91
RRS	1.789	1.692	1.498	1.340	1.250	1.2

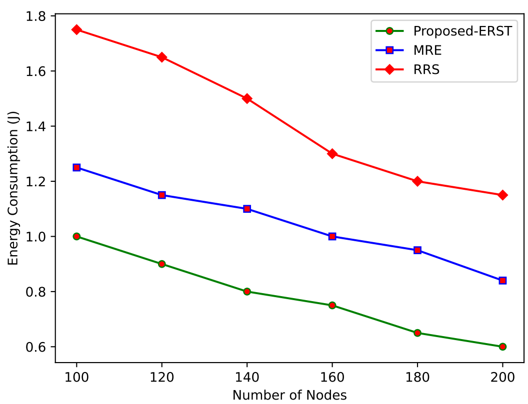


Figure 12. Energy Consumption

Figure. 12 describes the energy consumption of sensor nodes at varying node densities, in which the proposed ERST retains the maximum amount of energy at each node as compared to existing protocols (MRE and RRS). It reduces nearly 4% of energy consumption because it selects the high residual energy node on the high-quality link as the next forwarder by applying neuro fuzzy rules. Each node energy is utilized efficiently by applying a backpropagation technique at each hidden layer of a neural network to fine-tune the parameters. This shows that the proposed ERST promises a long-term sustainable link. The existing MRE and RRS protocols do not consider link quality metrics such as path loss and ETX while selecting a relay. MRE works on random selection in such situations as the same node is repeatedly selected as a relay node, which creates a dead node and link failure problem. For this reason, the existing RRS protocol consumes more energy during data transmission, reducing network life. That can be seen in Figure 12. When the number of nodes increased, the energy consumption also increased, leading to the network's early death. Table VI represents the obtained energy values for all considered protocols.

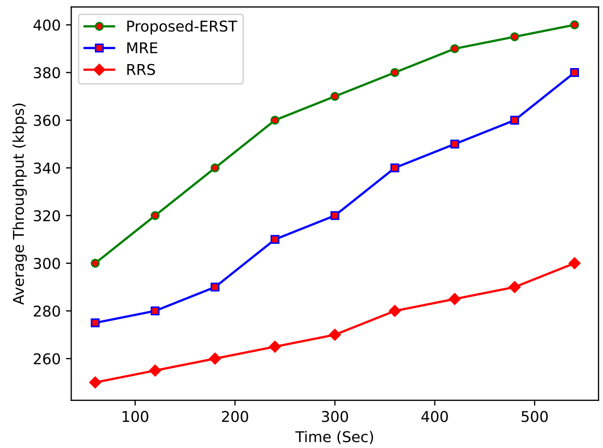


Figure 13. Average Throughput

TABLE VII. Average Throughput

Average Throughput (kbps)					
Time (s)	100	200	300	400	500
Proposed-ERST	320	340	370	385	400
MRE	280	285	320	355	360
RRS	255	260	270	285	290

Figure. 13 and Table VII illustrate the suggested ERST protocol average throughput it increases the network throughput by more than 8% compared to MRE and RRS protocols. The proposed ERST chooses the best relay on the reliable link to maximize data delivery and minimize packet loss. The proposed work uses the ANFIS model to select the energy-efficient relay node based on the fuzzy rules and consider the nodes' mobility factors. The proposed ERST selects the robust routing path from source to sink. The resultant of this provides good throughput. However, in the existing work, RRS chooses the relay based only on probability and ignores the energy factor and mobility. The MRE protocol only concentrates on energy but does not consider link quality factors; for these reasons, existing protocols lose more packets at the intermediate nodes because of poor link reliability due to the improper selection of routing parameters.

Figure. 14 illustrates that the proposed ERST protocol has more active nodes than the existing MRE and RRS protocols. In the proposed ERST, the first node dies in about 200s, whereas in MRE, the first node dies at about 150s, and in RRS, the first node dies at about 100s, respectively. Finally, the proposed ERST extends the network lifetime in terms of the alive nodes involved in different simulation times, as shown in Figure. 14. It shows that the proposed ERST has been sustained for a long time because the network is alive after the 500s of simulation time. The results are compared with the prior routing protocols: MRE

and RRS. All the sensor nodes are active in the initial stages and up until the 100s. After that, their energy begins to drain gradually, decreasing the number of active nodes. The network using the existing protocol RRS died faster because of the random selection of relay nodes. The MRE is better compared to RRS but not as good as the proposed ERST. This proves that the proposed ERST outperforms both existing protocols. It is due to the proposed ERST selecting the next relay using the neuro-fuzzy model to increase the IoT network lifetime.
The main strength of the proposed ERST protocol is that it applies to mobility-based dynamic IoT networks. It provides energy-efficient and reliable data routing during transmission and can also be applied to dense networks for large-scale applications. The limitation of the proposed work is the synchronization problem of the moving relay nodes due to mobility; sometimes, nodes receive duplicate packets.

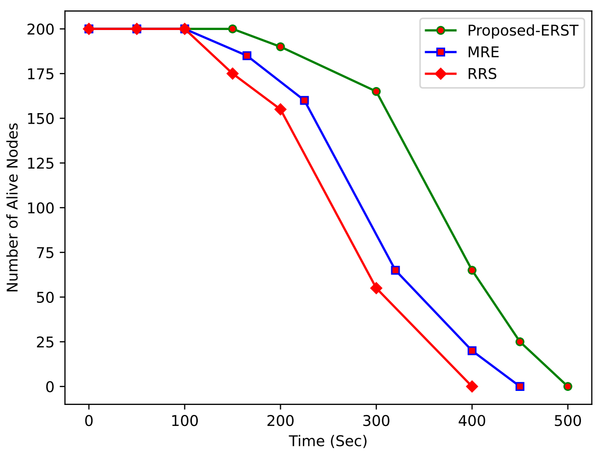


Figure 14. Network Lifetime

A. *The practical implications of the findings*

The Figure. 15 shows the practical implications of the proposed energy-aware relay selection in IoT. It is broadly categorized into network performance, operational cost, sustainability, and application-specific benefits. **Network performance:** Using the energy-aware relation approach enhances the network lifespan because of less energy consumption during data transmission. It also provides stable communication links that enhance reliable data transfer and data integrity. Finally, optimize the latency and response time due to energy-aware relay selection.
Operational cost: Reduced energy utilization leads to long-lasting IoT devices, which reduces the cost of replacements. Lower energy consumption reduces power costs, which is beneficial for large-scale IoT applications.
Sustainability: The proposed ERST approach is more energy efficient, consumes less energy for data transfer, and reduces the overall carbon footprint to support green and sustainable technologies.

Application-specific benefits: The IoT applications, such as health care, environmental monitoring, industrial, and smart agriculture, generate huge data to transfer over the network. In this context, the proposed ERST ensures energy-aware relay selection, guarantees critical health data transmission reliably, long-term monitoring of environmental data, provides continuous operations in industrial automation, and energy-aware ERST ensures cost savings and more effective monitoring of crops to promote sustainable farming practices.

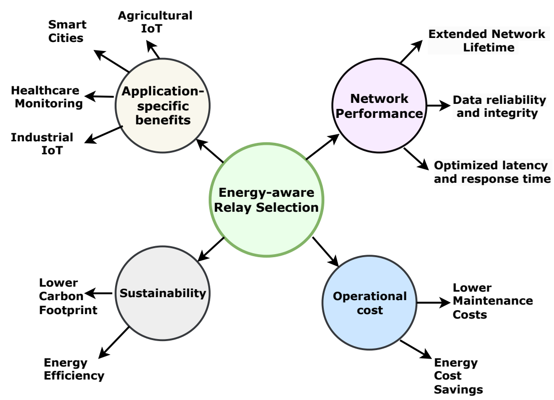


Figure 15. The practical implications.

B. *Abbreviations and Acronyms*

The Table. VIII presents the notations used in the proposed work.

TABLE VIII. Notations and Description

Notation	**Description**
n_k	K_{th} sensor node
n_j	Jth sensor node
di	Distance between i^{th} node
TR_r	Transmission range of a node
t_i	Time instance of relay node movement
T$_E$	Total Energy
p	p number of bits
E_{elec}	Energy required for transceiver circuit
rs, ϵamp	Energy required for amplification of the receiver and received signal noise
Ie	Initial energy of the sensors
Ep, Total	Total energy required to transfer p bits
C_{ij}	Duration of connectivity b/w two devices di & dj,
Tn	n^{th} time instance
Tr	Transmission range
RE	Residual Energy
PL	Path Loss
ETX	Expected Transmission Count
Di	Distance between source-destination
M	Variable with zero mean
df	Probability of the successful packet being received
dr	Probability of a successful acknowledgment packet reception
NC	Network Controller
L, M, H	Low, Medium, High
Le, Mo, Mr	Less, Moderate, More
S, A, La	Short, Average, Long
I_{RE}, I_{PL}, I_{ETX}	Linguistic values of residual energy, path loss and ETX
y	Output set
E, F	Support of membership function
c1, c2	Trapezoidal membership kernel
ET	Energy Threshold
S	Source
D	Sink
R1,...Rn	Relay nodes
$\mu_{RE}, \mu_{PL}, \mu_{ETX}$	Membership functions

7. Conclusion And Future Enhancement

This paper proposed an energy-aware relay selection (ERST) technique using an adaptive neuro-fuzzy-based model (ANFIS). It adapts fuzzy logic and neural network concepts to choose the optimal relay and routing over a dynamic IoT network. The ERST approach selects an energy-efficient relay by considering factors such as the node's remaining energy, the link's path loss ratio, and the ETX of nodes to identify the next relay node from source to sink. The fuzzy model generates the member functions, and the neural network optimizes the membership functions that help to find the optimal relay node. A reliable and energy-aware routing path is constructed using the proposed ERST, which saves energy over the network and increases the lifetime. The simulation was performed in MATLAB and NS-3.37 to analyze the proposed protocol. The proposed ERST improves the delivery ratio of packets by 8%, reduces energy utilization by 4%, minimizes End-to-End delay by 5%, and increases network lifetime and average throughput by 8%. The proposed ERST protocol provides efficiency, high scalability, and reliability for IoT networks.

Future Enhancement: In the future, the clustering architecture can be used to reduce energy utilization by selecting the optimal relay for the nearest cluster head to transfer the data to the sink. Relay node placement and intelligent algorithms can be applied to choose the optimal relay based on the different routing parameters. The selection of a relay on Vehicular Ad-hoc networks and Low-Power Wide-Area Networks to solve the network coverage problem with mobility is a future field that will provide more robust and scalable network performance.

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