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Efficient Neuro-Fuzzy based Relay Selection in IoT-enabled SDWSN

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Abstract: The Internet of Things is made up of wireless sensor devices (nodes) that work together to create a dynamic network without central management or continuous assistance. High mobility sensor nodes cause periodic topological changes in the network and link failures, which frequently force nodes to rediscover new routes for efficient data transmission in IoT, this brings attention to the issue of energy management and improvement in network lifetime. The relay selection is one method to reduce the node energy in the IoT network. However, designing communication protocols for relay selection, especially for dynamic networks, is a big challenge for researchers. To overcome these challenges, Software Defined Networking (SDN) architecture is used to minimize the overhead of sensor nodes by managing the topology control and routing decisions through artificial intelligent algorithms. The fuzzy logic and neural networks are combined to solve more complex problems such as decision-making, and optimization. This paper presents an Energy-aware Relay Selection Technique using an adaptive Neuro fuzzy-based model (ERST) to optimize the overall energy usage and improve the span of the network, a relay node is selected depending on remaining energy, signal strength, and expected transmission ratio. The proposed ERST uses a fuzzy logic inference system to make intelligent decisions based on the fuzzy rules. The neural network can be trained to fine-tune the fuzzy system using the feedback concepts to select the optimal relay node. In addition, the simulation results prove that the suggested work outperforms the previous protocols in terms of an 8% improvement in packet delivery ratio, reduces 5% of end-to-end delay, 4% minimization of energy usage, and an 8% increase in average throughput and overall network lifetime.

Keywords: Internet of Things, Relay 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 their critical tasks without the need for human intervention. Over the past ten years, the more utilization of energy has raises at alarming rates this leads to the growing number of digital users and gadgets. There are estimated to be 50 billion IoT-connected devices by 2030 [1–3]. The WSN (Wireless Sensor Network) is a eminent element of the IoT. It quickly spreads into many new fields, like smart cities, smart 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 datavia 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 [4].

The sensors over dynamic IoT are resource-constrained (resources like battery, memory, and processor), the battery is one of the major resources becauseit is irreplaceable. In order to keep the network alive, we wisely use energy, designing an efficient routing protocol is one way to reduce energy consumption. For example, consider healthcare

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applications in which all the sensors or devices gather the medical data related to patient health and medical conditions, then transmit these data to the sink. We can optimize the energy During data transmission by selecting an efficient route. Additionally, developing energy-aware routing strategies for dynamic WSNs to meet QoS (Quality-of-Service) objectives such as longevity of the network, link reliability, scalability, etc., is still difficult, particularly in situations with limited resourcesin real-time applications [5]. 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 data. These sensor nodes relay the perceived data to the controller [6]. A versatile network structure known as SDWSNs was created by combining the SDN and WSN to satisfy the application requirements in IoT networks [7–9].

Many researchers have concentrated on developing optimal link stability/reliability solutions, including performance detection, AI-assisted security, mobility-based link existence time prediction, and intersection-aware stable routing. The neuro-fuzzy-based system, which combines many fuzzy rules and a neural network model to logically integrate the link-related metrics, outperforms all other solutions in terms of ensuring reliable data transfer [10].

Motivation

The selection of relay nodes is a key strategy for reducing energy consumption at sensor nodes. An energy-efficient route (from source to sink) is necessary for large-scale IoT networks to improve dynamics in SDWSN. It motivated us to propose an energy-aware relay selection technique for dynamic networks to optimize the network's energy.

Contributions

The key contributions of the suggested paper are as follows:

- Proposed an energy-efficient relay node selection algorithm by considering the various network performance factors such as remaining energy, link condition, traffic pattern, and mobility.
- 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-turn 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.

Organization of the paper

The remaining paper structure is as follows: Section 2 explains the existing survey, section 3. discusses the problem statement and aim of the study, in Section 4 the proposed algorithm is explained. Section 5 discusses performance evaluation, simulation metrics, and parameters. The conclusions and the potential future improvements are discussed in Section 6.

2. LITERATURE SURVEY

The previous energy-aware routing protocol chose an efficient relay node between the source and sinks in WSN-assisted IoT. Shukla and Tripathi [11] proposed a hierarchical framework based on clusters to choose the optimal relay in a static network by taking into account the density of the node, less distance, and setting the less transmission range threshold values for the intermediate node selection. According to the experimental results, the proposed approach surpasses existing protocols regarding network longevity and energy efficiency but can not apply to dynamic networks. Redhu et al. [12] presented a routing algorithm to select the best intermediate node to overcome a static routing problem and to achieve reliable transmission by applying efficientrelay-chosen criteria such as the distance between the sensing device and the next for- warder. The proposed paper chooses the following relay node based on a threshold value for packet loss risk. The results demonstrate that the suggested routing approach performs better than the existing scheme in terms of packet loss and delay.

Dynamic optimal forward node selection using radio frequency interface technique were presented by Ghasri and Hemmatyar [13] to maximize the network lifespan in high-density architecture. At the relay node, the buffer concept was introduced by Alkhawatrah et al. [14]. The next-hop selection depending on a prioritization technique to boost throughput in the multiple access non-orthogonal relay network. Ouhab et al. [15] introduced the Q-routing method to manage the network and proposed a revolutionary routing technique like multi-hop clustering to reduce energy consumption. When it comes to the ratio of packet delivery, delay (end-to-end), and energy usage, the suggested work provides better results than the prior one. They weren'tconsidering the mobility of the devices, which is essential to IoT.

Sankar et al. [16] presents a routing protocol (FLEARPL) for maximizing the network lifetime

using fuzzy-logic by considering routing parameters such as network load, leftover energy, and ETX. According to the experimental results the proposed algorithm performs good than the existing algorithms. But this protocol does not consider mobility. Mehbodniya et al. [17] suggested an energy-aware routing protocol for IoT, in which the suitable route is chosen based on ETX, load, and remaining energy parameters. It also recommended clustering architectures to reduce energy by using fuzzy logic and enhance mobility with blockchain. The simulation shows thatthe proposed work (MCEA-RPL) extends the network's performance as compared to the prior routing scheme. The further enhancement, more sink nodes will be used to collect the data.
Nasri et al. [18] proposed a protocol based on fuzzy logic and a cross-layer scheme (CLRP-LEACH) for solving the problems of healthcare applications.The proposed protocol uses the fuzzy logic concept for selecting the CH (cluster head), in which the remaining energy, short distance of the sensor nodes, and cross-layer metrics are used. The results of the suggested scheme prolong thelife of the network compared with the existing one. Further, consider the security issues to increase the network's performance. Jain, Yahav, and Verma [7] proposed a new algorithm to balance the sensor node energy by selecting the high residual energy path, additionally, by creating a data packet aggregation scheme and minimizing the management cost by keeping track of the sensor node routing tables using a straightforward checksum function. The proposed method maximizes the ratio of packet delivery and reduces control packet overhead. In the future, apply different techniques to reduce the NA control overhead of the network.

3. PROBLEM DESCRIPTION

The problem description of the proposed research is to identify an energy-aware relay node in a dynamic network by taking link dynamics and mobility factors into account to maximize the energy efficiency, reduce the delay, and increase the ratio of packet delivery. To attain this, a Neuro-fuzzy-based intelligent algorithm is used in the relay selection process.

The major objective of the proposed study 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.

4. PROPOSED SYSTEM DESIGN

The proposed algorithm enhances the network life time by solving the energy hole problem in the network and also finding the optimal relay node for data communication overthe web. We considered an SDN architecture scenario for environment monitoring as shown in Fig. 1, which consists of three layers, such as the upper layer, the middle layer, and the lower layer. All the network applications like traffic engineering, load balance, network monitoring and analytics, etc., are executed on the upper layer (application plane). The Northbound APIs are interfaced between the upper layer and the middle layer. The lower layer 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 both the upper layer and lower layer. The Southbound APIs provide the OpenFlow interface between the middle layer and the lower layer. The SDN controller takes the routing decisions on the neuro-fuzzy logic concept, manages the flow table, and adopts the topology dynamically according to the information obtained by the data plane.We 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={ $n_1, n_2, n_3, \ldots, n_M$ } , where n_k represents the k^{th} node in the network. Consider a graph that represents an IoT-based sensor network, in which sensors denoted as vertices and connections between vertices represented as edges. 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) [12].

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

Where distance between sensor pairs (n_k, n_j) is calculated. IoT network is dynamic and consists of both stationary or moving nodes. In this network, the relay node moves randomly at different occurrences of time (t_1, t_2, and t_3), which is presented in Fig. 2.

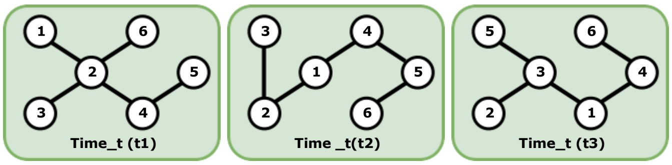

Fig. 2: Network Graph in Different Time Instance

Network Energy Model

In the this work, we implement a basic energy model based on [20]. Equation (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 energyconsumed by their electric components like E_{elec} and energy required for amplification such as ε_{rs} and ε_{amp}. This approach takes into account both signal sensitivity and noise disturbance levels of the node received signals. The distance between the nodes is denoted *di*, comparedwith the threshold distance (d_0).

The energy required for transmission is proportional to two if the transmission distance is shorter than the threshold value; otherwise, it is four,as shown in Eq. (3).

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

The term path loss describes the decrease in signal strength when a wireless signal travels between a transmitter and a receiver over a distance through the

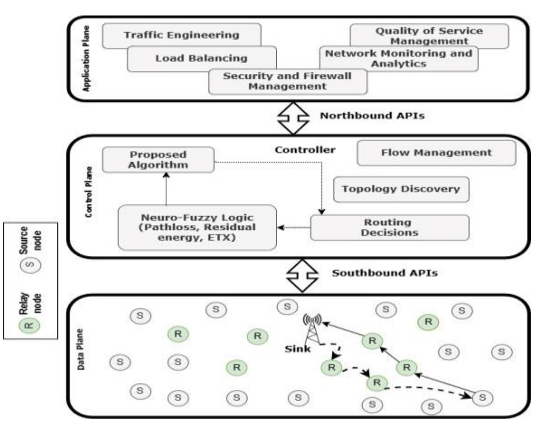

Fig. 1: Proposed SDNWSN architecture

propagation medium. That can be calculated by using Eq. (7) [22].

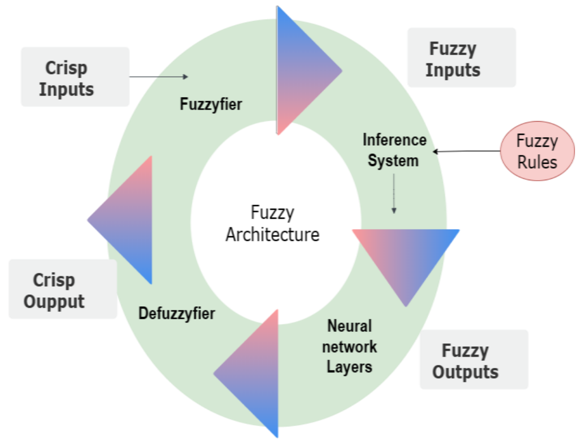

Fig. 3: Neuro-fuzzy Architecture for Relay Selection

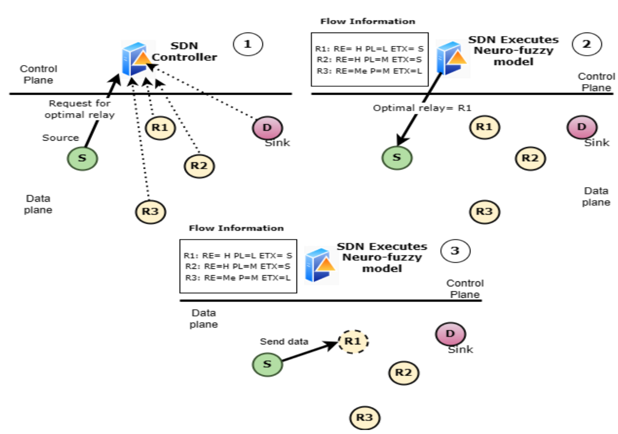

Fig. 4: Proposed relay selection process

$$PL(Di)_{dB} = PL(Di_0) + 10_{nlog}10\ (Di/Di_0) + M_\sigma \quad (7)$$

The distance between (source-sink) 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 is a metric used to estimate the successful data transmission that can be calculated by Eq. 8.

$$ETX = (1/(dF * dR)) \quad (8)$$

Where *dF* represents the probability of a packet being received by a node, while *dR* represents the probability of a successful ACK (acknowledgment) packet receipt. The residual energy is calculated using Eq. 8 The proposed protocol ERST utilizes a Neuro-fuzzy architecture as shown in Fig. 3, which includes a fuzzyfier phase that convertscrisp inputs (RE, PL, and ETX) and feeds them into a fuzzy inference system. The inference system applies fuzzy rules to generate fuzzy outputs, which are then usedto tune the parameters of the neural network layers. Finally, the defuzzifier providesa crisp output in the form of a degree, based on the fuzzy inputs.

To select the best relay for data communication, the source node first requests the SDN controller for guidance. The SDN neuro-fuzzy controller then runs the proposed algorithm and assigns the optimal relay node to the source. Finally, the source begins transmitting data. This process is outlined in Fig 4. The optimal relay nodes in a dynamic network are chosen using the Algorithm 1. Every sensor node in the network must exchange its routing information, which contains neighbor node details as wellas source and destination addresses with its neighbors. Within the SDN architecture,

the Network Controller (NC) takes charge of managing all sensor nodes and their applications. The sensor nodes exchange routing and flow details with the NC. When there is data to transmit from the source node (S), it reaches out to the NC for guidanceon which relay to use. The NC then uses neuro-fuzzy rules to choose a node with high-degree as the next forwarder, taking into account RE, PL, and ETX.

The proposed flowchart is shown in the Fig. 5. We are utilizing the Fuzzy LogicDesigner to design the three inputs fuzzy system.

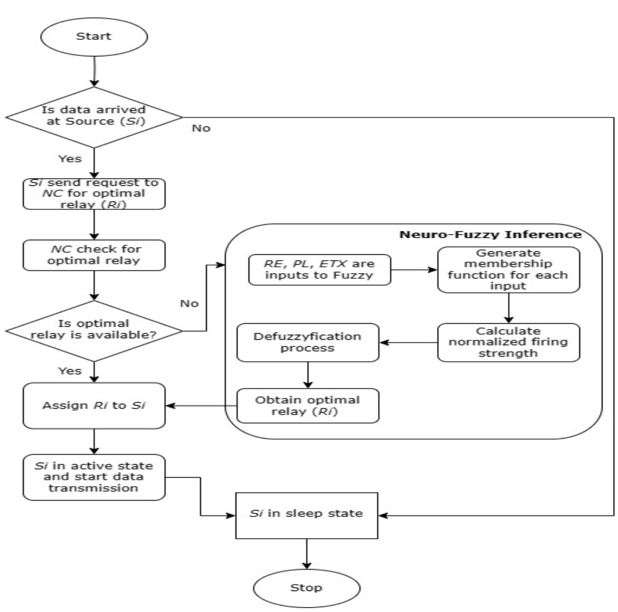

Fig. 5. Flow Chart for Relay Selection Process

Fuzzification phase

Fuzzification is defined as the mapping of crisp (precise or numerical) input values to fuzzy linguistic terms in fuzzy logic systems. In fuzzy logic, linguistic terms represent qualitative concepts and allow for reasoning and decision-making in situations where uncertainty and imprecision are present. It involves assigning membership degrees to fuzzy sets or linguistic terms based on the input values. These membership degrees represent the degree of membership or the degree of truthfulness of the input value toeach linguistic term, as shown in Figure.6. It shows the fuzzy membership functionsfor 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 L-(Low), M-(Medium), and H-(High) shown in Figure. 6(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. 6(b). The ETX (range from 0 to 10) is divided into S-(Short), A-(Avg), and L-(Long) are shown in the Figure. 6(c). The Figure. 6(d) explains the degree with respect to residual energy and path loss, the node having high

RE and less path loss rate having a high degree of membership. Figure 6(e) demonstrates that the node has high RE with less ETX and has the highest degree.

Fuzzy Inference System

The fuzzy inference system generates fuzzy rules based on the membership function states, the inputs are RE, PL, and ETX. The proposed inference rules are presented in Table 1. The fuzzification stage, the linguistic variables 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 outcome 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, as described in the paper. In Eq. (9), the 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, the values of c1 and c2 are between E and F, with c1 being less than or equal to c2.

$$trape(y;\ E, c1, c2, F) = \begin{cases} \frac{y-E}{c1-E}, & if \quad y \in [E, c1] \\ \frac{F-y}{F-c2}, & if \quad y \in [y, c2] \end{cases} \qquad (9)$$

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 denoted as a function of the relay node's RE, with 50% beingthe 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 transmit a packet from the source-sink, ranging from 0 to 10.

$$S = trape(I_{ETX}; 0, 0, 3, 5.5)$$
$$A = trape(I_{ETX}; 3, 5.5, 5.5, 8)$$
$$La = trape(I_{ETX}; 6.5, 8, 10, 10)$$

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}.

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4.1 Relay selection using Neuro-fuzzy inference system

Initially, in the proposed ERST, the routing node metrics such as RE, path loss, and ETX of the sensor nodes are assumed for selecting the next reliable, energy-efficient relay node from the FSS (Fuzzy logic inference system). Consider NR notation used for choosing the next relay from the FSS, determined by ANFIS (anadaptive neuro fuzzy inference system).

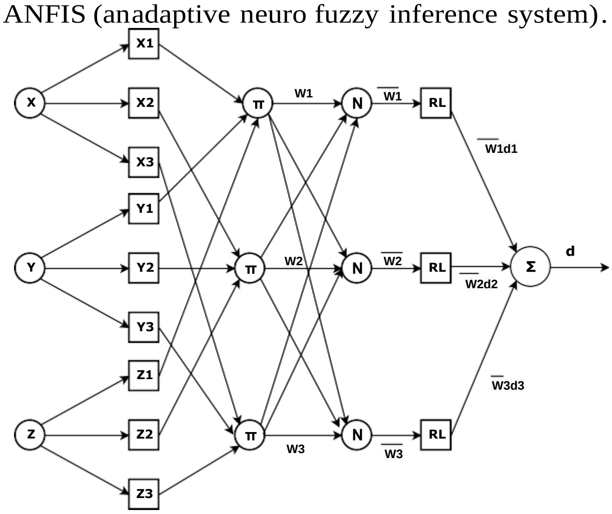


Fig. 7: Neuro-fuzzy inference system

Compared to a fuzzy logic inference system (FIS), it is significantly superior; it has higher functionality to adapt to dynamic learning practice, updates the membership function weight, and reduces the rate of error while determining the guidelines for "fuzzy". The ANFIS utilizes the Takagi-Sugeno fuzzy inference method with supervised learning as shown in Figure. 7 [23]. The ANFIS composed of five Layers. The beginning layer is the fuzzification layer, which generates the membership function (MF). The second layer, known as the rules layer, calculates the strength of a rules 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. Let us 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 The proposed three inputs structural designs of ANFIS can be seen in Figure. 8.

Table 1: Inference Rules

Rule	RE	PL	ETX	RI	Rule	RE	PL	ETX	RI
1	RE1	PL1	ETX1	RI1	15	RE2	PL2	ETX3	RI4
2	RE1	PL1	ETX2	RI2	16	RE2	PL3	ETX1	RI1
3	RE1	PL1	ETX3	RI3	17	RE2	PL3	ETX2	RI2
4	RE1	PL2	ETX1	RI1	18	RE2	PL3	ETX3	RI2
5	RE1	PL2	ETX2	RI1	19	RE3	PL1	ETX1	RI5
6	RE1	PL2	ETX3	RI2	20	RE3	PL1	ETX2	RI6
7	RE1	PL3	ETX1	RI2	21	RE3	PL1	ETX3	RI7
8	RE1	PL3	ETX2	RI1	22	RE3	PL2	ETX1	RI4
9	RE1	PL3	ETX3	RI1	23	RE3	PL2	ETX2	RI5
10	RE2	PL1	ETX1	RI3	24	RE3	PL2	ETX3	RI6
11	RE2	PL1	ETX2	RI4	25	RE3	PL3	ETX1	RI5
12	RE2	PL1	ETX3	RI5	26	RE3	PL3	ETX2	RI7
13	RE2	PL2	ETX1	RI3	27	RE3	PL3	ETX3	RI7
14	RE2	PL2	ETX2	RI3					

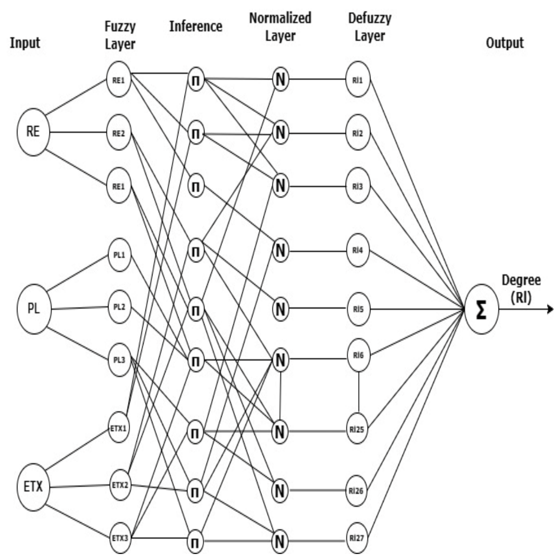


Fig. 8: Proposed Neuro-fuzzy inference

takes three inputs RE, PL, and ETX. We consider the 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,

Algorithm 1 Optimized Energy-aware RS

Input data: source *(S)*, Sink *-(D)* relay (*R1, R2, R3,. Rn)*
Outcome: *Ri* optimal RN (relay node)
Initialization: *Ie* (Initial energy), *TR* (Range of Transmission), *ET* (EnergyThreshold) *S=idle*
Sensors *Si* and relays *Ri* exchange their flow table and neighboring informationto *NC*
while *data arrival at Si* **do**
Si request the *NC* for optimal relay within its expected *TR*
The *NC* executes neuro-fuzzy function /* Selecting the best relay based on
RE(6), PL(8) and ETX (9) value*/
for *i=0 t 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 execute 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

Number equations consecutively. Equation numbers, , 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. 2. In the neuro-fuzzy inference system, the first layer called Fuzzy Layer (membership function layer) consists of several nodes. Generates a degree of membership ranging from 0 to This layer applies different membership functions like triangular, trapezoidal, and Gaussian. The proposed work uses the Trapezoidal membership function. The outcome of the first layer can be calculated using Eq. 10, 11, and 12

$$\mathbf{O_{1,j} = \mu_{X_j}(X) \quad for \quad j = 1, 2, 3} \qquad \mathbf{(10)}$$

$$\mathbf{O_{1,j} = \mu_{Y_{j-2}}(Y) \quad for \quad j = 3, 4, 5} \qquad \mathbf{(11)}$$

$$\mathbf{O_{1,j} = \mu_{Z_{j-3}}(Z) \quad for \quad j = 4, 5, 6} \qquad \mathbf{(12)}$$

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) (Fig 8). 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. 13

$$\mathbf{O_{2,j} = \mu_{RE_j}(X) \times \mu_{PL_j}(Y) \times \mu_{ETX_j}(Z)} \quad \mathbf{where, \quad j = 1, 2, 3} \qquad \mathbf{(13)}$$

The following layer is called the normalized layer, it is non-adaptive and is representedby N in the figure (Fig 8). Every node in this layer generates the output by taking the ratio of the i^{tj} rule produced by the inference layer. The outcome of this layer can be obtained by using Eq. 14.

$$\boldsymbol{O_{3,j} = \overline{Wj} = \frac{wj}{w1+w2+w3} \quad j = 1, 2, 3} \quad \mathbf{(14)}$$

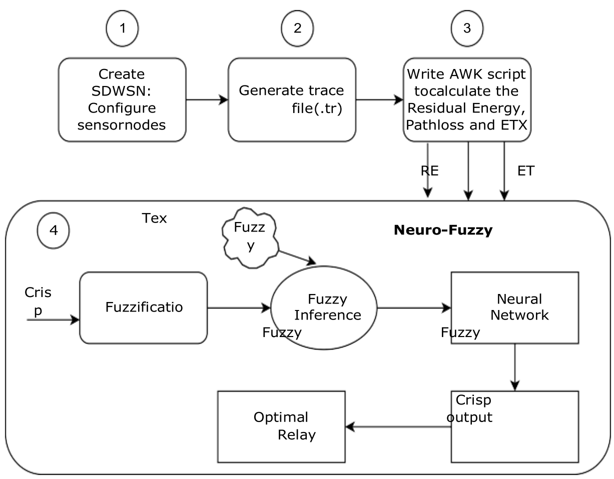


Fig. 9: Hybrid Simulation System

A fourth layer is called the adaptive defuzzification layer. This gives the output as a product of the normalized layer, firing strength and output of individual rule. The outcome of the normalized layer is as follows Eq. 15

$$O_{4,j=}\overline{wj}\,\mathbf{dj} = O_{\ 4,j}(p_i\mathbf{X} + q_j\mathbf{Y} + r_j\mathbf{Z} + C_{\ j}\ \ j = 1,2,3 \qquad (15)$$

Where p_j, q_j, r_j, C_j are constants. Finally, the last layer is known as the non-adaptive output layer. The single aggregated output is generated at this layer by using Eq. 16.

$$O_{5,j} = \sum\overline{wj}\,\mathbf{dj} = \sum_j Wj\mathbf{dj} \Big/ \sum_j Wj \qquad (16)$$

Algorithm 2 RL selection using Neuro-fuzzy

1: Input: *RE, PL, ETX, and N*

2: Output: *Rl*

3: for *n=1 to* N_{epoch} do

4:Input *RE, PL, ETX* to fuzzy inference engine

5: Generate membership functions ($\mu_{RE\boldsymbol{j}}$ $\mu_{PL\boldsymbol{j}}$ *and* $\mu_{ETX\boldsymbol{j}}$) for each node by fuzzy layer using Eq.(6)

6:Calculate the normalized firing strength of each node based on Eq.(14) andEq(15)

7:Defuzzification process done based on Eq.(16) for each node

8:Calculate the final output *Rl* using Eq. (17)

9: end for

Our 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, we use gradient descent and the least mean squares hybrid algorithm. During the forward pass, we provide the static input parameters (RE, PL, ETX) to the fuzzy layer. The information then passes through the intermediate (hidden) layers and reaches the defuzzy layer, where we analyze the output with errors. In the backward pass, we send these errors back to the fuzzy layer. 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).

5. Performance Evaluation

To evaluate the performance measures, average values from the findings are extracted. Table 2 provides a summary of the simulation parameters. We evaluated the ratio of packet delivery, end-to-end delays, average throughput, energy consumption, and network life-times of the algorithms for a comprehensive analysis. The simulation's outcomes are compared with the earlier routing protocols like MRE and RRS [24, 25].

The performance analysis of the suggested study has been done using simulators (NS and MATLAB). The proposed hybrid simulation process is explained in Figure. 9. In 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 is used to calculate 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 both fuzzy and neural network operations.

Table 2: Parameters

Parameters	Symbol	Values
Network Size	Sq.mt	300*300
Transmission Range	TR	50m
Sink Node	D	(0,0)
Source coordinates	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

Simulation Setup Metrics

- The ratio of packet delivery (PDR) is a metric used in computer networking to measure the success rate of transmitting packets in a network.

- The node energy consumption is the energy used over time.
- The E-t-E(End-to-End) Delay defines the total time taken for a packet transmission from the source node to the destination within a computer network.
- The Average throughput indicates the average rate of data transfer or the volume of data successfully transmitted over a network during a given time period.
- Network lifetime defines to the duration or lifespan of an IoT network before its nodes become unable to communicate or exhaust their energy resources.

Proposed System Results and Discussion

In this section the experimental findings of suggested protocol ERST has explained with figures.

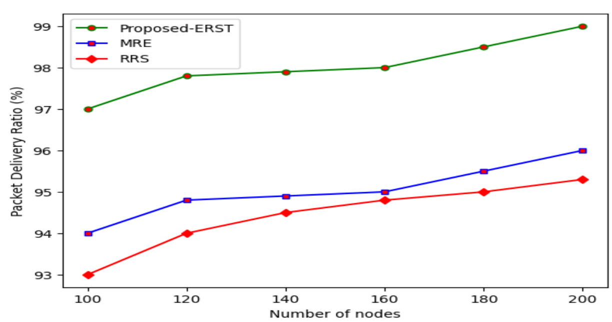


Fig. 10: Packet Delivery Rate

Figure. 10 shows the ratio of the packet delivery of the proposed study. The proposed ERST algorithm demonstrates an 8% increase in successful packet transmission rate compared to existing MRE and RRS protocols. This is achieved through the selection of an optimal relay node using a neuro-fuzzy model, which applies various fuzzy rules for reliable data transmission. As the nodes density increases, the number of potentially available relay nodes also increases, results to an increase in the packet reception ratio at the sink. This indicates that the proposed algorithm is highly scalable. In contrast, the previous MRE protocol only selects the next relay based on the RE of a node without considering link quality. 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.

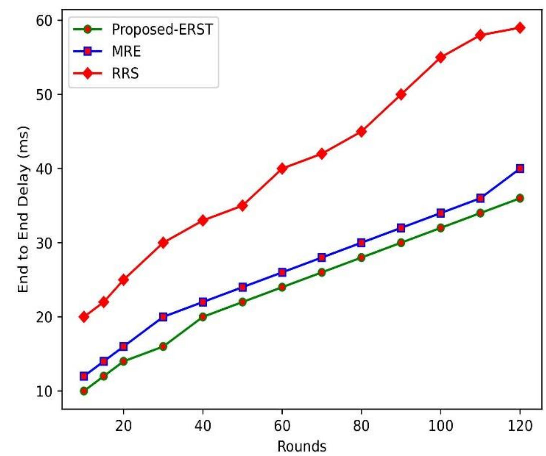


Fig. 11: Delay (End-to-End)

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 path over the network, as shown in Figure. 11. The MRE protocol is currently 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, resulting in additional transmission delays.

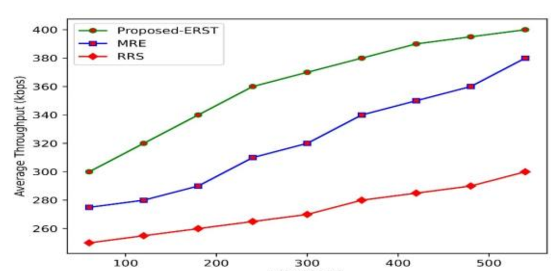


Fig. 13: Average Throughput

The proposed ERST protocol improves network throughput by over 8% compared to MRE and RRS protocols as shown in Figure. 13. ETST selects the optimal relayon the reliable link, which maximizes the data delivery and reduces the packet loss. Finally, the proposed ERST extends the network span in terms of the alive nodes involved in different simulation times, as shown in Figure. 14. The obtained results are compared with the prior routing protocols: MRE and

RRS. At the beginning up until the 100s, all the sensor nodes are active. After that, their energy beginsto drain gradually, resulting in a decrease in the number of active nodes.

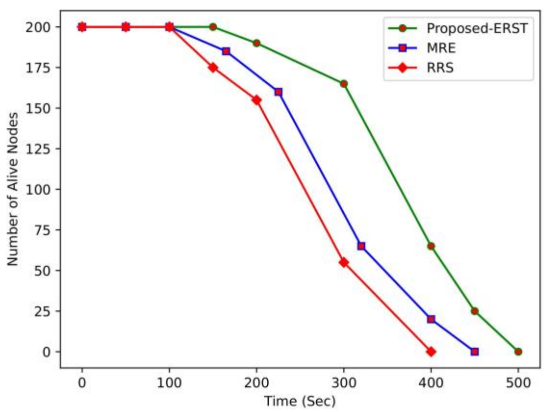


Fig. 14: Network Lifetime

Fig 14 illustrates that the suggested ERST protocol has a higher number of active nodes compared to 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 about150s, and in RRS, the first node dies at about 100s, respectively. It is due to the proposed ERST selecting the next relay using the neuro-fuzzy model to increase thenetwork lifetime.

6 Conclusions

This paper proposed an energy-aware relay selection (ERST) technique by using an adaptive Neuro fuzzy-based model. 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 route by considering factors such as the remaining energy of the nodes, path loss ratio of link, and ETX of nodes to identify the next relay node from source to sink. The fuzzy model and neural network optimize the energy over the network and increase the network 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 protocol provides high scalability and reliability for IoT networks.

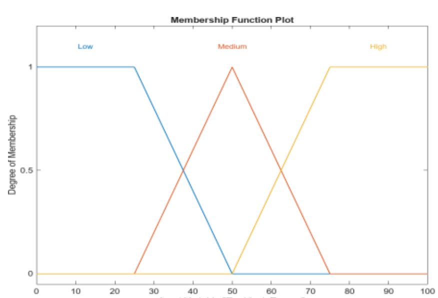
Future enhancement

In the future the clustering approaches are used to reduce the energy consumption by selecting the optimal cluster head to transfer the data and the swarm intelligent concept are adapted to organize the optimal network structure to boost network performance.

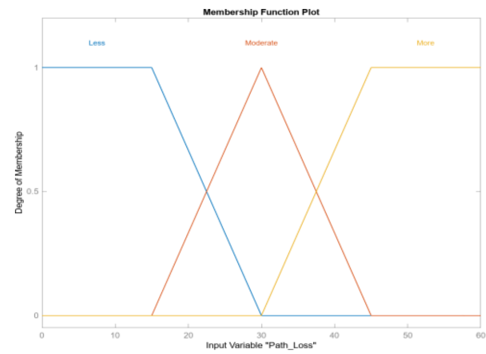
List of abbreviations

Notation	Description
n_k	Kth sensor node
n_j	Jth sensor node
d_i	Distance between ith node
TRr	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
$\varepsilon_{rs}, \varepsilon_{amp}$	Energy required for amplification of the receiver and received signal noise
I_e	Initial energy of the sensors
$E_{p,\ Total}$	Total energy required to transfer p bits
$C_{ij}{}^{T}{}_{n}$	Duration of connectivity b/w two devices d_i &d_j
T_n	$_n{}^{th}$ time instance
T_r	Transmission range
RE	Residual Energy
PL	Path Loss
ETX	Expected Transmission Count
D_i	Distance between the source-sink
M_σ	Variable with zero mean
dF	Probability of packet being received
dR	Probability of a successful acknowledgement packet reception

NC	Network Controller
L, M, H	Low, Medium, High
L_e, M_o, M_r	Less, Moderate, More
S, A, L_a	Short, Average, Long
I_{RE}, I_{PL}, I_{ETX}	Linguistic values of residual energy, pathloss and ETX
Y	Output set
E, F	Support of membership function
C_1, C_2	Trapezoidal membership kernel
ET	Energy Threshold
S	Source
D	Sink
$R_1, ... R_n$	Relay nodes
$\mu_{RE}, \mu_{PL}, \mu_{ETX}$	Membership functions



(a)



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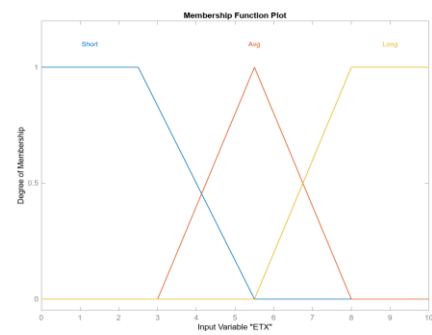

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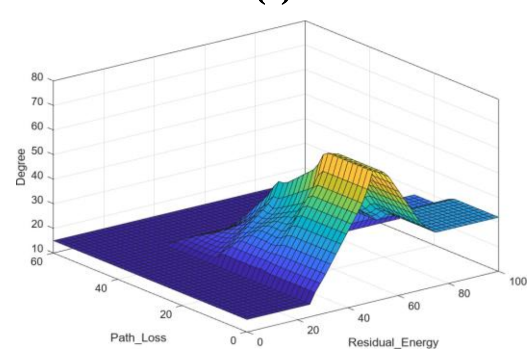

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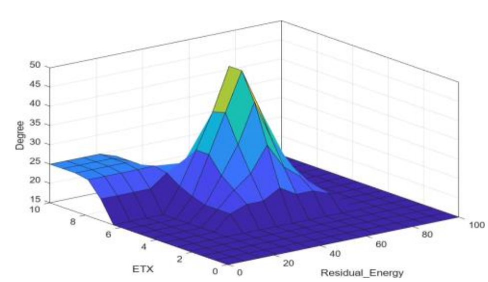

(e)

FIG. 6: DEGREE OF MEMBERSHIP FUNCTIONS

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All authors approved the version of the manuscript to be published.

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