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Explainable Hybrid ANFIS-Based Multi-Objective Relay Selection Framework for Energy-Efficient Internet of Healthcare Things

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ABSTRACT: Efficient, dependable transmission of physiological data is necessary to ensure optimal healthcare monitoring efficiency in Internet of Healthcare Things (IoHT) using IEEE 802.15.6-based networks. However, relay selection remains a major challenge because reliability, latency, throughput, and energy efficiency conflict under variable network conditions. In this light, the paper suggests an Explainable Hybrid ANFIS-based Relay Selection Framework. This novel system combines the Adaptive Neuro-Fuzzy Inference System (ANFIS) with the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to enable energy-conscious relay selection and dynamic routing. In addition, Shapley Additive exPlanations (SHAP) has been used to improve the interpretability of relay-selection decisions by explaining how specific input feature values contribute to the overall decision. Furthermore, we conduct an ablation study and statistical significance analysis on the effectiveness of different components of the optimization framework. Simulations conducted in IEEE 802.15.6 networking conditions show that the proposed system yields a packet delivery ratio, end-to-end delay, throughput, and residual energy of 98.44 percent, 5.80 milliseconds, 1140 kbps, and 0.860 J, respectively, demonstrating its potential to improve efficiency, latency, throughput, and reliability of healthcare communication using IoHT solutions.

1. INTRODUCTION

The increasing adoption of Internet of Healthcare Things (IoHT), combined with advances in low-power sensing and wireless communication technologies, has changed key aspects of smart healthcare ecosystems. Physiological signals collected from a number of body sensors are sent to a coordinator and are then passed on to healthcare providers via cloud or edge-enabled infrastructure [1]. This enables early detection of disease, remote diagnosis, emergency response, and the delivery of personalised medical services [2]. For this reason, IEEE 802.15.6 [3] has become the communication standard of choice for IoHTs because it supports reliable, low-power, and short-range wireless communications. However, the communication protocols used in IoHTs remain a considerable challenge since the sensor nodes worn on the body function under strict energy constraints as well as under constantly changing propagation conditions [4]. The biosensors are generally powered by small batteries that are hard to replace. Increasing the lifetime of the network has therefore become a central purpose of this type of healthcare application, it is essential to have a highly reliable and low-latency communication [5] system because delays or packet losses could affect swift healthcare judgments when transmitting time sensitive physiological data. Furthermore, patient movement, shadowing, channel fading, interference, and fluctuating traffic patterns often lead to a deterioration in communication quality, result in high packet retransmission rates, increase energy consumption, and reduce the quality of service. As a result, an

intelligent relay-selection mechanism is able to improve at the same time the reliability, energy efficiency, and communication performance. In order to overcome these difficulties, a number of relay-assisted Medium Access Control (MAC) protocols have been developed for IEEE 802.15.6 WBANs[6]. Relay nodes [7,8]bridge the gap over which transmissions must take place, enhance the quality of the link, by forwarding packets via intermediate nodes each time when direct communication with the coordinator becomes unreliable.

Recent developments in artificial intelligence have shown that adaptive learning models can vastly surpass legacy production systems when it comes to network optimisation. In particular, the Adaptive Neuro-Fuzzy Inference System (ANFIS) combines fuzzy logic reasoning with artificial neural networks, allowing the automatic optimisation of membership functions, learning, and fuzzy rules using training data. It has been found that relay selection in WBANs involves several conflicting objectives, such as maximising the packet delivery ratio and throughput while at the same time minimising latency and energy consumption. For this reason, multi-objective optimisation techniques have led to balanced relay-selection strategies that meet a variety of quality-of-service requirements.

This study presents an Explainable Hybrid ANFIS-Based Relay Selection Framework which enhances the traditional AFBM protocol by combining Adaptive Neuro-Fuzzy Inference System (ANFIS) learning with the Non-Dominated Sorting Genetic Algorithm II (NSGA-II). The proposed design automatically learns adaptive relay-selection strategies from a range of network features while at the same time optimising the conflicting objectives of packet delivery ratio, end-to-end delay, throughput, and residual energy. The inclusion of Shapley Additive exPlanations (SHAP) allows the trustworthiness of the relay selection to be assessed and provides explainability. The main contributions are outlined below

- Multi-objective optimisation to balance packet delivery ratio, latency, throughput, and residual energy has been enabled through integration of NSGA-II.
- To interpret relay-selection decisions and improve model transparency is induced by SHAP-based explainability.
- To quantify the contribution of each proposed component author has used comprehensive ablation analysis and statistical validation.

In addition to the aforementioned contributions, Section 2 provides a summary overview of relevant research conducted thus. Section 3 delivers a thorough explanation of the suggested method. Section 4 discusses the performance evaluation measures for the proposed framework and its equivalents, and Section 5 concludes with a summary of future work.

2. LITERATURE STUDY

The researchers have come up with several MAC-layer techniques to improve the performance of Wireless Body Area Networks (WBANs), particularly in terms of energy efficiency, packet delivery reliability, transmission delay, and reliable communication under resource-limited and rapidly changing environment. Table 1 summarizes two performance assessment and improvement mechanisms for MAC protocol performance in WBANs. Much of existing studies were based on the IEEE 802.15.6 standard and its versions to meet Quality of Service (QoS) requirements for medical and non-medical traffic. The Dynamic Medical Traffic Management MAC (DMTM-MAC) protocol [12] uses dynamic slot allocation and priority-based access to manage heterogeneous medical traffic more effectively. Although the method improves resource utilization, it does not fully resolve QoS issues, regardless of the traffic priority level. The BCR-MAC protocol was introduced in [13] to achieve reliable frame transmission in a WBAN system that uses IEEE 802.15.6 and addresses contention-related problems. The purpose of introducing the OPR MAC protocol is to extend network lifetime using both predetermined and opportunistically selected relay nodes. In this method, relay nodes are opportunistically selected based on outage probability. A star topology is adopted in the network at the same time. Under the normal conditions of communication, a slot is reserved for direct communication between the sensor node and the main node. Upon failure of direct transmission, TTR MAC [15] commences a relay-discovery scheme. For data-burst and periodic-data transmissions, TTR MAC uses two reservation methods. Additionally, the protocol enables flexible, energy-conserving communication through token-based transmission scheduling and the introduction of the Severity Index (SI). Nonetheless, when a select group of nodes reserves unused slots, it leads to inefficient resource utilization and excessive energy consumption. Kim et al. [16] introduced a method for flexible relay-node selection based on the Analytical Hierarchy Process (AHP). The proposed method considers several criteria, such as mean Signal-to-Noise Ratio (SNR), remaining energy, and traffic load, when selecting potential relay candidates. Suitable relay candidates are found by exchanging control messages when direct communication with the main coordinator fails. However, the method does not directly account

for the different types of traffic and user priority presented in IEEE 802.15.6. To minimize delays when sending important medical packets, the authors of [17] proposed TP-CAT, as well as LT-CATA and HT-CATA, which aim to minimize the chances of collision for nodes with different priorities. A priority-based packet-balanced queue MAC protocol [18], developed in accordance with the IEEE 802.15.6 architecture, provides priority transmission of important packets to users compared with other packet types, enabling differentiation of service requirements. The Adaptive MAC (A-MAC) protocol [19] splits the IEEE 802.15.6 superframe into four main sections: beacon phase, Contention Access Phase (CAP), non-contention access period, and inactive period. Depending on the traffic type, it is assigned to one out of the three service types. The contention and non-contention phases change based on the number of nodes and their priorities. Even though this approach allows efficient use of the communication channel, it does not guarantee reliable work of the network nodes. The authors of [20] designed an analytical framework to assess WBAN performance based on the IEEE 802.15.6 MAC under heterogeneous priority-type traffic. They discussed channel behavior under fading and shadowing, which are especially important for WBANs because wireless signals are affected by the human body. The authors from [21] proposed to use Request-to-Send/Clear-to-Send (RTS/CTS) to resolve the hidden node issue. The authors' solution, however, has limitations in relation to the application of scheduling type transmission in WBANs. The DSA-NOBA [22] technique is introduced for reducing packet collisions and increasing channel usage. The approach increases CW based on bottlenecks under different traffic conditions and thus dynamically allocates slots to improve superframe utilization. Another modified MAC approach for IEEE 802.15.6 [23] enables simultaneous transfer of several streams of emergency data while incorporating energy-saving methods. This approach builds on the solutions and concepts proposed in [24], which used the dynamic superframe structure of IEEE 802.15.6 to improve transmission opportunity allocation for nodes. In addition, [25] proposes a MAC solution with priority-based operation that uses an adjustable superframe structure to allocate slot usage based on the priorities of various sensors.

In this protocol, each sensor device is given an urgency value, which determines how slots are assigned during the Managed Access Phase (MAP) and the Enhanced Access Phase (EAP) [26]. GFuCWO is a genetic fuzzy logic method that combines fuzzy logic (FL) and a genetic algorithm (GA) to increase the contention window in IEEE 802.15.6. The GA is used to adjust the FL for better results. This GFuCWO approach can help the medical sector by removing barriers to better performance and offers a new way to improve the efficiency of IEEE 802.15.6. [27] introduces the Adaptive MAC (ADT-MAC), a QoS-aware MAC protocol designed to handle both emergency and regular medical traffic. ADT-MAC uses a flexible superframe structure based on the IEEE 802.15.6 model. However, direct communication between the biosensor node and the coordinating node can be blocked by the Line-of-Sight Problem. [28] presents a fuzzy-based relay MAC protocol built on the IEEE 802.15.6 architecture. It considers both invasive and non-invasive nodes to compare the importance of emergency data. During the EAP, emergency data can be sent directly to the hub, freeing it from other nodes. If direct emergency transmission fails, communication switches immediately to predefined relay nodes. For medium-priority node failures, relay nodes are chosen using fuzzy rules. However, this method uses fixed membership functions and manually designed rules, and it lacks optimization and explainability.

Table 1: Summarization of Research Gap of various state of the art

Author [Ref.]	Year	Algorithm	Delay	Energy Consumption	Throughput	Reliability	Explainability	Advantage	Research Gap
Negra[9]	2013	DMTM MAC	•	o	o	o	•	Dynamic Channel Access Mechanism	Emergency Traffic transmitted in EAP, which raises a contention problem

Shin[10]	2015	BCRMAC	•	o	o	o	•	Reliable Frame Transmission	Fixed contention Window
Panetet.all[11]	2015	OPRMAC	o	o	o	o	•	Reduce the possibility of data relaying failure	Channel access not considered
Yuan et.all[12]	2016	TTR MAC	o	o	•	o	o	Highly adaptive High power efficiency	Unused fixed reserved slot
Kime et.all[13]	2016	AHP	•	o	•	o	•	Flexible Relay Selection	Does not consider user Priorities.
Ambigavathi[14]	2018	TPCAT	•	o	•	o	•	Solve the slot contention.	Neighboring nodes may lead to severe collision and packet loss.
Sahoo et.all[15]	2019	PBQ MAC	•	o	•	o	•	Two separate queues for critical data transmission	Relay node is not considered
Yuan et al. [16]	2019	AMAC	•	o	•	o	•	Reduce Collision	Relay node is not considered.
Benmasour et.all[17]	2020	Performance Analysis of IEEE 802.15.6	•	o	o	•	o	Handle Packet length variation and Ack frame failing transmission	Channel fading and shadowing are not considered
Ullah et.all[18]	2020	RTS/CTS Scheme	o	•	o	•	o	Solve the exposed	Schedule-based transmissio

								node problem.	n is not considered.
Saboor et.al[19]	2020	DSA NOBA	•	o	•	o	o	Reduce Collision	Increase collision for high-priority tasks due to short CW range.
Samalet.all[20]	2021	EDMAC	•	o	•	o	•	Energy Saving Techniques are used.	Reliability is not considered.
Das et al. [21]	2022	-----	•	o	o	o	•	Dynamic Superframe Structure	Produce High Delay
Das et al. [22]	2023	-----	o	o	•	o	•	Placement of Relay nodes	Traffic priority and channel access are not considered.
Qureshi et.al[23]	2024	GFuCWO	o	o	o	o	•	Optimize the contention Window.	Direct Transmission between the sensor node and the coordinating node Line of Sight problem
Hassan et.al[24]	2024	ADT MAC	•	o	•	o	•	Dynamic slot allocation	Direct Transmission between the sensor node and the coordinating node

									Line of Sight Problem
Aishwarya et al[25]	2026	AFBM	•	o	•	o	•	Transmission between the sensor node and the coordinating node through a relay node Solution of the Line of Sight problem Channel Access Traffic Priority	It has fixed membership functions; manually designed rules; no optimisation or explainability
Proposed		Proposed	•	•	•	•	•	Energy Efficient Dynamic scheduling Fault Recovery	

3. PROPOSED METHODOLOGY

(i)ANFIS

ANFIS is estimated as autonomous decision unit to assess relay suitability by learning the nonlinear relationship among residual RSSI, energy, throughput, mobility, and delay parameters. Relay selection involves assessing divergent objectives such as maximizing reliability and throughput while minimizing delay and energy consumption. Relay optimization is essential in IEEE 802.15.6 WBANs because direct communication suffers from high energy consumption, unreliable links, and increased latency due to the dynamic human body channel. An optimized relay selection strategy improves network lifetime, packet delivery reliability, throughput, and delay performance by selecting energy-efficient and stable forwarding nodes. Therefore, relay optimization is formulated as a multi-objective problem considering energy, link quality, delay, throughput, and mobility constraints. NSGA-II is integrated as a multi-objective optimizer to obtain Pareto-optimal relay configurations. In our proposed framework, ANFIS learns the relationship (Energy, RSSI, Delay, Throughput, Mobility) w.r.t Relay Utility. Thus, ANFIS provides accurate relay ranking, whereas NSGA-II performs global optimization among competing network objectives.

(ii)NSGA-II

NSGA-II (Non-dominated Sorting Genetic Algorithm II) handles this as a multi-objective optimization problem where multiple conflicting objectives are optimized simultaneously. NSGA-II is optimized for relay selection by addressing the

inherent trade-offs among multiple Quality of Service (QoS) and energy-related objectives in IEEE 802.15.6 Wireless Body Area Networks (WBANs).

(iii) Simulated Binary Crossover (SBX) and Polynomial Mutation

In a IoHT optimization problem, if you are using a real-coded evolutionary algorithm such as NSGA-II, SBX and Polynomial Mutation (PM) are the two main genetic operators used to generate new solutions.

Algorithm.1 SBX creates new offspring by combining two parent solutions

Input: Parent1(Z1), Parent2(Z2), η_c

for each variable do

 generate $u \in [0,1]$

 if $u \leq 0.5$ then

$$\beta_q = (2u)^{1/(\eta_c+1)}$$

 else

$$\beta_q = (1/(2(1-u)))^{1/(\eta_c+1)}$$

 end if

$$\text{child1} = 0.5 * ((Z1 + Z2) - \beta_q * (Z2 - Z1))$$

$$\text{child2} = 0.5 * ((Z1 + Z2) + \beta_q * (Z2 - Z1))$$

 enforce variable bounds

end for

In NSGA-II, the Crowding Distance (CD) metric is calculated to maintain diversity among solutions in the same Pareto front. Polynomial Mutation introduces small random changes to maintain diversity. It measures how close a solution is to its neighbouring solutions in the objective space. A solution with a higher crowding distance is preferred because it represents a less crowded region of the Pareto front.

(iv) Shapiro Wilky Test

The Shapiro–Wilk test is a statistical test to ascertain whether a dataset is normally distributed or not. Primarily it verifies whether the shape or distribution of your data is consistent with normality.

$$W = \frac{(\sum_{i=1}^n a_i * X_i)}{\sum_{i=1}^n (X_i - \bar{X})^2} \quad (3)$$

$$H0: X \sim N(\mu, \sigma^2) \quad (4)$$

$$H1: X \sim ! N(\mu, \sigma^2) \quad (5)$$

$p > 0.05$, Fail to reject $H0$, if $0.05 \geq p$ reject $H0$

Where, μ : Mean of the dataset, σ^2 : Variance and spread, $H0$: Null hypothesis, $H1$: Alternate hypothesis

Algorithm 2: Explainable Hybrid ANFIS–NSGA-II Relay Selection

Input: WBAN sensor nodes $N=16$, coordinator C , feature matrix X , population size $P=50$, maximum generations $G=100$, learning rate $\eta=0.01$, epochs $E=100$

Output: Optimal relay R_{opt} , SHAP feature importance Φ

- 1: Deploy IEEE 802.15.6 WBAN with $N = 16$ sensor nodes.
- 2: Initialize coordinator C and sensor nodes.
- 3: Set simulation parameters: Initial Energy = 1.0 J/node, TX Power = 0.001 W, RX Power = 0.0005 W, Packet Size = 512 bits, Simulation Time = 1000 s
- 4: while Network is Active do
- 5: Collect node-level scientific measurements:
 - RE: Residual Energy [0, 1.0] J
 - RSSI: Received Signal [-90, -30] dBm
 - LQI: Link Quality [0, 255]
 - Dist.: Distance [0.1, 2.0] m
 - Temp: Node Temperature [30, 40] °C
 - QL: Queue Length [0, 50] packets
 - Delay: Transmission Delay [1, 100] ms
 - PDR: Packet Delivery Ratio [0, 1]
- 6: Construct feature vector:
 - $X_i = \{RE, RSSI, LQI, Dist., Temp, QL, Delay, PDR\}$
- 7: Normalize each feature using Min-Max normalization:
 - $X_i' = (X_i - X_{min}) / (X_{max} - X_{min})$
- 8: Initialize first-order Sugeno ANFIS.
- 10: Initialize Gaussian Membership Functions(x) = $\exp[-(x-c)^2/(2\sigma^2)]$
- 11: Initialize premise parameters $\{c, \sigma\}$.
- 12: for epoch = 1 to E do
- 13: Calculate rule firing strength: $W_i = \prod \mu_{ij}(x_i)$
- 14: Normalize firing strength:
 - $\bar{w}_i = w_i / \sum w_i$
- 15: Estimate consequent parameters using LSE.
- 16: Calculate prediction error:
 - $e = t - \hat{y}$
- 17: Update premise parameters:
 - $c = c - \eta(\partial E / \partial c)$
 - $\sigma = \sigma - \eta(\partial E / \partial \sigma)$
- 18: end for

```
19: Calculate:
    RMSE =  $\sqrt{[\Sigma(y_i - \hat{y}_i)^2 / n]}$ 
    MAE =  $\Sigma |y_i - \hat{y}_i| / n$ 
20: Predict relay suitability:  $S_r = \text{ANFIS}(X_i)$ 
21: Rank sensor nodes according to  $S_r$ .
22: Select Top-K relay candidates:  $R_c = \text{Top-K}(S_r)$ 
23: /* NSGA-II Optimization */
24: Encode  $R_c$  as chromosomes.
25: Initialize population: P = 50 chromosomes.
26: Evaluate four optimization objectives:
    f1 = Min (Energy Consumption)
    f2 = Min (End-to-End Delay)
    f3 = Max (Throughput)
    f4 = Max (Network Lifetime)
27: Perform Fast Non-Dominated Sorting.
28: Calculate Crowding Distance.
29: for generation = 1 to G do
30:     Select parents using Binary Tournament Selection.
31: Apply SBX crossover: Crossover Probability = 0.9
32: Apply Polynomial Mutation: Mutation Probability = 0.1
33:     Evaluate offspring using f1, f2, f3 and f4.
34:     Merge populations:  $R_t = P_t \cup Q_t$ 
35:     Perform Fast Non-Dominated Sorting.
36:     Calculate Crowding Distance.
37:     Select next generation using: Pareto Rank and Crowding Distance
38: end for
39: Extract final Pareto-optimal relay set.
40: Select relay with maximum composite fitness:
 $R_{opt} = \text{argmax}(\text{Fitness}(R_i))$ 
41: End
```

4. RESULT ANALYSIS

The simulation is set up with 16 sensor nodes, representing a WBAN comprising multiple body-mounted sensing devices. These values show how much energy is used to send and receive data packets. Each packet has a size of 512 bits/bytes, depending on the implementation, and the overall network is evaluated for a simulation duration of 1000 time units. These parameters regulate the environment for evaluating packet delivery, energy efficiency, delay, throughput, and network lifetime in the proposed IOHT protocol. The proposed relay-selection framework was assessed under IEEE 802.15.6 Wireless Body

Area Network (WBAN) conditions. The network configuration takes in the number of sensor nodes, relay candidates, coordinator, simulation area, initial node energy, packet size, traffic generation rate, communication range, channel characteristics, and simulation duration. A multi-parameter optimization approach identifies the best relay by balancing these factors for reliable communication. In IoHT, body movements can continuously change the quality and stability of wireless links. For example, wrist sensor as Chest coordinator generally, provides a relatively stable link. Leg sensor as Coordinator may experience frequent link degradation during walking or other body movements. Nominating the nearest node alone does not guarantee optimal communication, as it may have low energy, high mobility, poor link quality, or heavy queue load. Therefore, relay selection should jointly consider energy, RSSI, delay, and network conditions. In WBAN, RSSI is used as a link quality indicator when selecting the best relay node as:

$$RSSI = 10 \log_{10} \frac{P_r}{1mW} \quad (6)$$

Relay optimization progressively picks nodes that are marginally influenced by mobility and can maintain more stable communication paths.

$$\text{Standard deviation of residual energy}(\sigma E) = \sqrt{\frac{1}{N} \sum_{i=1}^N (E_i^{res} - E_{avg}^{res})^2} \quad (7)$$

Maximizing residual energy that provides longer network life time, reduced energy imbalance and fewer node failures by:

$$\max_R [\alpha E_{avg}^{res} - \beta \sigma_E] \quad (8)$$

Where, N: Total number of sensor nodes, E_i^{res} : Residual energy of node I, E_{avg}^{res} : Average residual energy of all nodes

The objective is to maximize Packet Delivery Ratio (PDR) by selecting reliable relay nodes based on RSSI, channel reliability, and packet success probability despite body-channel variations by:

$$PDR = \frac{N_{received}}{N_{transmitted}} * 100 \quad (9)$$

$$\max_R PDR(R) \quad (10)$$

This ensures reliable medical data transmission, fewer retransmissions, and improved QoS. The link-quality formulation selects the optimal relay by maximizing a weighted combination of normalized RSSI, channel reliability, and packet-success probability as:

$$\max_R [w_1 * RSSI + w_2 * CR + w_3 * PSP] \quad (11)$$

The weights are set so that their total is one. The Packet Loss Ratio (PLR) represents the fraction of transmitted packets that are not successfully received.

$$PLR = 1 - N_{received}/N_{transmitted} \quad (12)$$

Therefore, **maximizing PDR directly minimizes PLR**, resulting in more reliable and efficient medical data communication.

$$\max(PDR) \equiv \min(PLR) \quad (13)$$

The objective is to **minimize communication delay** by avoiding congested nodes, weak links, and unnecessarily long routing paths.

$$f(R) = \min_R Delay(R) \quad (14)$$

This enables faster end to end emergency response and real-time patient monitoring in healthcare WBANs by taking into account transaction, queuing, processing, propagation, and relay delay:

$$D_{E2E} = D_{tx} + D_{queue} + D_{proc} + D_{prop} + D_{relay} \quad (15)$$

Human body movement impacts wireless link conditions, so relay selection must dynamically identify stable and reliable nodes. Trivializing mobility impact reduces packet loss, changing of route, and retransmission overhead, thereby improving overall network reliability and lifetime. minimizing DE2E, helps select relay nodes that provide low-latency communication, which is particularly important for emergency traffic.

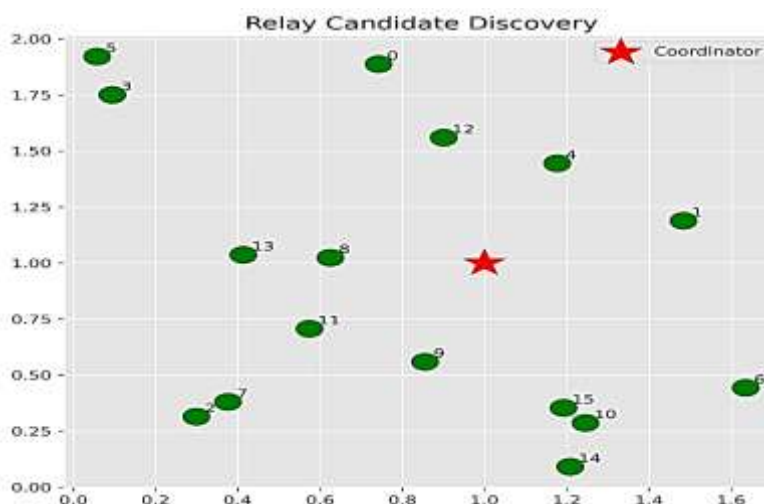


Figure.1: Relay candidate discovery and their spatial distribution

The discovery diagram for the relay candidate in Figure.1 illustrates the spatial distribution of potential relay nodes around a central Coordinator, represented by the red star at approximately (1.0, 1.0). The nodes, numbered 0 to 15 in green circles, typify candidate relay devices positioned at different locations within the network.

The distance differential between the coordinator and the nodes affects communication efficiency. For example, the closer the node is to the coordinator, the less power it would consume. Therefore, nodes such as Node 9, Node 11, Node 13, and Node 8, which are regarded as closer to the coordinator, would require less power and relays. On the other hand, the peripheral nodes, such as Node 5 and Node 3, would consume more power to communicate with the coordinator. Thus, the distance of the node from the coordinator plays a pivotal role in determining relay capability and increasing the efficiency of transmission in the network.

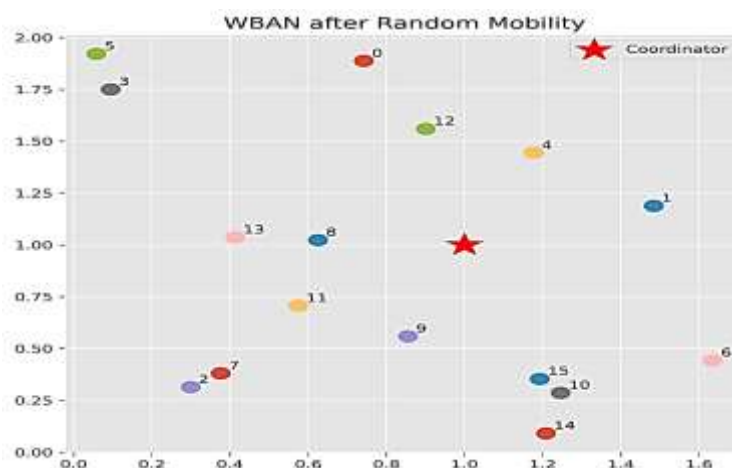


Figure.2: Spatial redistribution of nodes after random mobility

The unpredictable variations in placements of sensor nodes in a IoHT is illustrated in Figure. 2. The figure shows how 16 sensor nodes were moved around randomly by mobility. The red star shows the position of the coordinator located approximately at (1.0, 1.0). According to the image, the sensors have moved from their initial configuration to new locations indicating that WBANs change constantly due to the movements of people using the devices, their postures, variation in the placement of the sensors on the body, and body movements. Some nodes like Nodes 8, 9, 11, and 13 have not moved far from the position of the coordinator, while others like Nodes 3, 5, and 6 have moved away from it. This movement has great effects on many communication parameters like Received Signal Strength Indicator (RSSI), link quality, the ratio of packet delivery, energy consumption levels, and the end-to-end delay. The approach that is used in the research is not similar to those using fuzzy logic because the method involves development of a system which would learn how to select new relays at any given moment instead of following the initial rules.

4.1 ANFIS intelligent relay selection framework for IEEE 802.15.6 Wireless Body Area Networks

ANFIS predicts relay quality and ranks nodes by combining multiple network parameters into a single utility score, helping select the most suitable relay. The suggested approach has employed a Hybrid Adaptive Neuro-Fuzzy Inference System (ANFIS) to enhance relay selection by combining the learning capability of Artificial Neural Networks (ANNs) with the reasoning mechanism of Fuzzy Inference Systems (FIS). Adoption of a first-order Sugeno-type Fuzzy Inference System where the input variables are residual energy, received signal strength indicator (RSSI), link quality indicator (LQI), distance to the coordinator, node temperature, queue length, transmission delay, and packet delivery ratio (PDR). These are first normalized using Min–Max normalization. Each input is fuzzified through Gaussian membership functions, and fuzzy IF–THEN rules are generated using either grid partitioning or subtractive clustering. The firing strengths of the activated rules are computed and normalized during the forward pass. While the subsequent metrics are estimated using Least Squares Estimation (LSE). In the backward pass, the premise parameters (membership function centres and widths) are iteratively updated using the Gradient Descent algorithm to minimize the prediction error. This hybrid learning strategy supports parallel refinement of both premise and consequent parameters. Accelerated convergence as well as improved prediction accuracy w.r.t conventional fuzzy logic systems. The trained ANFIS model accomplished for relay suitability score for each candidate node, which demonstrates its communication reliability, energy availability, and link quality under dynamic WBAN conditions. Relay selection has been incorporated using the current network state of each candidate relay. Four relay-specific characteristics are incorporated i.e. residual energy ((E)), RSSI, data rate ((DR)), and mobility ((M)). Relay appropriateness is estimated using the ANFIS model based on four input variables: residual energy, RSSI, data rate, and mobility. An input layer, membership-function layer, fuzzy-rule layer, consequent layers, and output layer made up the ANFIS architecture. While the fuzzy-rule layer has recorded nonlinear correlations among the relay-state characteristics, the membership functions have converted the numerical relay-state variables into fuzzy language representations. The final relay appropriateness score is then developed using the resulting parameters. The simulated relay-state observations are used to create the ANFIS training samples. The four input features and the matching relay suitability target are present in every sample. The Hybrid ANFIS model provides a self-regulating data-driven mechanism for intelligent relay prediction, thereby improving energy efficiency, packet delivery reliability, and network lifetime in IoHT. It finds Pareto-optimal relay combinations in addition to predicting promising relay candidates as:

$$(\text{Energy, RSSI, Delay, Throughput, Mobility}) \rightarrow \text{RelayUtility} \quad (16)$$

$$\text{MAX}(\text{PDR, Throughput, Energy}) \quad (17)$$

$$\text{MIN}(\text{Delay}) \quad (18)$$

4.2 NSGA-II performs, balancing energy, PDR, delay, and mobility to identify Pareto-optimal relay solutions

The Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is used to resolve the relay-selection problem, which is described as a four-objective optimisation problem. Five factors are taken into account when making decisions: mobility, RSSI, throughput, end-to-end delay, and residual energy.

It first generates initial population and relay selection criteria's as below:

$$S = \{s_1, s_2, s_3, \dots\} \quad (19)$$

$$X = [x_1, x_2, x_3, \dots, x_N] \quad (20)$$

$$x_i = \begin{cases} 1, & \text{node is selected as relay} \\ 0, & \text{otherwise} \end{cases} \quad (21)$$

Table.2 has provided the parameters of NSGA-II for multi-objective relay optimization. The relay-selection problem is formulated as a multi-objective optimization problem involving residual energy, end-to-end delay, throughput, and packet delivery ratio. In NSGA-II, solutions are first selected based on their Pareto rank, with lower rank indicating better solutions. When solutions have the same rank, crowding distance is used to prefer more diverse solutions.

Table.2 Selected NSGA-II Parameters and their typical values

NSGA-II Parameters	Typical Value
Population Size	50–100
Maximum Generations	100–200
Crossover	Simulated Binary Crossover (SBX)
Crossover Probability (Pc)	0.8–0.9
Mutation	Polynomial Mutation
Mutation Probability (Pm)	1/L (where L is chromosome length)
Selection Method	Binary Tournament
Ranking	Fast Non-dominated Sorting
Diversity Metric	Crowding Distance

This helps maintain a balanced set of relay configurations, considering objectives such as maximum lifetime and minimum delay.

The crowding distance of each intermediate solution is calculated using its neighbouring objective values and normalized objective range by:

$$CD_i = CD_i + \frac{f_m(i+1) - f_m(i-1)}{f_m^{max} - f_m^{min}} \quad (22)$$

This process is repeated for each objective to preserve solution diversity in NSGA-II.

The objective function in NSGA-II accumulates (i)Energy, ii) Network life time, iii) Minimizing delay, iv) Link quality

Residual energy of node i is given as:

$$\min f_1(X) = -\sum_{i=1}^N E_i \quad (23)$$

Maximizing Network life time is given as:

$$f_2(x) = \frac{1}{T_{life}} \quad (24)$$

Communication delay consisting of 'H' hops by:

$$D = \sum_{i=1}^H T_{tx} + T_{queue} \quad (25)$$

H: number of hops

$$\min f_3(x) = D(x) \quad (26)$$

Maximizing Packet delivery ratio by:

$$\min f_4(x) = 1/PDR \quad (27)$$

$$PDR = \frac{N_{Received}}{N_{sent}} \quad (28)$$

The relay selection fitness function in NSGA-II is developed by:

$$\text{Fitness} = ET * F_E + PT * F_P + AT * F_A + NT * F_N \quad (29)$$

It represents weights (importance factors) assigned to different criteria in a multi-criterion decision-making (MCDM) model as below:

$$\text{Fitness} = 0.40 * F_3 + 0.30 * F_P + 0.20 * F_A + 0.1 * F_N \quad (30)$$

In a WBAN relay selection or routing optimization problem, these weights indicate how much each parameter contributes to the final relay selection score. The sum of weights is: $ET+PT+AT+NT=0.40+0.30+0.20+0.10=1.0$. So, assign_slot () is deciding when a packet is transmitted, while NSGA-II decides through which relay the packet should travel.

The spreadfactor(β_q) is calculated as

$$\beta_q = \begin{cases} (2u)^{\frac{1}{nc}+1}, & u \leq 0.5 \\ 1/2(1-u)^{\frac{1}{nc}+1}, & u > 0.5 \end{cases} \quad (31)$$

u: random number

The generated offspring are:

$$c_1 = \frac{1}{2} [(x_i + y_i) - \beta_q(y_i - x_i)] \quad (32.i)$$

$$c_2 = \frac{1}{2} [(x_i + y_i) + \beta_q(y_i - x_i)] \quad (32.ii)$$

The crossover distribution index (η_c) controls exploration by:

$$\eta_c(\text{Crossover distribution index}) = \begin{cases} \text{Low, more exploration} \\ \text{High, offspring closer to parents} \end{cases} \quad (33)$$

The suitable metric result after NSGA-II simulation is given in Table.3. Together, they model both the MAC layer and the routing optimization in your WBAN simulation.

Table. 3: Optimized result obtained in NSGA-II simulation

SL-NO	Metric	Value
0	Best Utility	0.837418
1	Average Energy	0.933424
2	Average Delay	5.560047
3	Average Throughput	1174.703

In IoHT communication, different traffic types are assigned to appropriate access phases based on their priority and transmission requirements in Table.4. The `packet_delay(priority)` function is used to simulate the delay experienced by network packets based on their priority level. It takes the packet priority as an input and assigns a random delay value using `np. random. Uniform ()`. If the priority is "ET", the function generates a delay between 5 and 15 milliseconds, representing the highest priority traffic with the least delay.

Table.4: Priority traffic assignment to the packet

PRIORITY	ASSIGNED PHASE	DELAY
ET (Emergency Traffic)	EAP	5-15ms(Fastest)
PT(Periodic Traffic)	MAP	15-30ms
AT(Asynchronous Traffic)	RAP	30-60ms
NT(Normal Traffic)	CAP	50-120(Slowest)

So, network simulates the function where higher-priority packets experience lower delays, while lower-priority packets wait longer. The `packet_delay(priority)` function is used to simulate the delay experienced by network packets based on their priority level. It entails the packet priority as an input and assigns a random delay value using `np. random. uniform ()`. This function helps to emulate empirical system operations by introducing stochastic latency according to packet priority. `packet_delay(priority)` calculates a random packet delay based on the priority type of a packet.

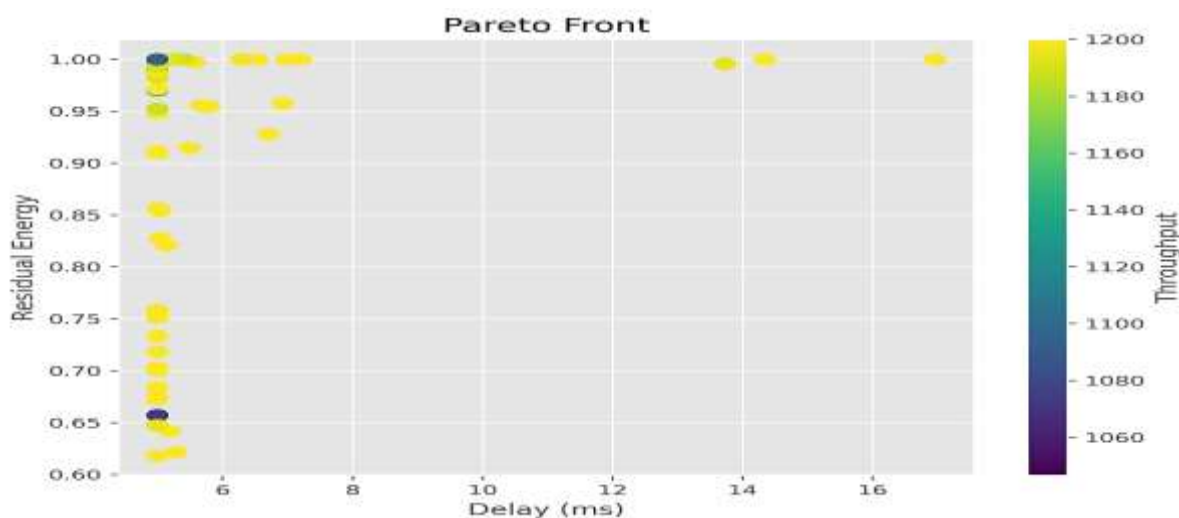


Figure.3: Trade-off between Delay and Residual Energy and Delay

This Pareto Front plot in Figure.3 find the trade-off between delay and residual Energy. The X-axis (Delay) represents communication delay in milliseconds i.e., lower delay is preferable. The Y-axis (Residual Energy) represents the remaining energy of sensor nodes; here, higher residual energy is better. Each dot represents a possible solution, while the colour indicates its throughput, with yellow indicating higher throughput. The Pareto-optimal solutions provide a balance between low delay, high residual energy, and high throughput. Discover the best relay in a MAC configuration without optimizing only one performance metric. it has attained low delay while maintaining high residual energy and high throughput. Thus, the Pareto-optimal counter balanced the parameters in an energy-efficient WBAN.

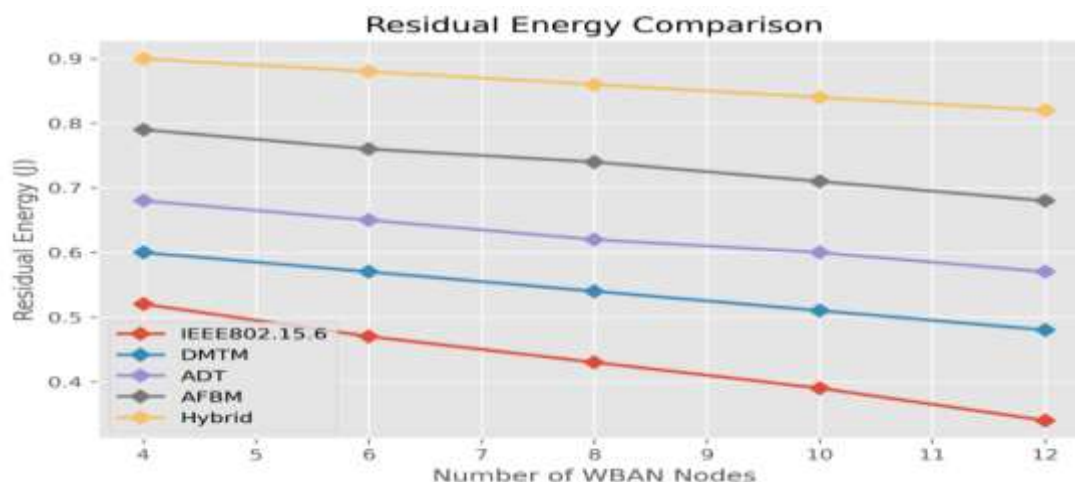


Figure.4: Residual Energy Comparison graph

Figure.4 has juxtaposed the remaining energy of WBAN nodes as the network size increases from 4 to 12 nodes for five approaches: IEEE 802.15.6, DMTM, ADT, AFBM, and the proposed Hybrid approach. A gradual diminishing effect of residual energy across all methods as the number of nodes increases, indicating that larger networks impose greater communication and forwarding demands. Among the explored strategies, the Hybrid method continually contends for the highest residual energy, declining from approximately 0.90 J at 4 nodes to 0.82 J at 12 nodes, demonstrating better energy conservation and scalability. AFBM and ADT [21] show intermediate performance, while DMTM [] preserves reduced reserves. IEEE 802.15.6 exhibits the fastest energy depletion, approaching roughly 0.34 J at 12 nodes. Overall, the results indicate that the Hybrid approach ensures maximized energy efficiency and system endurance.

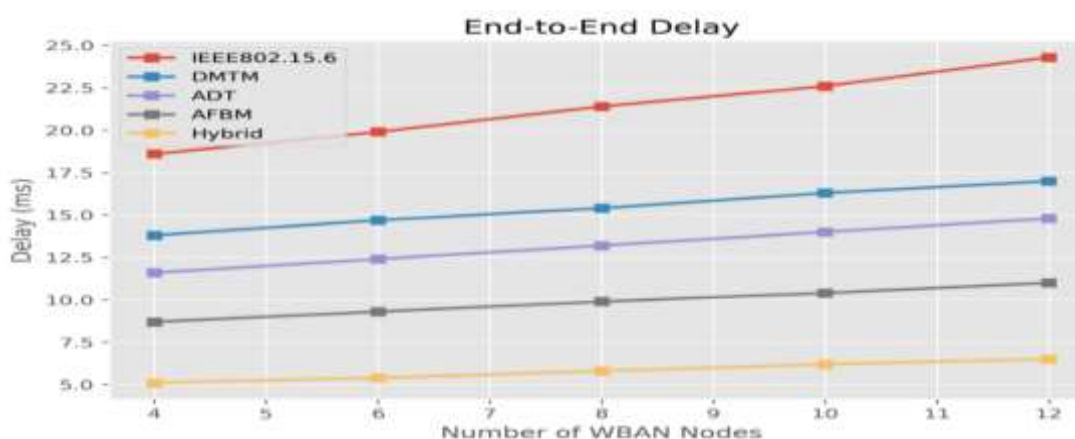


Figure.5 End-to-End Delay graph

Figure 5 provides a comparative analysis of communication latency of IEEE 802.15.6, DMTM, ADT, AFBM, and the proposed Hybrid Model at different number of WBAN nodes in the range from 4 to 12. The simulation results show that the end-to-end delay increases as the number of nodes increases, because of the increased level of contention for the channel, packet-forwarding tasks, processing overhead, and communication distance involved. However, it can be noted that the Hybrid Model approach provides the lowest latency, from about 5.1 ms for 4 nodes to 6.4 ms for 12 nodes. Whereas AFBM experiences an increase of around 8.7 ms to 11.0 ms, ADT's level also increases from 11.6 ms to 14.8 ms and DMTM from 13.8 to 17.0 ms. IEEE 802.15.6 shows the worst latency properties, which increases from approximately 18.6 ms to 24.3 ms. Thus, the Hybrid Model has been proven to help overcome the issue of high latency under the condition of growing network density. Advanced low latency capability of the proposed Hybrid Model solution can improve the level of communication efficiency in WBAN communication while also making this approach a good fit for different delay-sensitive applications requiring timely and reliable transmission of crucial physiological information.

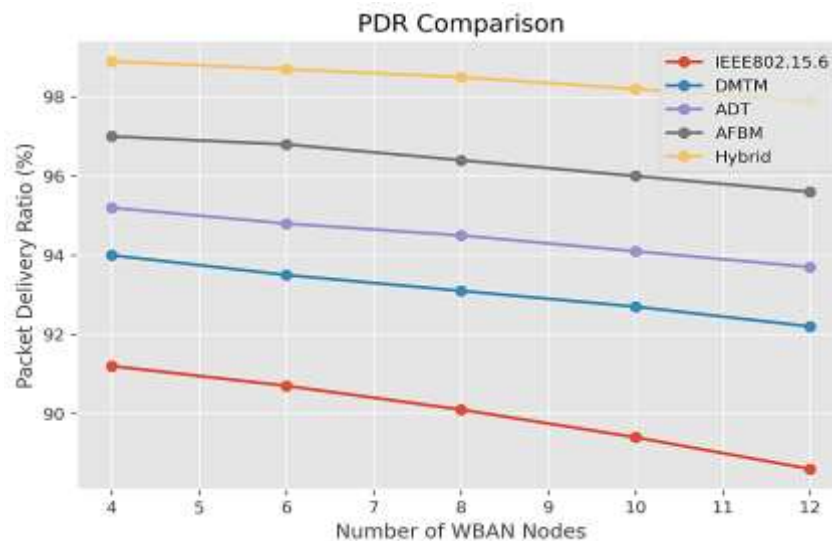


Figure.6: PDR comparison graph

In Figure. 6, a comparative study of Packet Delivery Ratio (PDR) achieved by five WBAN communication technologies is displayed. These approaches are IEEE 802.15.6, DMTM, ADT, AFBM, and the Hybrid proposed method. From the results, it is clear that, for all methods, the PDR drops gradually as more nodes of the network are added. The decline in the PDR is attributable to increased packet transmission rate and other interference due to more nodes joining the network. Despite these setbacks, the hybrid proposed method produces the best PDR results (98.9% with 4 nodes, and 97.9% with 12 nodes). The only reduction in this innovative method proves that it is capable of ensuring the maximum number of transmitted packets during the process. AFBM is the second choice in PDR according to the results of PDR achieved (with it going down from about 97.0% to 95.6%). Next is ADT, with its PDR rate going down from about 95.2% to 93.7%. From the data provided it is very clear that PDR is further reduced in DMTM technology, with its PDR going from about 94.0% to 92.2%. The IEEE802.15.6 has the lowest PDR of about 91.2% at 4 nodes then 88.6% at 12 nodes.

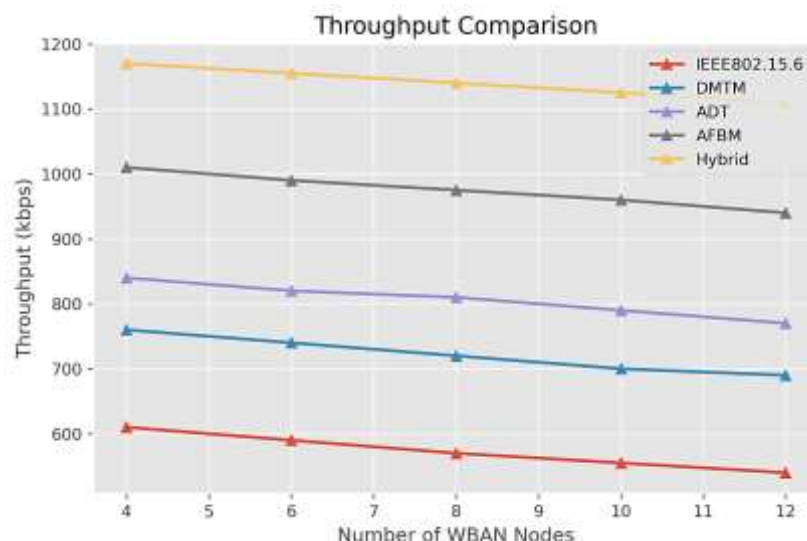


Figure.7: Throughput comparison graph

The graph in Figure. 7 depicts the performance of throughput of WBAN procedures as the quantity of node rises in the network. It is observed that all techniques eventually show reduced throughput with the increase in number of nodes and therefore increasing traffic, congestion and contention of channel. Various methods yield average throughput performance in the order of Hybrid technique, AFBM, ADT, DMTM, and IEEE 802.15.6. Hybrid method achieves a better throughput than

all other methods due to better channel usage, lesser communication overhead and effective data transmission procedure. Thus, the authors prove that Hybrid method is capable of sustaining good performance for various type of WBAN while maintaining efficient data processing

4.3 Shapiro–Wilk test

The paradigm of normal distribution of the testing data collected for the five protocols was checked using the Shapiro–Wilk test. The statistical measure for the IEEE 802.15.6 protocol was 0.9751, while the p-values of ADT, DMTM, AFBM, and the proposed Hybrid were 0.9130, 0.3654, 0.1565, and 0.2481, respectively. The results that yielded p-values higher than the significance level of 0.05 means that the null hypothesis of normality can be accepted for every protocol tested. This means that the measurements obtained for the protocols do not have a statistically significant tendency to deviate from the normal distribution. Therefore, parametric methods of statistical data processing can be used, which means that it will be possible to conduct mean comparison tests and calculate confidence intervals, assuming that the other necessary conditions for using such methods shall be met. It is also necessary to prove the appropriateness of the parametric methods for processing the data based on the independence of observations and other required parameters of variance and design for the experiment

Table.5: Comparison result

Protocol	PDR	Delay	Throughput	Energy
0 IEEE802.15.6	90.00	21.36	573.0	0.430
1 DMTM	93.10	15.44	722.0	0.540
2 ADT	94.46	13.20	806.0	0.624
3 AFBM	96.36	9.86	975.0	0.736
4 Hybrid	98.44	5.80	1140.0	0.860

According to the comparative results shown in Table 5, the Hybrid approach outperforms other protocols, namely IEEE 802.15.6, DMTM, ADT, and AFBM, in all the four main metrics of WBAN performance. In particular, the Hybrid method achieves the highest value of PDR (98.44%), which indicates the robustness of this method in terms of data delivery. Moreover, the Hybrid method records the least end-to-end delay (5.80 ms) that is of crucial importance for time-sensitive medical communication. In addition to that, the Hybrid method achieves the highest throughput (1140 kbps), which indicates that it performs better in terms of network capacity than IEEE 802.15.6 (573 kbps) and AFBM (975 kbps). It is also worth mentioning that the Hybrid method has the largest value of remaining energy (0.860 J), which means that it provides higher efficiency in terms of energy consumption. In contrast, IEEE 802.15.6 exhibits the lowest PDR (90.00%), highest end-to-end delay (21.36 ms), lowest throughput (573 kbps), and lowest remaining energy (0.430 J). Thus, the results of the comparison prove that the developed method provides the aforementioned advantages, which make it a handy tool for medical purposes.

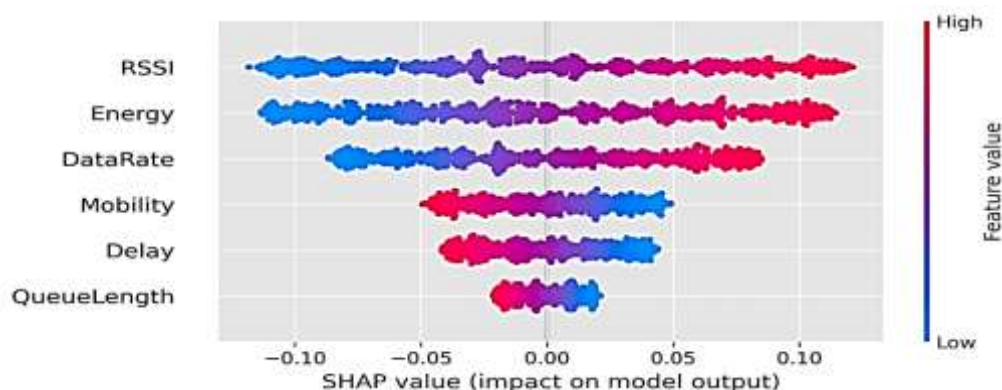


Figure.8: SHAP summary plot

According to Figure. 8 SHAP summary plot, the impact of six input variables which are RSSI, residual energy, data rate, mobility, delay, and queue length on the proposed model's relay-selection predictions is shown. The dimension of x-axis is used to illustrate the direction and the size of the effects of each variable on the prediction made by the model. Positive values of SHAP imply that the variable has a positive effect on the variable, while negative values of SHAP imply that the variable has a negative effect. The ANFIS-based relay-suitability prediction is explained in an understandable manner using SHAP. The estimated relay appropriateness score for each relay instance is broken down by SHAP into baseline and feature-specific contributions. The variable's values are represented by a colour gradient where blue shows low values and pink shows high values. Out of six variables RSSI and residual energy have the biggest SHAP-value ranges indicating that these variables play a key role in determining the results of relay-selection. In fact, high values of both RSSI and residual energy have positive SHAP values meaning that a better quality of connection and more available energy makes the selected node to do the relay function properly. In addition, the value of data rate indicates that this factor is also very important for effective and reliable data transmission

On the other hand, the relationship between mobility and delay is characterized by the notion of the negative SHAP values associated with the higher values of these parameters indicating the reduction in relay suitability due to adverse effects of high mobility and communication delay in terms of link stability and information delivery problems. Queue length has the narrowest distribution of the SHAP values indicating the smallest influence of this variable in the predictions made by the model overall. Thus, the SHAP analysis shows that the model is mainly based on RSSI, residual energy and data rate while considering mobility, delay and queue length variables. The feature-level interpretation contributes to making the decision-making process more transparent and shows the ability of the model to make the efficient and comprehensible decisions on relay selection in the changing IoHT conditions. The ablation analysis is employed to identify if the NSGA-II multi-objective optimisation, the ANFIS-based relay prediction, or both are responsible for the performance benefits. The statistical test chosen based on the distribution and pairing of the experimental observations is used to compare the suggested framework with the baseline and ablated configurations in order to determine statistical significance. A statistically significant difference is indicated by ($p < 0.05$), and a significance level of ($\alpha = 0.05$) is used.

Table.6: Ablation Report

Method	MEAN	Std	Improvement (%)	PDR	Throughput	Energy	Delay
AFBM	97.03415	0.315002	0	96.36	975	0.736	9.86
ANFIS Only	97.86365	0.279331	0.854856	NA	NA	NA	NA
Optimization Only	98.20361	0.277755	1.205204	NA	NA	NA	NA
Hybrid (ANFIS+MOO)	99.09636	0.163588	2.125238	98.44	1140	0.86	5.8

The Hybrid approach in Table.6 demonstrates superior overall performance, achieving higher PDR, throughput, and energy efficiency while maintaining lower delay. This indicates that the proposed Hybrid method provides a better balance between reliability, efficiency, and communication performance.

CONCLUSION

This research put forward an Explainable Hybrid ANFIS-Based Relay Selection Framework that expands the traditional AFBM protocol through three vital upgradations in order to surpass these constraints. To begin with, a learning-based Hybrid ANFIS model has adjusted relay-selection decisions from multidimensional network properties. Secondly, with the intention of Pareto-optimal relay-selection strategies, NSGA-II concurrently optimizes end-to-end delay, packet delivery ratio, residual energy and throughput. In order to give a white box view of relay-selection decisions and rigorous evaluation of the contribution of each suggested component, SHAP-based explainability is finally integrated with ablation analysis and statistical significance testing. Together, these improvements create a relay-selection framework for next-generation IEEE 802.15.6 WBAN-enabled healthcare systems that is more flexible, comprehensible, and high-performing. By keeping distinct transmission queues based on packet significance, the Priority-Based Packet Balanced Queue MAC (PBQ-MAC) protocol gives priority to emergency medical packets over periodic and on-demand traffic. Relay-assisted communication is not included, which limits communication dependability under unfavourable channel conditions, even if this method lowers the transmission latency of crucial physiological information.

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AUTHOR CONTRIBUTIONS

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Tusharkanta Samal: Supervision, Conceptualization.

Nayan Ranjan Samal: Investigation, Review & Editing.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

Ethical approval was not required for this study.

DATA AVAILABILITY STATEMENT

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

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