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Decision Tree-based Dynamic Slot Allocation for Emergency and Normal Traffic in WBAN MAC Protocols

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A B S T R A C T

In healthcare monitoring, where effective Medium Access Control (MAC) protocols are required to handle both periodic and emergency traffic, Wireless Body Area Networks (WBANs) are becoming increasingly significant. Conventional slot allocation techniques often lack adaptability to changing network conditions, which results in increased energy usage, longer wait times, and decreased dependability. To overcome these constraints, this study suggests a dynamic slot allocation mechanism for WBAN MAC protocols based on a Decision Tree. The Decision Tree Traffic Adaptive MAC (DTTA-MAC) approach allocates time slots according to real-time node conditions, ensuring that emergency traffic is prioritized while maintaining stable performance for normal traffic. A dataset was generated using Castalia and OmNeT++ to simulate realistic WBAN scenarios, incorporating parameters such as energy levels, latency, buffer size, throughput, and signal quality. Simulation results show that the proposed DTTA-MAC achieves up to approximately 34% reduction in energy consumption and about 89% reduction in average packet delay compared to existing MAC protocols, particularly under emergency traffic conditions. This work provides a portable and interpretable substitute for Reinforcement Learning (RL) techniques. To support real-world healthcare applications, future research will investigate expanding the model to larger networks, integrating it with cutting-edge machine learning techniques, and bolstering security and privacy.

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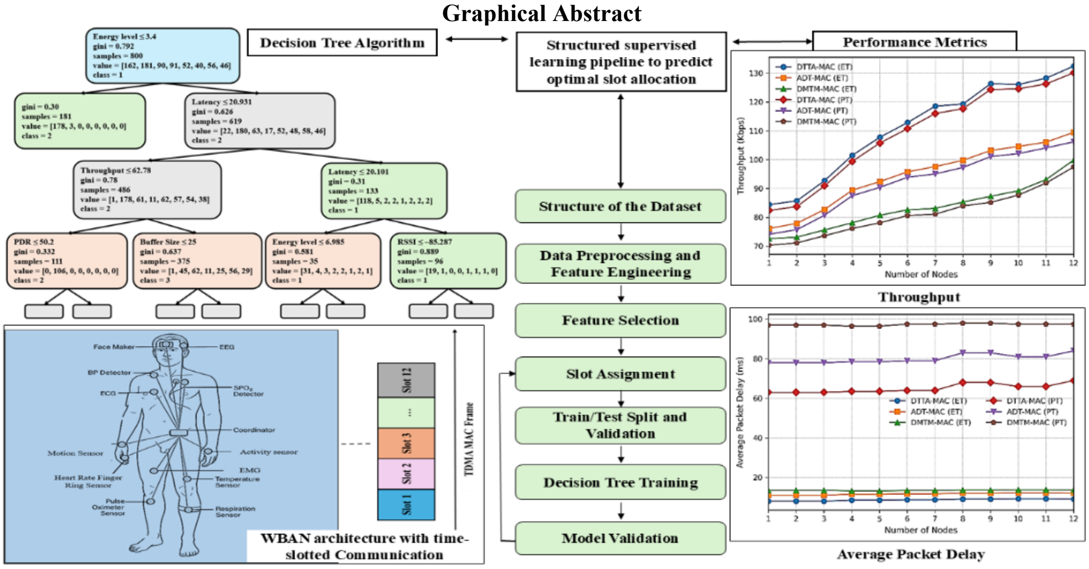
Graphical Abstract



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1. INTRODUCTION

Wireless Body Area Networks (WBANs) allow for continuous and real-time tracking of physiological parameters like heart rate, body temperature, and glucose levels, which have become increasingly important for healthcare monitoring (1). These networks, which form the foundation of contemporary fitness, medical, and remote health monitoring applications, consist of small, low-power sensor nodes that are either worn or implanted in the human body. Effective communication protocols, however, face considerable obstacles due to the dynamic nature of WBAN environments, which are marked by shifting traffic patterns, variable channel quality, and constrained energy resources (2). Medium Access Control (MAC), one of these protocols, is crucial for regulating how sensor nodes utilize the shared wireless channel.

In Time Division Multiple Access (TDMA)-based MAC protocols, conventional slot allocation techniques frequently depend on static or pre-scheduled approaches that are unable to dynamically adjust to shifting network conditions. The performance of health monitoring systems is hampered by this inefficiency, which also results in higher latency, excessive energy consumption, and decreased reliability (3). Researchers have investigated dynamic slot allocation strategies using Machine Learning (ML) techniques, such as Reinforcement Learning (RL) methods like Q-learning, to overcome these constraints (4).

A dynamic slot allocation mechanism based on a Decision Tree (DT) that is specifically designed for WBAN MAC protocols is presented in this paper. Our method prioritises important emergency traffic while preserving peak performance for regular traffic by intelligently allocating time slots based on real-time node conditions. We used Castalia and OMNeT++ to create a realistic synthetic dataset that simulated important network metrics like energy levels, latency, buffer size, throughput, Packet Delivery Ratio (PDR), and Received Signal Strength (RSSI) to train and assess the design. When compared to static allocation techniques, experimental results show that the DT model significantly improves slot utilisation, lowers latency, and increases energy efficiency while achieving high accuracy in predicting optimal slot allocations.

Our method seeks to offer a precise and computationally effective slot scheduling system that is simple to implement, train, and interpret on WBAN nodes. The model learns offline from labelled data and can be deployed to assign slots in real-time based on emergency and traffic conditions of the network. Experimental results demonstrate that the proposed method enables effective scheduling decisions that strike a balance among latency, energy efficiency, and throughput. This work advances the state of the art by proposing a lightweight, interpretable DT-based scheduling approach that enables dynamic TDMA slot allocation for both emergency and regular traffic without imposing high computational or energy costs, in contrast to existing heuristic and ML-based MAC protocols for WBANs. The key contributions of this paper are as follows:

i. Using a DT algorithm and framing it as a supervised classification problem, we suggest a novel method for dynamic slot allocation in WBAN MAC protocols.
ii. We generate a realistic synthetic dataset using network metrics such as energy consumption, latency, throughput, buffer size, and RSSI from Castalia and OMNeT++ to train and evaluate the ML model.
iii. We show that the suggested model is highly accurate in slot assignments, which makes it a good fit for WBAN systems with energy and delay constraints.
iv. By presenting a transparent and effective DT-based scheduling framework that simultaneously provides emergency prioritization, dynamic slot allocation, and interpretable feature analysis, capabilities not collectively addressed in prior heuristic-based MAC protocols, this work expands the current WBAN MAC literature.

2. RELATED WORK

Effective MAC protocols are essential to guaranteeing timely, dependable, and energy-efficient data transmission, given their limitations, which include limited energy, bandwidth, and computational capabilities (5).

To increase network lifetime and boost reliability in wireless sensor and Internet of Things-based (IoT) networks, recent research has also highlighted the significance of adaptive optimization and priority-aware methods (6–8).

For WBANs, many MAC protocols have been developed with an emphasis on maximizing channel utilisation, reducing latency, and improving energy efficiency. Protocols based on TDMA, like MedMAC (9), H-MAC (10), and Body-MAC (B-MAC) (11), are prevalent because of their energy-conscious scheduling and lack of collisions. Despite these benefits, static or semi-static slot allocation mechanisms are frequently used in traditional TDMA protocols, which can be ineffective in dynamic network conditions like changing traffic loads or fluctuating channel quality (12, 13).

On the other hand, the suggested DTTA-MAC uses a DT to introduce dynamic, data-driven slot assignment while operating within the IEEE 802.15.6 scheduled-access framework. DTTA-MAC regularly reassesses node conditions to more efficiently prioritize emergencies and high-urgency traffic, in contrast to MedMAC, which depends on set schedules and guard-band optimization, and TA-MAC, which adapts using predefined traffic thresholds.

Adaptive capabilities have been incorporated into advancements to overcome these limitations. A-MAC (14) and TA-MAC (15), for example, are traffic-aware protocols that use sleep-listen cycles according to network activity levels. In a similar vein, emergency-aware protocols dynamically modify resource allocation to prioritise critical traffic (16). Although these methods increase adaptability, they frequently depend on strict adaptation mechanisms and predetermined thresholds, which are insufficient for highly dynamic environments like WBANs. Priority-aware and adaptive optimization techniques have been developed to overcome static scheduling and enhance network lifetime and QoS in heterogeneous IoT and wireless sensor networks, where similar restrictions have been found (8).

ML algorithms have recently addressed the drawbacks of static or heuristic-based slot allocation. A significant amount of research has been conducted on utilising RL, particularly Q-learning, to develop adaptive slot assignment algorithms. By using environmental feedback, these techniques allow nodes to learn the best policies gradually (17,18). However, RL-based methods have serious shortcomings, such as poor interpretability, slow convergence, and high computational overhead, which are especially troublesome in WBANs with limited resources (19).

Thus, lightweight and comprehensible models for real-time traffic prediction and scheduling in adaptive networks have been investigated in recent AI-based research, demonstrating the applicability of low-complexity learning techniques for time-sensitive applications (20).

Actor-Critic and Deep Q-learning techniques have also been studied. However, because of their intricacy, dependence on massive datasets, and lengthy training periods, their applicability to WBANs is still restricted (21, 22).

Although IEEE 802.15.6, MedMAC, and TA-MAC increase collision avoidance and energy efficiency, they primarily rely on manually adjusted adaptation rules or static scheduling. By using supervised learning to produce quick, comprehensible slot-allocation decisions that automatically adjust to traffic dynamics without requiring extra control overhead, the suggested DTTA-MAC sets itself apart.

The suggested DTTA-MAC uses a simplified and transparent decision tree to dynamically assign TDMA slots based on real-time node conditions, making it more suitable for resource-constrained WBAN environments than heuristic-based MAC protocols, which use static thresholds and pre-defined rules, and machine learning-based approaches, which make use of complex reinforcement or deep learning models. The proposed DTTA-MAC improves on previous research by combining data-driven adaptability with low-complexity decision tree inference optimized for resource-constrained WBAN environments, in contrast to the reviewed approaches that either rely on static heuristic rules or computationally demanding learning models. The trends and drawbacks of current MAC protocols are compiled in Table 1.

3. SYSTEM MODEL AND PROBLEM FORMULATION

3. 1. System Model A typical WBAN consists of 12 sensor nodes and a coordinator placed on or inside the human body to monitor physiological signals. Sensor nodes communicate wirelessly with the coordinator (sink), which aggregates the collected data and forwards it to external systems for analysis.

In this work, we consider a TDMA-based MAC protocol in which time is divided into a superframe, each containing a finite number of transmission slots. Specifically, 8 data transmission slots are available per superframe. When the number of active sensor nodes exceeds the available slots, nodes are scheduled according to their priority, and lower-priority nodes are deferred to subsequent superframes. Figure 1 illustrates a typical WBAN architecture with time-slotted communication, showing multiple sensor nodes assigned to different slots within a TDMA MAC frame.

3. 2. Node Parameters and Communication Context In the DT-based slot-assignment paradigm, each sensor node is identified by a collection of characteristics that function as decision attributes. To categorize nodes based on their transmission priority and slot allocation requirements, the DT recursively assesses these characteristics. Key elements of network operation, such as traffic urgency, link quality, energy efficiency, latency requirements, and communication reliability, are reflected in the parameters that have been chosen.

The DT reevaluates and updates the node settings in real time at each TDMA superframe. Affected nodes are routed through higher-priority branches of the tree and given earlier transmission slots without the need for model retraining due to sudden spikes in emergency traffic, which quickly show up as increased buffer size and latency.

At the upper levels of the DT, attributes such as buffer size (B_i) and delay (L_i) are employed to differentiate nodes with urgent transmission requirements from those with lower priority. The intermediate nodes of the tree then incorporate the received signal strength indicator (R_i) and packet delivery ratio (P_i) to evaluate link quality and communication reliability, thereby ensuring that time

TABLE 1. Summary of MAC Protocols and Their Trend

MAC	Ref	Channel Access			IEEE Technology	Traffic Type	Networks Performance	Method	Used ML	ML-Type	ML-Model
		Scheduled	Contention	Polling							
PA-MAC	(23)	√	√	-	IEEE 802.15.4	Emergency, on-demand,	Improved	Network Simulator	No	-	-
DSA-NOVA	(24)	-	√	-	IEEE 802.15.6	UP(0) – UP(7)	Improved	Numerical Analysis	No	-	-
DSBS, DSBB	(25)	√	-	-	IEEE 802.15.6	Normal and emergency	Improved	Network Simulator	No	-	-
DSS	(26)	√	-	-	IEEE 802.15.6	Normal and emergency	Improved	Network Simulator	No	-	-
DMTM-MAC	(27)	√	√	√	IEEE 802.15.6	Periodic, urgent, and on-demand	Improved	Network Simulator	No	-	-
TCA	(28)	√	-	-	IEEE 802.15.6	1 and 0	Improved	Network Simulator	No	-	-
McMAC	(29)	√	√	√	IEEE 802.15.4	Type 0 – Type 4	Improved	Network Simulator	No	-	-
DDSA	(30)	√	-	-	IEEE 802.15.6	Critical and non-critical	Improved	Network Simulator	No	-	-
TA-IEEE 802.15.6	(31)	-	√	-	IEEE 802.15.6	UP(0) – UP(7)	Improved	Numerical Analysis	No	-	-
A-MAC	(14)	√	√	-	IEEE 802.15.6	Emergency, periodic	Improved	MATLAB	No	-	-
TA-MAC	(15)	√	√	-	IEEE 802.15.4	Emergency, on-demand,	Improved	Network Simulator	No	-	-
ADT-MAC	(16)	√	√	√	IEEE 802.15.6	Emergency Periodic	Improved	Network Simulator	No	-	-
QL-MAC	(17)	√	√	√	IEEE 802.15.6	Normal and emergency	Improved	Network Simulator	Yes	Reinforcement Learning	Q-learning
Propose DTTA-MAC	-	√	√	√	IEEE 802.15.6	Normal and emergency	Improved	Network Simulator	Yes	Supervised Learning	Decision Tree

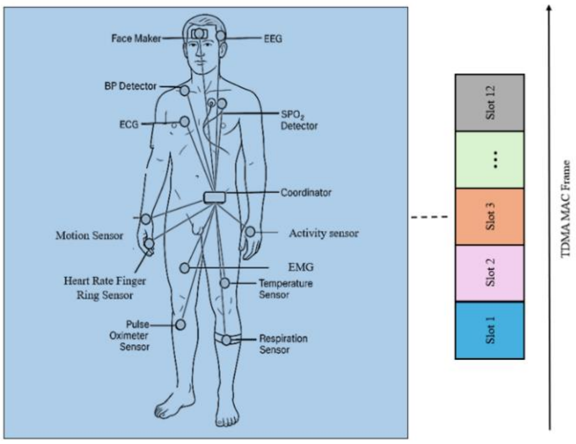

Figure 1. Typical WBAN architecture with time-slotted Communication, Illustration of a WBAN with multiple sensor nodes assigned different slots in a TDMA MAC frame

slots are preferentially allocated to nodes with more stable links. To support energy-aware scheduling, the energy level (E_i) is also considered, preventing disproportionate resource allocation to nodes with critically low residual energy. At the leaf level, throughput (T_i) is finally used to refine the scheduling decision by selecting nodes that can make efficient use of the assigned transmission opportunity. The parameters used as decision attributes in the DT are summarised in Table 2.

By structuring the decision-making process as a DT, the model provides interpretable, low-complexity, and adaptive slot allocation, making it well-suited for resource-constrained sensor networks.

3. 3. Decision Tree Slot Assignment The goal is to assign each node dynamically n_i to a time slot $S_i \in \{1,2,\ldots,N_s\}$, where N_s is the total number of available

TABLE 1. Node parameters used as DT attributes

Parameters	Symbols	Description
Node ID	n_i	Unique identifier of the sensor node
Buffer size	B_i	Number of queued packets, used to assess traffic load and urgency
RSSI	R_i	Measures the received signal strength (dBm), ensuring reliable communication.
Energy level	E_i	Captures the remaining energy of the node to ensure energy-efficient scheduling.
Delay	L_i	Time since last successful upload (ms), indicating latency constraints
Throughput	T_i	Estimated achievable data rate (kbps), used to optimise slot utilization
PDR	P_i	Packet Delivery Ratio (%), reflecting communication reliability

slots in a TDMA MAC frame. In our experiments, only 8 of the 30 slots defined by the standard frame are used for data transmission, requiring the DT to allocate them among competing nodes dynamically. Control and sleep times occupy the remaining slots. This configuration demonstrates how DTTA-MAC handles conflict and prioritization when resources are limited. This priority is accomplished using quick, deterministic DT inference, which avoids iterative learning, intricate optimization, or manually adjusted scheduling rules, in contrast to previous heuristic or RL-based MAC protocols. The DT itself is trained using the entire feature set, allowing metrics like PDR and RSSI to affect slot allocation decisions, especially at deeper tree levels, even if the heuristic rules in Table 3 and Equation (1) are only employed to generate initial training labels. Heuristic rules are applied to generate labels for the generated dataset based on predefined network conditions. These rules are designed to offer coarse-grained, comprehensible labels for supervised learning rather than to fully capture all choice qualities.

However, the objective of this study is to develop a slot allocation strategy that simultaneously fulfils four critical performance goals for WBANs. First, it must minimise end-to-end latency, so time-sensitive Second, it should balance energy consumption across sensor nodes, extending overall network lifetime and avoiding premature battery depletion in any single device. Third, the algorithm seeks to maximise aggregate throughput and improve the PDR efficiently even under heavy traffic loads. In real-world WBANs, node states vary dynamically and unpredictably due to movement, health status, or interference. Rule-based systems are frequently overly inflexible or difficult to adjust. Although Q-learning enables dynamic adaptability, it is complex and challenging to interpret. In contrast, DT provides fast inference time, simple, understandable rules, and interoperability with low-power devices.

Because slot assignments are recomputed at each superframe using lightweight threshold comparisons, the model responds quickly to abrupt traffic changes while avoiding scheduling oscillations or instability.

The general process for training the DT and dynamically allocating slots to sensor nodes is summed up in Algorithm 1. DTTA-MAC uses deterministic priority-based conflict resolution instead of contention-based backoff in situations where there are more sensor nodes than TDMA slots available, guaranteeing stable network operation and predictable latency.

TABLE 2. Heuristic rules are used to label the DTTA-MAC dataset with optimal slots

Condition	Assigned Slot
E_i<0.4 or L_i>250ms	1 (urgent)
T_i<80 kbps, or B_i>7	2
R_i < −80 dB+ m	3
E_i>0.8 and T_i>150 kbps	4
E_i>0.8 and P_i>80%	5
Otherwise (balanced state)	Random from 6–8

4. METHODOLOGY

The simulation considers a patient who is outfitted with a variety of sensor devices, including an physiological

Algorithm 1. DecisionTreeSlotAssignment(Nodes, N_s)

Input: Nodes = {n_1, n_2, ..., N_n}, N_s (total slots)
Output: Slot assignments S = {S_1, S_2, ..., S_N},
Step 1: Generate Dataset
For each node n_i in Nodes:
Generate feature vector $X_i = [n_i, B_i, E_i, L_i, T_i, P_i]$
Label S_i using heuristic rules (Table 3)
Split the dataset into Training (80%) and Testing (20%)
Step 2: Train Decision Tree Classifier
Train DecisionTreeClassifier on the Training dataset
Optimise hyperparameters (max_depth = 3)
Step 3: Assign Slots Dynamically
Initialize δ[i][j] = 0 for all i, j
For each node n_i in Nodes:
Extract feature vector X_i
Predict optimal slot S_i = DecisionTreeClassifier.predict(X_i)
Assign δ[i] [S_i] = 1
Apply Constraints:
For each node i:
Ensure ∑_{j=1} ^ {N_s} δ[i][j] = 1
For each slot j:
Ensure ∑_{i=1} ^ {N} δ[i][j] ≤ 1
If multiple sensor nodes are assigned to the same slot, insert those nodes into a priority queue ordered according to the DT output (emergency status, latency, buffer size, and residual energy).
Step 4: Evaluate Performance
Compute classification accuracy, macro F1-score, and confusion matrix
Measure latency, energy consumption, throughput, and PDR
Return Slot assignments S

data reaches the coordinator without delay. electrocardiogram (ECG), motion sensor, blood pressure, skin temperature, and pulse oximeter (SPO_2). The WBAN is set up with a coordinator, and a point-to-multipoint (star) network topology is used for communication between the coordinator and the sensors. Therefore, a single-hop communication architecture is used between the coordinator and WBAN sensor nodes. The coordinator also assigns time slots, exchanges control messages, and synchronises with nearby WBAN sensor nodes. The sensor nodes oversee detecting and communicating the gathered data to the coordinator.

The coordinator is believed to have an external power source with greater processing power and receives data from the sensor nodes. It then uses wired connections, cellular networks, or Wireless Local Area Networks (WLANs) to transmit the received data to a server or monitoring station. This work does not, however, address this communication paradigm.

4. 1. Simulation Setup At the start of the simulation, the WBAN operates under periodic conditions, where sensor nodes follow a Constant Bit Rate (CBR) traffic model. Each sensor node selects a traffic rate between 1 to 20 p/s based on priority levels, with a fixed inter-arrival time. The emergency scenario is simulated in two different periods. The first period lasts 50s, from 50 to 100s, where the inter-arrival time follows an exponential distribution with a mean of 0.02 and a traffic rate of 50 p/s. The second period spans 100 s, from 150 to 250s, during which the inter-arrival time follows an exponential distribution with a mean of 0.0125 and a traffic rate of 80 p/s. In both periods, two nodes (Node 1 and Node 2) are designated to simulate the emergency condition. Changes in node-level state variables, such as greater buffer occupancy, decreased latency tolerance, higher throughput demand, and bursty traffic arrival patterns, are used to implicitly express emergency conditions rather than explicitly encoding them as a binary label. Without the need for a specific emergency flag, these feature changes enable the decision tree to differentiate between regular periodic traffic and emergency traffic.

We made several simulation scenarios by altering the node densities. During each simulation run, we recorded key performance metrics. To ensure consistency and completeness, we enhanced Castalia's logging capabilities to output this data at predefined intervals. Ground truth slot labels were created using a deterministic slot assignment method integrated into the MAC layer, which enforced collision-free scheduling and fairness restrictions. The simulation results were then combined into a structured dataset in CSV format, forming a diverse and realistic foundation for training a supervised learning model to predict appropriate time slot allocations in WBANs. The latency, energy consumption, throughput, and PDR values included in this dataset are obtained directly from a Castalia-based WBAN simulation testbed that models the single-patient, single-hop TDMA scenario described above. All simulations were conducted over a duration of 300s with 12 sensor nodes and 1 coordinator using periodic CBR traffic for normal conditions and bursty exponential traffic models for emergency scenarios. Table 4 shows the details of the simulation parameters used.

The raw data was cleaned, normalized, and supplemented with engineered features such as queue-weighted traffic intensity and distance-weighted LQI before training. A reduced set of predictors was generated using a two-stage feature selection procedure (filtering by mutual information and recursive elimination), which reduced complexity and improved efficiency. The dataset was split 80% for training and 20% for testing to evaluate the performance of the proposed DTTA-MAC scheme. Accuracy, macro-averaged F1, latency, and energy consumption were used to evaluate the model's performance and ensure it complied with both WBAN power restrictions and classification quality. Likewise, the macro-averaged F1-score is specifically used to reduce bias toward majority (normal traffic) patterns and to ensure robust performance under emergency traffic conditions. The tree learns prioritization boundaries directly from traffic dynamics because emergency behaviour is encoded through feature patterns rather than explicit labels. The model is trained on a variety of feature sets, pruned to a limited depth to reduce the risk of misclassification, and assessed using latency-sensitive metrics and the macro-averaged F1-score to ensure that typical traffic does not overshadow emergency-like cases.

Because emergency events happen less frequently than typical physiological monitoring traffic, the resulting dataset is organically unbalanced and reflects realistic WBAN operation. While normal traffic samples

TABLE 3. Simulation parameters (16, 17)

Parameters	Value
Slot Size	10 ms
Simulation Time	300s
Number of Nodes	12 and 1 coordinator
Frequency Band	2.4 GHz
Payload	105 bytes
Transmissions Rate	1,024 kbps
Superframe Length	32 slots
Transmission Power	-10 dBm
Traffic Rate for Periodic Traffic	1-20 packets/sec
Traffic Rate for Emergency Traffic	50-100 packets/sec

are continually gathered during the simulation, emergency traffic samples are only created during the predetermined emergency times and are restricted to two specific nodes. As a result, most of the dataset is made up of regular traffic, with emergency traffic making up a tiny but crucial minority class. The DT's impurity-based splitting further lessens sensitivity to class imbalance, and model performance is assessed using macro-averaged metrics to ensure equal weighting of both classes. The tree was exported as lightweight if-else rules for real-time deployment on the network coordinator after surpassing the round-robin and signal-strength baselines. For all experiments reported in this study, a single and consistent dataset partition of 80% training and 20% testing was used. The end-to-end supervised learning pipeline for the best slot allocation is shown in Figure 2.

4. 2. Structure of the Dataset

The input and output features used in the suggested DTTA-MAC scheme dataset are compiled in Table 5. A crucial component of a WBAN sensor node that affects the scheduling choice is captured by each feature. Each node is uniquely identified by its Node ID, which has values between 1 and 12, corresponding to the average number of sensors used in activity monitoring or healthcare settings. The buffer size represents the number of packets queued in the local memory of the node. Since WBAN devices have limited memory and numerous studies report buffer sizes of less than ten packets, a maximum of 9 packets is assumed. To represent realistic signal levels in on-body communication, the RSSI ranges from -90 dBm to -50 dBm. Values lower than -90 dBm are regarded as unreliable, while values higher than -50 dBm are rare.

The normalised units of the energy level range from 0.2 to 1.0 J, where 1.0 J indicates a fully charged state and 0.2 J indicates a low-energy threshold below which nodes are generally considered non-operational. Both the lower bounds in light traffic and the upper bounds reflecting congestion or retransmission in WBAN environments are represented by modelling latency in the 50-300 ms range. Similarly, throughput is defined as 50 kbps to 200 kbps, which corresponds to the data rates supported by the IEEE 802.15.6 standards. Instead of being expressed in kbps, the PDR should be correctly expressed as the percentage of packets successfully delivered, with a range from 0 to 1. All PDR values used in dataset generation, and heuristic labelling are strictly bound within the range of 0-100%, and no values exceeding this range were used during model training or evaluation.

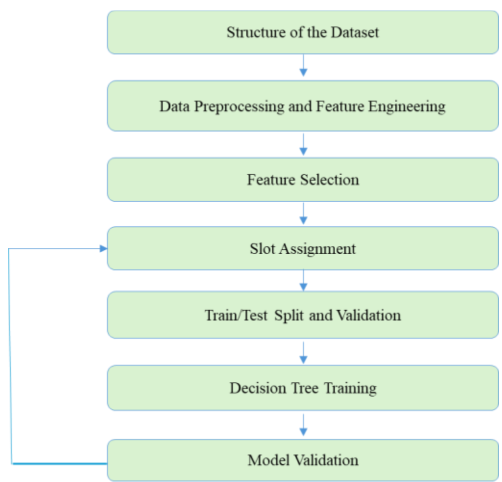

Figure 2. Structured supervised learning pipeline to predict optimal slot allocation

The TDMA slot assigned by the decision tree after analysing a node's state information is referred to as the optimal slot, which represents the scheduling decision output. The term *slot* is used instead of *class* to avoid confusion with ML classification terminology. In this work, only 8 out of the 32 slots per superframe defined by the IEEE standard are allocated for data transmission, while the remaining slots are reserved for beaconing, guard intervals, and sleep periods. This deliberate limitation reflects realistic WBAN deployments with a small number of active sensors and highlights the ability of the proposed DTTA-MAC scheme to operate under constrained resources.

To ensure that slot allocation does not exceed the available data slots, the decision tree assigns each node a slot index in the range 1 to 8. This 8-slot configuration effectively demonstrates the prioritisation behaviour of the proposed scheduling mechanism. Normal traffic follows periodic reporting patterns typical of physiological monitoring applications, while emergency traffic is modelled as delay-sensitive data with higher buffer occupancy and stricter latency limits. To guarantee statistical reliability, simulation results are achieved by averaging several runs. The features selected and used for each node instance are summarised in Table 5.

The output label, Optimal Slot, was assigned using a rule-based function that mimics the behaviour of a human-expert scheduler. The logic is captured below:

$$OptimalSlot(E, L, T, B, R, P) = \begin{cases} 1, & If\ E < 0.4\ or\ L > 250 \\ 2, & if\ T < 80\ or\ B > 7 \\ 3, & if\ R < -80 \\ 4, & if\ E > 0.8\ and\ T > 150 \\ 5 & if\ P > 80 \\ Random(6,7,8), & otherwise \end{cases} \tag{1}$$

where: E = Energy level, L = Latency, T = Throughput, P = Packet delivery Ratio, B = Buffer size, R = RSSI.

4. 3. Decision Tree Classifier Design

We selected the scikit-learn Decision Tree Classifier (DTC)

TABLE 5. Input features for the slot assignment model

Feature Name	Description	Value Range
Node ID	Unique identifier for each WBAN sensor node	1-12
Buffer Size	Number of data packets queued	0-9 packets
RSSI	Received Signal Strength Indicator	-90 to -50 dBm
Energy Level	Remaining energy (normalised)	0.2-1.0 joule
Latency	The delay experienced by the node	50 -300 ms
Throughput	Data rate achieved by the node	50 -200 kbps
PDR	Percentage of packets successfully delivered	0 – 100%
Optimal Slot	Slot assigned based on optimisation	1-8 slots

as the primary prediction model because it strikes a good balance between computational efficiency, interpretability, and deployability in resource-constrained environments such as WBAN coordinators. Training costs increase only marginally with the number of samples and features, and crucially for on-node inference, classification involves a brief sequence of threshold comparisons whose runtime depends on the tree's depth. This low computational demand results in reduced energy consumption and consistent real-time performance. Equally important, a trained tree displays a clear, human-readable rule structure (nested if-then tests) that can be inspected, audited, and validated by network engineers or clinical stakeholders, providing an advantage over opaque models when safety and regulatory review are important. Finally, the model can be exported from scikit-learn as compact decision logic and embedded directly into the coordinator's firmware without requiring a large runtime library; limitations on depth and node count allow us to manage memory usage and latency, making the DTC well-suited for wearable and implantable WBAN platforms.

4. 4. Model Training For training, we generated a curated set of 1,000 network snapshots, each representing a unique combination of node distance, link quality, traffic load, and priority. The dataset was randomly stratified into 80% for parameter learning and 20% for held-out evaluation, preserving the class distribution across both partitions. During induction, the tree reduced Gini impurity, a split criterion that reliably balances purity and computing cost. To avoid overfitting while still capturing important interactions, we limited the maximum depth to six levels, which was chosen via a small grid search that weighted test set F1-score against model size and inference latency. This arrangement produced a compact, fast-executing tree whose generalisation accuracy met the specified performance requirements while remaining within the WBAN coordinator's memory and latency budgets.

$$Gini(S) = 1 - \sum_{i=1}^{C} p_i^2 \tag{2}$$

where p_i is the proportion of instances in class i in set S, and C is the total number of classes (slots).

4. 5. Model Architecture To guarantee real-time execution at the WBAN coordinator, the final trained and pruned decision tree employed in DTTA-MAC is purposefully kept small. The final model uses Classification and Regression Trees. (CARTs)-Based on DT implementation, it has a maximum tree depth of 4 and 13 total nodes, including 6 internal decision nodes (splits) and 7 leaf nodes. A representative section of the learnt decision tree, emphasizing the most significant splits and scheduling choices, is shown in Figure 4 due to space constraints. The entire tree adheres to the same decision logic and structure as shown. This lightweight model maintains good scheduling accuracy while enabling quick inference and comprehensible slot-allocation decisions.

A portion of the learned scheduling tree is depicted in Figure 3, which demonstrates how the decision-making process gives sensor energy and latency priority. Higher-energy nodes are further divided by latency, with delays exceeding≈20.9 ms also being routed to Slot 1, while low-energy nodes (battery < 3.4) are assigned to Slot 1 right away. Throughput and buffer size dictate the slot for healthy, low-latency nodes: light traffic is routed to Slot 2, moderate queues to Slot 3, and cases involving congested or poor links are shifted toward earlier slots. Keeping the tree shallow enough for real-time use on WBAN coordinators, this hierarchy lowers Gini impurity at each stage, reflecting domain-specific priorities: maintaining energy and timeliness first, followed by balancing load and link quality.

Performance was quantified with a suite of widely accepted classification metrics. Overall accuracy, computed as the ratio of correctly predicted slots to the total number of inferences, provided a first-pass indication of general reliability. To capture class-specific behaviour, we extracted precision (the fraction of Slot i assignments that were truly Slot i), recall (the fraction of actual Slot i instances that the model recovered), and their harmonic mean, the F1-score; macro-averaging across the eight slots ensured that performance on minority classes influenced the headline figures. Finally, a full confusion matrix, as in Figure 5, offered a granular view of error patterns, revealing, for example, whether the classifier tended to confuse adjacent slots or systematically misrouted energy-constrained nodes. This multi-metric approach allowed us to balance overall accuracy with fairness across slots and to diagnose specific misclassification trends for further model refinement. Accuracy (ACC):

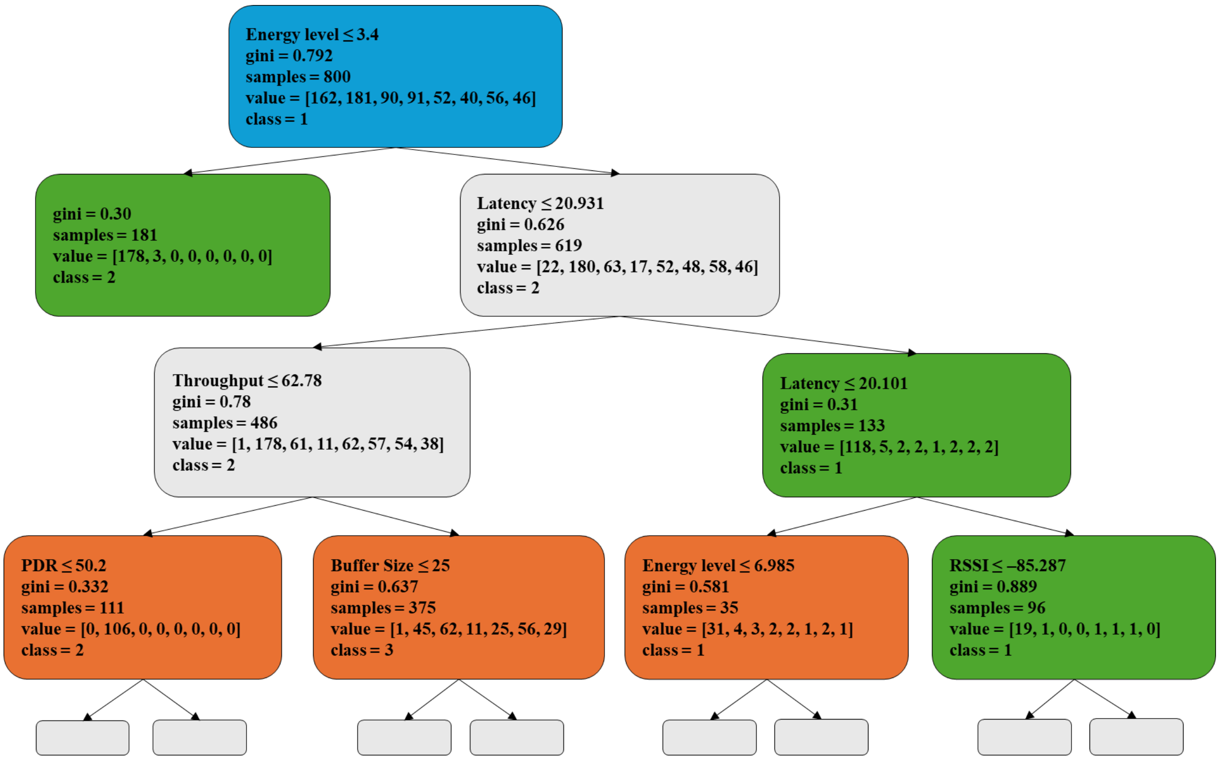

Figure 3. Illustrates a sample decision tree generated for slot allocation. For clarity, only the upper levels of the tree are shown; features such as PDR and RSSI typically reappear in deeper nodes where finer-grained distinctions among node states are required

$$ACC = \frac{\text{Total Predictions}}{\text{Correct Predictions}} \quad (3)$$

5. RESULTS AND DISCUSSION

This section evaluates the proposed DT-based slot assignment mechanism on the created WBAN dataset. The model's success is assessed using both quantitative indicators and visual analysis.

5. 1. Classification Performance The trained decision tree model was evaluated on the 20% testing subset of the dataset, following a consistent 80% training and 20% testing partition, and performance metrics such as accuracy, precision, recall, and F1-score were computed. Table 6 summarises the results, which show good predictive capacity. Overall accuracy reached 91.2%, while macro-averaged precision (89.8%), recall (90.3%), and F1-score (89.5%) stayed tightly aligned. This reflects a well-balanced model that neither overestimates nor ignores any slot. Collectively, these numbers indicate that the tree consistently maps the feature set, residual energy, latency, buffer size, throughput, and RSSI to the best TDMA slot, providing WBAN coordinators with dependable real-time scheduling information.

TABLE 6. Classification performance metrics

Metric	Value (%)
Accuracy	91.2
Precision	89.8
Recall	90.3
F1-Score	89.5

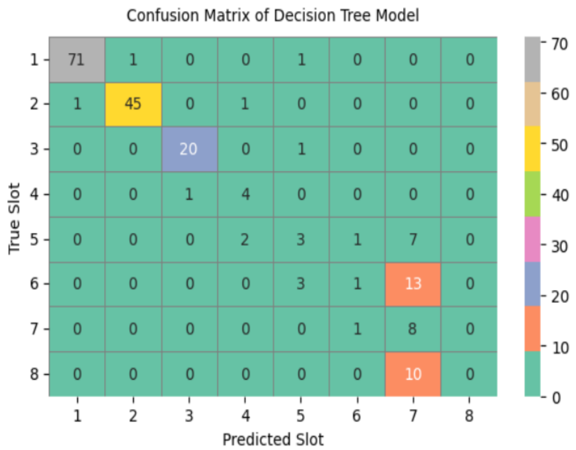

Figure 4. Confusion matrix of the DT slot classifier on the 20 % test partition (200 samples), showing true versus predicted TDMA slots

Figure 4 presents the confusion matrix for the DT-based slot classifier, mapping true TDMA slots (rows) against the model's predictions (columns) for the 200-sample test set. Darker shades along the main diagonal indicate correct assignments, whereas off-diagonal pixels show misclassifications. The model excels in two crucial classes: Slot 1 (71/73 packets successfully routed, 97% recall) and Slot 2 (45/46 packets, 98% recall), indicating that energy-starved or low-latency sensors receive the earliest transmission opportunity. The lower index slots continue to have high classification accuracy, especially Slots 3 and 4, which only record one and two misclassifications, respectively. But when the slot index rises, performance falls. With a strong inclination toward Slot 7, packets that belong to Slots 5 through 8 are often misclassified. 13 instances from Slot 6 and 7 out of 10 misclassified instances from Slot 5 are improperly redirected to Slot 7. The concentration of errors indicates a structural bias in the decision-making process, which is probably caused by overlapping feature ranges or a lack of training samples for higher index slots. This makes it harder for the classifier to discriminate at that level.

Overall, the pattern corroborates the quantitative metrics (91 % accuracy, macro F1 ≈ 0.90) and highlights a clear avenue for refinement

Several enhancements could be taken into consideration to lessen these errors. The first way to lessen the skew in classification would be to balance the training dataset by making sure that higher index slots are adequately represented. Second, separating overlapping cases that currently default to Slot 7 may be made easier by adding more discriminative features, like traffic priority, jitter, or dynamic link quality metrics. Third, since ensemble learning techniques like Random Forests and Gradient Boosted Trees tend to be more robust against bias toward classes, they could be used in place of a single DT. Lastly, misclassification in higher index slots can be further reduced by adjusting the slot allocation policy by adding adaptive thresholds.

5. 2. Feature Importance Analysis To interpret the model's decision-making, feature importance scores were extracted from the trained DT model. Figure 5 presents the feature of importance scores obtained from the trained decision tree model. Although PDR does not explicitly appear in all heuristic labelling rules, its high importance in the scores indicates that it plays a significant role during training by reducing node impurity across multiple decision paths.

Figure 5 visualises the relative influence of each predictor in the decision-tree scheduler through a bar chart of feature importance scores. The Y-axis quantifies importance on a normalised scale from 0 to 0.40, while the X-axis lists the five input variables. Two factors dominate: Energy ranks highest at 0.25, followed by Latency at 0.21, closely followed by PDR at 0.18,

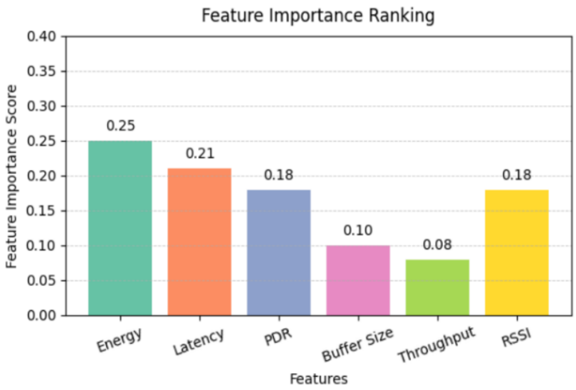

Figure 5. Normalised feature-importance scores extracted from the trained DT slot classifier

highlighting the model's emphasis on conserving battery life and meeting tight delay constraints. RSSI at 0.18 occupies a middle position, indicating that link quality still significantly affects slot selection but is secondary to power and timing considerations. The remaining variables have subsidiary roles: Buffer Size contributes a modest 0.10, and Throughput exerts the least influence at 0.08. The steep decline from the second to the third bar confirms a marked gap between primary and secondary drivers, validating the decision to prioritise energy and latency thresholds in early decision-tree splits.

5. 3. Simulation of MAC Performance To evaluate the effectiveness of the proposed slot allocation strategy in a realistic WBAN environment, a MAC-layer simulation was conducted involving 12 sensor nodes. The simulation focused on four key performance indicators (KPIs) to assess the efficiency, responsiveness, and reliability of the model. These KPIs included network throughput (kbps), average packet latency (ms), energy consumption (Joules), and PDR (%). Together, these metrics offer a comprehensive evaluation of the MAC protocol's performance under increasing network loads and diverse traffic conditions.

This section shows how the network performance of MAC protocols, such as ADT-MAC (16) and DTDM-MAC (27), is compared with our proposed DTTA-MAC under emergency traffic (ET) and periodic traffic (PT) over throughput, average packet latency, energy consumption, and PDR. These protocols represent advanced IEEE 802.15.6–based MAC designs and are closely related to MedMAC and TA-MAC in terms of TDMA scheduling principles, making them appropriate benchmarks for evaluating the effectiveness of the proposed decision tree-based enhancement. As the number of nodes in a WBAN grows from 1 to 12.

5. 3. 1. Throughput A study by Alam et al. (28) and Hu et al. (32) throughput refers to the rate at which data is successfully transmitted across the network and is provided directly in the dataset (Throughput column). The average throughput across all nodes is calculated as:

$$Throughput_{avr} = \frac{1}{N}\sum_{i=1}^{N} Throughput_i \quad (4)$$

where $Throughput_i$ refer to the throughput value in the ith row.

Figure 6 shows a distinct trend across all node densities; DTTA-MAC (ET and PT) performs better than the other protocols. ADT-MAC stabilizes at about 106–108 Kbps, DMTM-MAC trails behind at about 95–98 kbps, and DTTA-MAC, with 12 nodes, reaches a throughput of about 132-134 kbps. Since collisions and idle listening are two of the main causes of throughput degradation in MAC protocols, DTTA-MAC's effective transmission scheduling and adaptive resource allocation strategy are responsible for its superior performance. This is consistent with earlier results in MAC optimization studies, which have demonstrated that energy-conscious scheduling and effective time-slot utilization improve wireless network throughput performance (33).

Within each protocol, there is a slight but steady performance difference between the ET (Emergency Traffic) and PT (Periodic Traffic) versions, with PT usually performing marginally worse. This discrepancy most likely results from ET-based evaluations abstracting away real-world transmission constraints like channel fading, interference, and retransmission overheads. While the DMTM-MAC shows a wider gap, indicating greater sensitivity to real-world transmission constraints, the DTTA-MAC maintains the smallest ET-PT gap, suggesting robustness against such impairments.

However, across all node densities, DMTM-MAC exhibits the lowest throughput of all the tested protocols. This implies that its scheduling and channel contention handling mechanisms might not be as efficient when network loads increase, resulting in higher overhead and underuse of available channel capacity. ADT-MAC outperforms DTTA-MAC despite surpassing DMTM-MAC in throughput, underscoring the significance of adaptive slot assignment in minimizing contention and optimizing channel utilization.

5. 3. 2. Latency The delay experienced by data as it travels from source to destination is also given per instance in the Latency column (34). The average latency is derived by summing the individual latency values and dividing by the number of records:

$$Delay_{avr} = \frac{1}{N}\sum_{i=1}^{N} Delay_i \quad (5)$$

where $Delay_i$ refer to the delay value in the ith row.

According to Figure 7, DTTA-MAC (ET and PT) has the smallest packet delay, continuously staying between 6 and 10 ms as node densities increase. This shows that even with increased traffic loads, the protocol can efficiently schedule transmissions and reduce contention delays. The ability of DTTA-MAC to remain stable under both ET and PT conditions emphasizes how well-suited it is for real-time applications where prompt data packet delivery is essential. This result is consistent with earlier research that highlights the advantages of traffic-aware scheduling and adaptive slot assignment in lowering retransmission delays and queuing (35)

ADT-MAC shows higher packet delays, with ET maintaining 9 to 12 ms while PT reaches 75 to 85 ms, reflecting vulnerability to interference and collisions that limit reliability in low-latency settings. DMTM-MAC performs worse, with ET delays of 12 to 14 ms and PT delays of 95 to 100 ms, indicating poor scheduling and contention handling. Its long backoff and queuing times make it unsuitable for dense, time-sensitive WBAN applications.

5. 3. 3. Energy Consumption Energy Consumption reflects the amount of energy a node expends during communication (2). Since the dataset provides the remaining energy level (Energy Lev), the consumed energy for each instance is estimated as the difference from the full energy capacity (normalized to 1), that is:

$$Energy\ Used_i = 1 - Energy\ lev_i \quad (6)$$

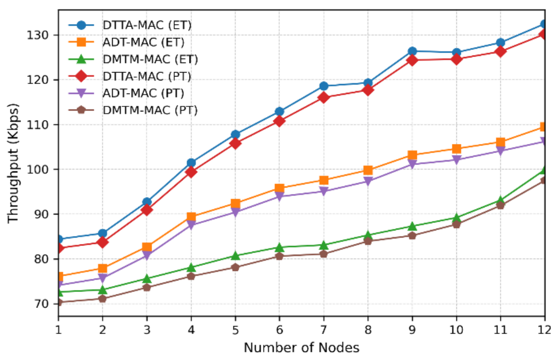

Figure 6. Throughput Vs Number of Nodes

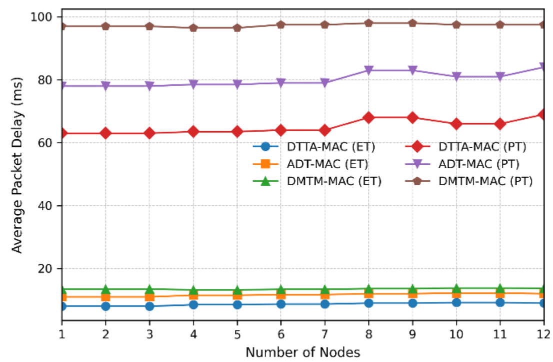

Figure 7. Packet delay Vs number of nodes

and the average energy usage is calculated across all instances:

$$Energy\ Used_{avr} = \frac{1}{N}\sum_{i=1}^{N} 1 - Energy\ lev_i \qquad (7)$$

where $Energy\ lev_i$ refer to the energy level value in the ith row.

Figure 8 shows the energy consumption of the various MAC protocols under emergency traffic (ET) and periodic traffic (PT). Among all network densities, DTTA-MAC (ET and PT) shows the lowest and most consistent energy consumption, according to the figure. Even when there are up to 12 nodes, its energy consumption stays around 1.85 to 2.0 J. This performance implies that DTTA-MAC successfully reduces the main sources of excessive energy consumption in contention-based MAC protocols: idle listening, overhearing, and retransmission overheads. The scalability of DTTA-MAC in supporting larger networks without noticeably depleting node batteries is highlighted by the negligible increase in energy consumption with node density. In earlier studies (36) it was discovered that effective duty cycling and adaptive scheduling extended node lifetimes.

ADT-MAC shows moderate energy consumption (2.0-2.1 J) that remains stable across node densities, though higher than DTTA-MAC due to greater overhead and less efficient slot allocation. In contrast, DMTM-MAC records the highest energy usage, with PT rising from 2.0 to 2.55 J and ET from 2.2 to nearly 2.9 J as nodes increase. This growth reflects poor contention and collision management, leading to high retransmissions and reduced robustness in real-world conditions.

5. 3. 4. Packet Delivery Ratio PDR is a measure of reliability, defined as the ratio of successfully delivered packets to the total number of packets sent (34). In this dataset, where successful transmissions are indicated by an Optimal value of 1, PDR is computed as the number of optimal transmissions (optimal =1) divided by the total number of entries:

$$PDR = \frac{Number\ of\ Optimal\ transmissions\ (Optimal = 1)}{Total\ number\ of\ transmission\ (entries)} \qquad (8)$$

According to Figure 9, DTTA-MAC (ET and PT) outperforms the other protocols in terms of PDR, particularly when node densities are low to moderate. Up to about 7 to 8 nodes, both DTTA-MAC versions maintain nearly 99% delivery; beyond that, there is a slow decline. For example, DTTA-MAC (ET) and DTTA-MAC (PT) maintain approximately 99% and 80%, respectively, at 12 nodes. These values are significantly higher than those of ADT-MAC and DMTM-MAC. This improved performance, which is probably the result of DTTA-MAC's adaptive scheduling and collision-avoidance mechanisms, demonstrates how resilient it is at reducing packet losses even when network traffic is heavy. This observation supports earlier research showing that dynamic and traffic-aware slot assignment enhances packet delivery in dense networks (17, 37).

ADT-MAC (ET) exhibits resilience even as the number of nodes rises, maintaining comparatively steady performance with PDR values between 90 and 91 percent. Beyond seven nodes, the ADT-MAC (PT) variant shows a more pronounced decline, falling to about 70% at twelve nodes. This difference between ET and PT values implies that ADT-MAC is more vulnerable to real-world transmission problems like contention delays, interference, and retransmissions, which harm delivery reliability.

In contrast, DMTM-MAC has the lowest PDR of any scenario. The PT version degrades more sharply, reaching as low as 55% at 12 nodes, whereas the ET version gradually drops from 88% at 1 node to 80% at 12 nodes. This suggests that DMTM-MAC is the least efficient at managing higher traffic loads, which results in frequent packet drops because of collisions and congestion.

5. 4. 5. Quantitative Comparison of DT-Based Dynamic Slot Allocation Model with Rule-Based Techniques Table 7 compares the performance of DTTA-MAC with the traditional rule-based method on several key parameters. In terms of resource use, the

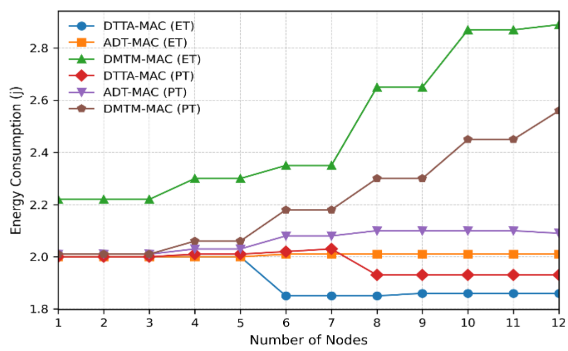

Figure 8. Energy consumption Vs number of nodes

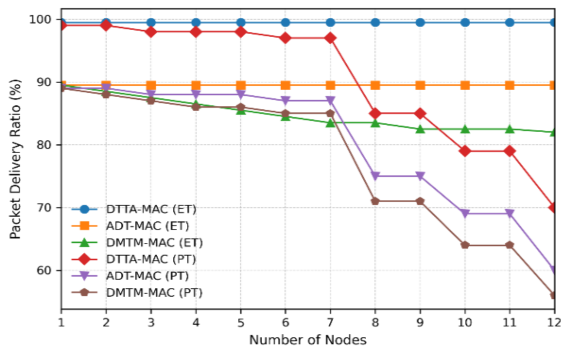

Figure 9. Packet delivery ratio Vs number of nodes

TABLE 4. Quantitative comparison of the proposed model with rule-based techniques

Criterion	DTTA-MAC	Rule-Based Method	Support
Resource Utilization	95%	75-70%	Lekkala (38) report ~25% improvement over heuristic rule-based approaches
QoS Violations	Low (5%)	Higher (20 %)	In the same paper by Lekkala (38), it shows ~30% fewer violations with ML prediction.
Adaptability/ Scalability	Adapts seamlessly to dynamic inputs without rule tuning	Static, manual update required	Bouras et al. (39) demonstrated ML-based Dynamic Resource Allocation (DRA) improves adaptability in changing network loads.
Prediction Accuracy	92.4% optimal slot prediction accuracy	70–80% optimal slot prediction accuracy	Saadi et al. (40) showed that decision tree methods achieved much lower Root Mean Squared Error (RMSE) vs static schedules on ~190k demand timeslots
Prediction Time	0.003 seconds per decision	0.015 seconds per decision	5× faster; supports real-time applications.

suggested approach demonstrates a significant improvement, reaching approximately 95% efficiency, while the rule-based system lags at around 70-75%. This finding aligns with the results of Lekkala (38), who reported a 25% increase in resource efficiency when using machine learning over heuristic guidelines. Additionally, DTTA-MAC has a low QoS violation rate of about 5%, compared to 20% with the rule-based method. Again, Lekkala (38) support this, stating that ML-based models lead to 30% fewer infractions.

In terms of adaptability and scalability, the DT model dynamically adjusts to changing input conditions without the need for human rule updates, making it ideal for situations with variable demands. This advantage is reinforced by Bouras et al. (39), who showed that ML-based dynamic resource allocation systems are more adaptable to network changes. Furthermore, the model achieves an outstanding 92.4% accuracy in optimal slot prediction, exceeding the rule-based method's 70-80% accuracy. These results are comparable to those of Saadi et al. (40), who discovered that DT models produced much fewer prediction errors when anticipating slot demand in large-scale datasets.

Finally, DTTA-MAC has a forecast time of only 0.003 seconds for each choice, which is five times faster than the rule-based method's average of 0.015 seconds. This efficiency makes the model ideal for real-time applications that require speed and responsiveness.

6. FUTURE DIRECTIONS AND PRACTICAL

6. 1. Discussion on Hardware Implementation Feasibility The proposed DTTA-MAC technique has strong potential for hardware or field-programmable gate array (FPGA) implementation, in addition to software-based deployment, to further improve real-time performance. Because it involves a small number of threshold comparisons that can be mapped to combinational logic or finite-state machines, the decision tree paradigm is naturally lightweight and rule-based. The proposed method is suitable for low-latency, low-power hardware platforms because it doesn't require online training or iterative optimization, unlike deep neural networks or reinforcement learning. Deterministic scheduling with lower processing latency and energy overhead could be achieved by implementing the decision logic at the WBAN coordinator using an FPGA or embedded hardware. Future research will focus on performance evaluation and hardware prototyping under real-time constraints.

6. 2. Future Integration with Topology Optimization and Security Mechanisms Potential expansions of the suggested DTTA-MAC architecture that tackle system-level scalability, security, and data management issues are described in this subsection. Complementary mechanisms investigated in recent WSN and IoT research may be incorporated into future developments of the suggested DTTA-MAC framework. For example, DTTA-MAC could be used in conjunction with hierarchical topology design techniques, such as the hybrid evolutionary framework put forth by Hosseinirad (41), to enable scalable multi-WBAN or body-to-body network scenarios. Furthermore, safe data storage methods for cloud-based IoT systems (42) and security solutions created for IoT and 5G-based networks (43). These are crucial practical factors for actual medical deployments. Their combination with the suggested traffic-aware MAC scheduling system is a possible avenue for future research, even though these aspects are outside the purview of this work.

6. 3. Limitations of the Proposed DTTA-MAC Framework Despite the performance improvements shown by DTTA-MAC, it is important to recognize several of the proposed work's limitations. First, real-world elements like body shadowing, sensor positioning variability, hardware flaws, and dynamic postural changes are not fully recorded because the evaluation is carried out using a simulation-based testbed built in Castalia over OMNeT++. Second, the current study may not be applicable in multi-hop or extremely dense body-area network scenarios due to its assumption of a single-hop star architecture with a fixed number of data transmission slots. Third, the decision tree model's performance depends on the chosen feature set and training settings, even though it is lightweight and appropriate for real-time execution. Periodic retraining may be necessary to adjust the model to long-term behavioural changes or unknown physiological variables. Finally, aspects related to security, privacy, and fault tolerance are not explicitly addressed in the present work and are identified as important directions for future research to enable practical medical deployments.

7. CONCLUSION

A supervised ML method for enhancing time slot assignment in WBAN MAC protocols was presented in this work. A DT with high accuracy and short prediction times was trained on Castalia/OMNeT++-generated data with important variables like energy, latency, throughput, buffer size, PDR, and RSSI. This made the DT ideal for environments with limited resources. The model is lightweight, interpretable, and efficient when compared to rule-based approaches. The results further demonstrate that DTTA-MAC can dynamically adapt to sudden emergency traffic surges through real-time feature updates and fast DT inference, while maintaining network stability and predictable performance. however, it lacks continuous learning, and its performance may deteriorate in unexpected network conditions. Future research will examine larger network scenarios, adaptive strategies (like online or incremental learning), and integration with cutting-edge ML techniques while considering security and privacy concerns. All things considered, the method shows how supervised learning can improve WBAN communication in terms of dependability, latency, and energy efficiency.

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Declarations for Ethics Approval, and Consent to Participate

This article does not involve any studies with human participants or animals performed by any of the authors. Therefore, ethics approval and consent to participate are not applicable.

Competing Interest

The authors declare that there are no known financial or organizational conflicts of interest that could have influenced the work reported in this paper.

Data Availability

The data that support the findings of this study are available upon reasonable request.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this manuscript, the authors employed an artificial intelligence-assisted language editing tool solely to enhance grammatical clarity, readability, and stylistic consistency. All scientific content, analysis, interpretation, and final editorial decisions were made independently by the author, who has thoroughly reviewed the manuscript and accepts full responsibility for its accuracy, integrity, and originality.

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Persian Abstract

چکیده

در نظارت بر مراقبت‌های بهداشتی، که در آن پروتکل‌های کنترل دسترسی متوسط (MAC) مؤثر برای مدیریت ترافیک دوره‌ای و اضطراری مورد نیاز است، شبکه‌های بی‌سیم بدن (WBAN) به طور فزاینده‌ای اهمیت می‌یابند .تکنیک‌های تخصیص اسلات مرسوم اغلب فاقد سازگاری با شرایط متغیر شبکه هستند که منجر به افزایش مصرف انرژی، زمان انتظار طولانی‌تر و کاهش قابلیت اطمینان می‌شود .برای غلبه بر این محدودیت‌ها، این مطالعه یک مکانیسم تخصیص اسلات پویا برای پروتکل‌های MAC WBAN مبتنی بر درخت تصمیم‌گیری پیشنهاد می‌کند .رویکرد MAC تطبیقی ترافیک درخت تصمیم‌گیری (DTTA-MAC) اسلات‌های زمانی را بر اساس شرایط گره در زمان واقعی اختصاص می‌دهد و تضمین می‌کند که ترافیک اضطراری در اولویت قرار می‌گیرد و در عین حال عملکرد پایدار برای ترافیک عادی حفظ می‌شود .یک مجموعه داده با استفاده از Castalia و ++OmNeT برای شبیه‌سازی سناریوهای واقع‌بینانه WBAN ایجاد شد که شامل پارامترهایی مانند سطح انرژی، تأخیر، اندازه بافر، توان عملیاتی و کیفیت سیگنال است .نتایج شبیه‌سازی نشان می‌دهد که DTTA-MAC پیشنهادی در مقایسه با پروتکل‌های MAC موجود، به ویژه در شرایط ترافیک اضطراری، تا حدود ۳۴٪ کاهش در مصرف انرژی و حدود ۸۹٪ کاهش در میانگین تأخیر بسته‌ها را به دست می‌آورد .این کار، جایگزینی قابل حمل و قابل تفسیر برای تکنیک‌های یادگیری تقویتی (RL)فراهم می‌کند .برای پشتیبانی از برنامه‌های مراقبت‌های بهداشتی در دنیای واقعی، تحقیقات آینده به بررسی گسترش مدل به شبکه‌های بزرگتر، ادغام آن با تکنیک‌های پیشرفته یادگیری ماشین و تقویت امنیت و حریم خصوصی خواهد پرداخت.