Machine Learning-Based Energy-Aware Routing for Wireless Body Area Networks

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ABSTRACT

Wireless Body Area Networks (WBANs) consist of small, low-power sensors placed on or inside the human body for real-time health monitoring. One of the primary challenges in WBANs is ensuring energy efficiency, given the limited power capacity of biosensor nodes. Recent advancements in the field, including sophisticated techniques such as clustering, Particle Swarm Optimization (PSO), reinforcement learning, and hybrid Machine Learning (ML) approaches, have demonstrated significant improvements over traditional routing methods. This paper investigates energy-aware routing in WBANs using ML models, specifically Decision Tree (DT), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Linear Regression (LinReg). The objective of this study is to predict energy consumption per transmission and analyze the resulting impact on network lifetime. The study visualizes results through energy depletion curves and alive node count plots. The findings demonstrate that ML models can effectively predict energy consumption, enabling optimized packet transmission and extended network lifespan. Moreover, the analysis identifies the most efficient ML-based routing strategy for WBANs and demonstrates that ML approaches outperform existing methods in the literature.

Keywords-Wireless Body Area Network (WBAN); network lifetime; ML; DT; K-Nearest Neighbors (KNN); Support Vector Machine (SVM); linear regression

I. INTRODUCTION

Wireless Body Area Networks (WBANs) employ low-power sensor nodes on or within the human body to monitor physiological signals [1]. Given their energy constraints, energy-aware routing is critical for prolonging network lifetime and ensuring reliable communication. Unlike traditional wireless networks [2], WBANs face unique challenges such as body-induced interference, mobility, and strict power limits. To overcome these challenges, energy-aware routing protocols employ various strategies to enhance energy efficiency, including multi-hop communication [3], adaptive transmission power [4], and intelligent relay node selection [5].

The objective of traditional routing protocols in WBANs is to optimize data transmission, energy consumption, and network stability. These protocols are generally categorized into temperature-aware, energy-efficient, Quality of Service (QoS)-aware, and cluster-based types. Temperature-aware protocols, such as Thermal-Aware Routing Algorithm (TARA) [6] and Hot-spot Preventing Routing (HPR) [7], avoid sensor overheating by choosing cooler communication paths. Energy-efficient protocols, such as Link-Aware and Energy Efficient Routing for Body Area Networks (LAEEBA) [8] and Mobility-supporting Adaptive Threshold-based Thermal-aware Energy-efficient Multi-hop Protocol (M-ATTEMPT) [9], prioritize the minimization of power usage to extend the lifespan of networks. QoS-aware routing, including Dynamic Multi-objective Quality of Service (DMQoS) [10] and emergency-prioritized schemes, ensures the timely and reliable delivery of data. Cluster-based approaches, such as AnyBody [11] and Reliability Enhanced-Adaptive Threshold based Thermal-unaware Energy-efficient Multi-hop Protocol (RE-ATTEMPT) [12], group nodes to reduce transmission redundancy and evenly distribute energy consumption.

Although traditional WBAN routing protocols are generally efficient, they often lack adaptability to real-time network changes. Their reliance on predefined rules limits their ability to respond to dynamic conditions, leading to suboptimal energy use. Additionally, temperature-aware protocols can introduce packet delays, whereas energy-efficient methods may compromise the QoS in critical applications. Recent advancements in Machine Learning (ML) and reinforcement learning [13, 14] have enabled intelligent, adaptive routing in WBANs. ML techniques, including Decision Tree (DT), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM), are employed to predict energy consumption, aiming to optimize packet forwarding. Additionally, reinforcement learning methods, such as Deep Q-Network (DQN) [15] and Proximal Policy Optimization (PPO) [16], learn from environmental feedback to improve long-term energy efficiency. Integrating these approaches enhances routing adaptability, extends network lifetime, and boosts data reliability, making them ideal for continuous health monitoring.

This paper presents a structured method to enhance WBAN network efficiency using ML models to predict energy consumption. The system under consideration simulates packet transmission among sensor nodes and applies models such as DT, KNN, SVM, and Linear Regression (LinReg) for optimal energy use. Key metrics such as node depletion, energy trends, and throughput are tracked to assess network performance. The result visualizations facilitate the comparison of the effectiveness of the models in prolonging the lifespan of the network.

Furthermore, several existing approaches highlight the significance of energy-aware routing to improve WBAN performance. Authors in [17] introduced the Energy-Efficient Adaptive Routing Technique (EEART) for WBANs, which integrates adaptive aggregation, clustering, cross-layered scheduling, and swarm intelligence to reduce latency and increase throughput and Packet Delivery Ratio (PDR). Clustering-based algorithms, such as Cluster Head Selection using Fuzzy Logic (CHSFL) and Improved CHSFL [18], leverage fuzzy inference methods to extend network lifetime by excluding sink-near nodes. Authors in [19] proposed a chain-based routing approach with sink repositioning via Fuzzy C-Means (FCM) clustering, significantly improving energy savings.

Other contributions include the GM-SDP-2 localization method [20], the ML-based healthcare platform [21], the Regional Energy-efficient Multipath Routing (REMR) protocol for regional multipath routing [22], the Bee Swarm Optimization (BSO) for cluster head selection [23], the genetic algorithm-based Energy-efficient Routing using Quantum-inspired Tuned Genetic Mechanism (ERQTM) [24], and the Modified Huffman method for compression [25]. All of the aforementioned models demonstrate notable improvements in energy efficiency and data handling.

In [26], the authors presented energy-efficient protocols that outperformed others terms of throughput and network lifespan. Additional techniques have been developed to address poor channel conditions through the optimization of waiting time and frame length [27] and to extend the life of medical implants through modified Low-Energy Adaptive Clustering Hierarchy (LEACH)-based clustering [28]. Authors in [29] introduced a Particle Swarm Optimization (PSO)-based routing protocol, whereas authors in [30] developed the Modified Stable Increased-throughput Multi-hop Protocol for Link Efficiency (M-SIMPLE) for hybrid communication strategies. Authors in [31] proposed the Zonal Energy Quality of Service (ZEQoS) model, which optimizes paths based on packet types in hospital environments.

Protocols such as LAEEBA [8], M-ATTEMPT [9], and DMQoS [10] further demonstrate the impact of intelligent routing design. LAEEBA achieves this by balancing reliability and energy via hybrid communication; M-ATTEMPT tackles thermal issues and mobility using linear programming; and DMQoS employs lexicographic optimization for QoS-aware routing. Despite these advancements, continued improvement is necessary to meet the growing demand for long-lasting, adaptive, and high-performance WBAN systems.

II. SENSOR NETWORK MODEL

In WBAN development, network lifetime and energy consumption present critical challenges, as recharging or replacing biosensor batteries can cause physical discomfort. Energy preservation is therefore a key consideration, requiring optimized battery usage to extend network lifespan. Biosensor nodes transmit data to the sink via relay nodes, selecting routes that minimize distance and energy consumption. This work proposes an optimal and efficient data transmission route. The route is determined using an energy model, which calculates energy consumption, and path loss models, which evaluate signal degradation. ML-based algorithms are employed to determine the optimal route for data transmission in WBAN. The subsequent sections outline the key steps of the proposed approach.

A. System Model

The WBAN network is established with eight biosensor nodes and one sink node. Each node senses and transmits data to the sink via the shortest route. All biosensor nodes are initially assigned an equal amount of energy for network communication. The deployment of biosensor nodes on the human body is detailed in Table I.

TABLE I. DEPLOYMENT OF BIOSENSOR NODES ON THE HUMAN BODY [27]

Node	S1	S2	S3	S4	S5	S6	S7	S8	Sink
X	0.55	0.25	0.28	0.48	0.3	0.5	0.45	0.35	0.4
Y	1	1	0.2	0.25	0.5	0.5	0.13	0.9	1.1

B. Energy Model

The proposed work utilizes a first-order radio model to estimate the energy consumed by a node during data transmission [32]. According to this model, the transmission energy required for a node to relay a data packet of W bits over a distance D is calculated as follows:

$$E_{Tx}(W, D) = E_{Tx-elect} * W + E_{Amp} * \eta * D^{\eta} * W \quad (1)$$

The model also considers the energy consumption of nodes when receiving a data packet of W bits, obtained by applying the equation given below:

$$E_{Rx}(W) = E_{Rx-elect} * W \quad (2)$$

Using the same model, the energy consumed by nodes for aggregating W bits is determined using the following formula:

$$E_{DA}(W) = E_{DA} * W \quad (3)$$

where $E_{Tx-elect}$, $E_{Rx-elect}$, and E_{Amp} denote the energy consumption per bit in the transmitter, receiver, and amplifier circuits of the operating node, respectively. E_{DA} refers to the energy consumption per bit for data aggregation. The path loss index η accounts for additional path loss in bodily communication channels. In the proposed approach, node processing energy losses are considered negligible compared to data transmission and are therefore ignored [33].

III. OVERVIEW OF MACHINE LEARNING ALGORITHMS USED

ML is a subset of Artificial Intelligence (AI) that enables systems to learn patterns from data and make predictions or decisions without explicit programming. It encompasses a range of learning methodologies, including supervised learning (labeled data), unsupervised learning (unlabeled data), and reinforcement learning (learning through rewards). ML algorithms, such as neural networks, DT, and SVM, have been shown to improve performance through adaptability to novel data.

A. Decision Tree

The DT algorithm [34] is a supervised learning technique used for classification and regression. It divides data into branches based on feature values, forming a tree-like structure where each internal node represents a decision, each branch represents an outcome, and each leaf node represents a final prediction. The algorithm selects splits using criteria like Gini impurity or entropy (information gain) for classification and Mean Squared Error (MSE) for regression. The model is characterized by its simplicity, interpretability, and effectiveness for structured data. However, it is prone to overfitting without pruning or regularization.

B. K-Nearest Neighbors

The KNN algorithm [35] is a simple, non-parametric, supervised learning method used for classification and regression. The classification of a data point is determined by the majority class of its k closest neighbors, whereas the prediction of a value is achieved through the averaging of the outputs of said neighbors. Distance metrics, such as the Euclidean, Manhattan, or Minkowski, determine the proximity of neighbors. KNN is characterized by ease of implementation; however, it is computationally expensive for large datasets.

C. Support Vector Machine

The SVM algorithm [36] is a supervised learning method used for classification and regression. It finds the optimal hyperplane that maximizes the margin between different classes in a high-dimensional space. SVM uses kernels (e.g., linear, polynomial, RBF) to handle complex data distributions and is effective for small to medium-sized datasets. However, for large datasets, the system can prove to be computationally intensive.

D. Linear Regression

LinReg [37] is a supervised learning algorithm that models the relationship between a continuous dependent variable and one or more independent variables using a linear equation. It minimizes the sum of squared differences between the actual and predicted values. The simple LinReg model fits a straight line, whereas the multiple LinReg model uses a hyperplane. Common applications include trend prediction and financial forecasting. Assumptions underlying this approach include linearity, minimal multicollinearity, and normally distributed residuals. The employment of techniques such as regularization (Lasso, Ridge) helps to enhance model performance and prevent overfitting.

IV. RESULTS AND DISCUSSION

In this section, an evaluation of the four approaches of ML-based models, including DT [34], KNN [35], SVM [36], and LinReg [37], will be conducted in the context of energy-efficient routing in WBAN. The analysis focuses on extending the network's lifespan by analyzing the evolution of residual energy over time and the total number of alive nodes throughout the simulation. Table II presents a synthesis of the parameters used in the simulation framework, which is implemented and evaluated using Python.

The data utilized for training the ML models are synthetically generated based on a WBAN energy consumption model. Specifically, the energy required to transmit data is calculated as a function of the distance between a node and the sink using (1). A range of distances from 0.1 to 1.5 m is simulated, and for each distance, the corresponding energy consumption is computed. To emulate real-world variability, Gaussian noise is added to the energy values. This results in a dataset where the distance serves as the input feature and the noisy energy consumption serves as the target output. This dataset is then used to train various ML models, including DT, KNN, SVM, LinReg. These models are used to predict the energy cost of transmission based on distance, enabling the evaluation of energy-efficient routing strategies in WBAN simulations.

TABLE II. WBAN SIMULATION PARAMETERS

Parameter	Description of parameter	Value	Unit
Energy	Initial energy	0.6	J
Nodes	Number of biosensor nodes	8	nodes
Sink position	Location of the sink	Center of the body	-
Packet size	Size of each data packet	4,000	bits
Rounds	Total number of rounds	10,000	rounds

Figure 1 illustrates the residual energy performance of four ML models—DT, KNN, SVM, and LinReg—across successive transmission rounds in a WBAN. Among all models, DT exhibits the most energy-efficient behavior, maintaining higher residual energy and extending network lifetime close to 9,500 rounds. KNN and LinReg follow closely, demonstrating comparable performance with only a slight drop near the end. In contrast, SVM consumes energy at a significantly higher rate, reaching zero residual energy before 8,000 rounds. This comparison clearly underscores the efficacy of DT, KNN, and LinReg as the most suitable models for energy-aware routing in WBANs, offering a substantial enhancement in network longevity when compared to SVM.

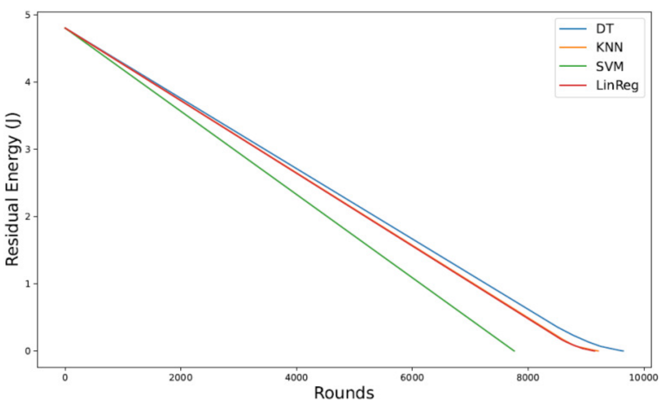

Fig. 1. Residual energy vs. rounds.

Figure 2 illustrates the number of alive sensor nodes over time for four ML-based routing models—DT, KNN, SVM, and LinReg—in a WBAN. Initially, all models maintain the full set of eight alive nodes; however, the duration for which nodes remain active varies significantly across the models. SVM performs the worst, with node deaths beginning shortly after 7,500 rounds and complete network depletion occurring before 8,500 rounds. LinReg performs moderately, with node deaths starting at 8,541 rounds and all nodes becoming inactive by approximately 9,150 rounds. KNN offers slightly better performance, sustaining some nodes up to 9213 rounds. DT outperforms all other models, maintaining node activity the longest, with gradual node failures starting near 8488 rounds and some nodes remaining alive until almost 9643 rounds. These results highlight that DT is the most energy-efficient model, ensuring prolonged node operation and enhanced network lifetime, whereas SVM is the least effective in this regard.

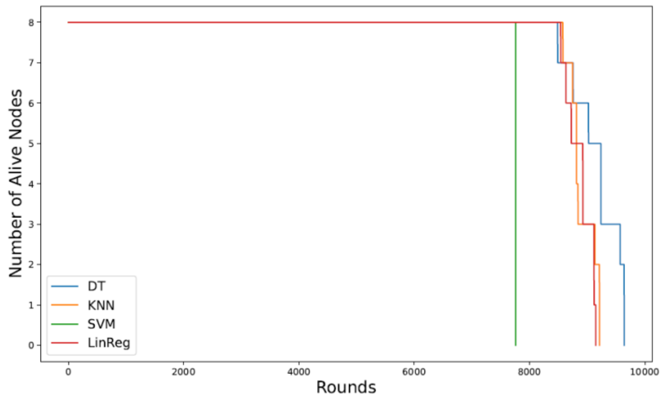

Fig. 2. Alive nodes vs. rounds.

V. COMPARATIVE STUDY

This section undertakes a comparative analysis of traditional approaches— Particle Swarm Optimization-based protocol for Body Area Networks (PSOBAN), RE-ATTEMPT, and the third approach of [19]—versus ML-based models: DT, KNN, SVM, and LinReg. The PSOBAN and RE-ATTEMPT approaches are thoroughly examined in [29], whereas the authors of [19] propose three approaches. Notably, the third approach, a chain-based method using FCM, achieves the best results. The comparison focuses on key metrics such as First Node Died (FND), Last Node Died (LND), and throughput (packets received).

The performance comparison of the WBAN routing techniques in Figure 3 demonstrates the superiority of ML-based models over traditional approaches in terms of network longevity and throughput. The FND rounds indicate that KNN (8,578 rounds) and LinReg (8,541 rounds) significantly outperform conventional methods like RE-ATTEMPT (2,480 rounds) and PSOBAN (3,800 rounds), demonstrating improved energy efficiency. Similarly, the LND rounds further reinforce this trend, with DT (9,643 rounds) ensuring the longest network lifespan. In terms of data transmission efficiency, throughput values reveal that ML models, particularly DT (73,595 packets) and KNN (71,347 packets), handle significantly more packets than traditional techniques like the RE-ATTEMPT (21,523 packets). These findings suggest that ML-based approaches, especially KNN, are highly effective for enhancing the energy efficiency, network lifespan, and data delivery performance in WBANs.

Figure 4 presents a side-by-side comparison study of residual energy for different routing methods in WBAN across 2,000, 4,000, 6,000, and 8,000 rounds. The results indicate that DT, KNN, and LinReg consistently maintain the highest residual energy across all rounds, with DT reaching 3.7545 J at

2,000 rounds and still retaining 0.6180 J at 8,000 rounds. In contrast, SVM exhibits a sharp decline, with its values missing at 8,000 rounds, suggesting complete energy depletion. KNN and LinReg also demonstrate significant energy depletion by 8000 rounds, retaining only 0.4920 J and 0.4785 J, respectively. Meanwhile, PSOBAN and RE-ATTEMPT [29] demonstrate moderate performance, though they are outperformed by DT, KNN, and LinReg. Overall, the results of this study indicate that DT, KNN, and LinReg are the most energy-efficient methods for WBAN routing, suggesting that they are promising choices for prolonging network lifespan.

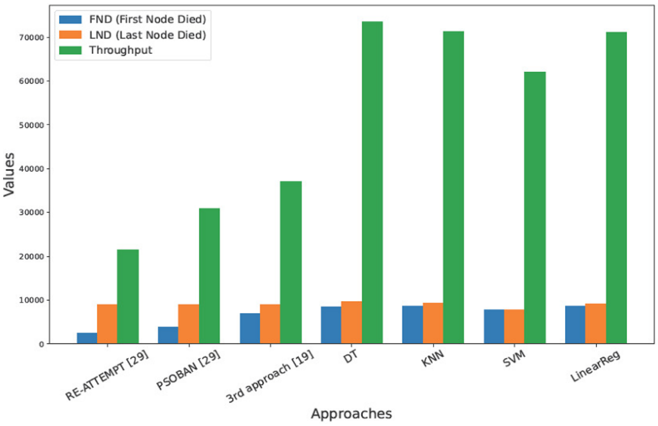

Fig. 3. Traditional approaches vs. ML-based models in terms of FND, LND, and throughput.

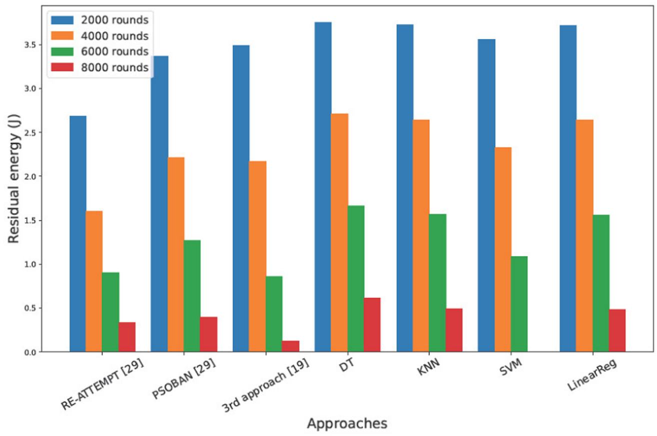

Fig. 4. Residual energy at different rounds.

VI. CONCLUSION

The present study evaluates several Machine Learning (ML) algorithms for routing in Wireless Body Area Networks (WBANs), with a focus on residual energy, network lifespan, and throughput. A detailed simulation was employed to compare Decision Tree (DT), K-Nearest Neighbors (KNN), Linear Regression (LinReg), and Support Vector Machine (SVM) against traditional methods such as Reliability Enhanced-Adaptive Threshold based Thermal-unaware Energy-efficient Multi-hop Protocol (RE-ATTEMPT) and Particle Swarm Optimization-based protocol for Body Area Networks (PSOBAN). The DT algorithm demonstrated the highest residual energy and the longest network lifespan, making it the most energy-efficient model. KNN and LinReg also demonstrated superior performance, significantly surpassing traditional methods in terms of First Node Died (FND) and data throughput. Conversely, SVM depleted energy at a faster rate and had a shorter lifespan, likely due to its higher computational complexity. The main contribution of this study is the demonstration that DT, KNN, and LinReg are more effective for energy-efficient and reliable WBAN routing in comparison to traditional approaches. Future research could explore hybrid models combining multiple ML techniques and incorporating multi-agent reinforcement learning for adaptive, real-time energy optimization.

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