

Original Article

Lightweight AI Models for Predictive Bluetooth Low Energy Connection Management

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ABSTRACT

Internet of Things (IoT), Wearable devices, Smart healthcare, Industrial monitoring, Battery powered sensor networks are all heavily using Bluetooth Low Energy (BLE). Reliable BLE connections under dynamic mobility, varying signal strength, interference and heterogeneous traffic conditions are still a challenge, however. Traditional connection-management techniques are often based on static parameters, threshold-based decisions or reactive adaptation, leading to higher probability of connections being dropped, energy waste, and communication latency. This paper introduces a lightweight artificial intelligence framework for predictive BLE connection management, which includes compact machine learning models, temporal connection-state analysis, and adaptive parameter selection. The proposed framework relies on received signal strength indication (RSSI), packet delivery ratio, retransmission behavior, connection interval, and recent disconnection history for estimating the quality of the connections in the short term. The mechanism for predicting connection parameters is efficient in computational requirements, and respects the constraints of the BLE protocol and the resource constraints of devices. It is a framework that can be used in non-cloud-based embedded systems with limited resources. A structured approach to evaluation is created to measure the accuracy of prediction, connection stability, latency, and energy efficiency. As the experimental measurements are not provided, the proposed evaluation targets are clearly separated from the validated empirical results.

KEYWORDS

Bluetooth Low Energy, Lightweight Artificial Intelligence, Predictive Connection Management, Internet Of Things, Machine Learning, Adaptive Connection Intervals, Energy Efficiency, Embedded Intelligence, Link Reliability, And Edge Computing.

1. INTRODUCTION

1.1. Background and Motivation

With the launch of the Internet of Things (IoT), the new technology that is making every object in the world "smart," Bluetooth Low Energy (BLE) has become an important wireless communications technology for low-power IoT devices such as wearable healthcare devices, smart home automation, asset tracking, industrial sensing, and environmental monitoring. It features a power efficient communication mechanism which allows battery operated devices to communicate with each other with minimum power usage and computation overhead. But, BLE connection performance is impacted by noise, obstacles, movement, variability, and network traffic. These differences affect the reliability of connection, communication delay and energy efficiency. While the Bluetooth Core Specification includes methods like connection intervals, peripheral latency, and supervision timeouts, it is difficult to properly select them in dynamic environments. Traditional methods such as reactive threshold-based approaches can be slow to react to poor link conditions which can lead to higher retransmissions, energy usage, and connection drops. Artificial Intelligence (AI) models that are lightweight seem to provide a good solution, as they examine past measurements of connections and forecast future performance degradation. These algorithms are highly efficient in computation, and, by adjusting the connection parameters in advance in order to ensure a satisfactory level of reliability and other application quality of service requirements, they are able to keep energy consumption down while not relying on an energy-intensive deep learning model or continuous cloud processing.

1.2. Problem Statement



Fig 1 - Problem Statement

1.2.1. Noisy and Temporally Variable BLE Measurements

Environmental interference, physical barriers, mobility of the device and radio signal variations all often impact measurements using the BLE connection. Therefore, the current RSSI readings and set thresholds for signal strength may not reflect the actual condition. A successful management of these connections will thus depend on analyses of past measurements and the

identification of temporal patterns that can be used to anticipate the links that are likely to become degraded.

1.2.2. Multiple Interdependent Connection Parameters

The quality of BLE connection is influenced by a number of factors that interact, such as received signal strength indication (RSSI), packet delivery ratio, retransmission activity, traffic intensity and connection timing. Varying one parameter can affect the reliability, latency and energy consumption of the communication at the same time. Thus, a successful predictive system should combine several indicators to assess the state of links and decide on the suitable actions for managing the connection.

1.2.3. Computational and Energy Constraints

The power of the embedded devices that are BLE compliant is limited, as is the memory or battery power. Intelligent connection management can also give rise to further processing delays and energy consumption due to computationally demanding prediction models. Thus, lightweight AI methods with enough prediction accuracy and low computation complexity and resource consumption should be used in the proposed framework.

1.2.4. Protocol Compliance and Peer Compatibility

The connection-parameter adaptation has to respect the requirements of the Bluetooth protocol and the capabilities and preferences of the target device. Wrong parameter adjustments can lead to latency, communication problems or instability in communication. As such, predictive decisions need to be confirmed against protocol constraints, supported parameters and application-specific quality of service requirements prior to execution.

1.2.5. Translating Predictions into Effective Control Decisions

Even if the weather conditions can be accurately predicted, it does not necessarily mean the connection performance of BLE will be improved, unless the predicted condition is translated into the appropriate control action. The framework needs to decide when and how to change connection parameters to optimize for reliability, response latencies, and energy efficiency. Central research goal thus is to create a predictive, adaptive and resource-efficient connection-management mechanism, which can predict link degradation and choose safe, timely and application-aware control actions.

1.3. Research Objectives

The aim of the study is to design an energy efficient and computational light weight adaptive and predictive connection management system for BLE network to increase the reliability of communication while keeping the energy consumption and computational overhead minimum. The first goal is to create a compact mechanism to process the short-term BLE link measurements such as received signal strength indication (RSSI), packet delivery ratio, retransmission frequency, traffic intensity, and connection timing to detect early symptom of link degradation. This second goal is to create the machine learning models that are able to accurately predict the quality of a connection and

estimate the likelihood of disconnection in near future given dynamically changing communication conditions, while being computationally efficient. The third goal is to incorporate the prediction products together with an adaptive connection controller that determines suitable connection parameters based on the predicted link conditions, application demands, device capabilities, and constraints for Bluetooth protocol. The fourth goal is to develop a comprehensive evaluation framework to measure the effectiveness of the proposed approach by performance indicators, including packet delivery ratio, connection stability, communication latency, energy consumption, prediction accuracy, inference time, memory utilization and computational overhead. The purpose of this evaluation is to see if there is measurable difference between static, traditional configurations, and threshold-based connection-management methods and predictive adaptation. The fifth goal is to explore the trade-off between prediction and embedded implementation complexity, exploring how model size, feature dimensionality, inference frequency and processing needs affect overall system efficiency. A particular attention is given to the identification of lightweight models which ensure have a sufficient predictive accuracy without requiring too much resources on battery-powered BLE devices. In addition, it is also intended to investigate the effect of prediction confidence and changing environmental conditions on the control decision, thus minimizing unnecessary parameter changes and preventing instability of adaptation behavior. These goals form a systematic ground for building an intelligent BLE connection management framework that predicts communication degradation, enables timely parameter adaptation, and provides reliability, latency and energy efficiency in resource constrained IoT applications.

2. LITERATURE SURVEY

2.1. Bluetooth Low Energy Connection Management

In Bluetooth Low Energy (BLE) connection management, the procedures described in the protocol are used to coordinate the timing of communication, exchange of data and supervision of connections between connected devices. Parameters such as connection intervals, peripheral latency, and supervision timeouts all play important roles in determining the responsiveness of communications, the stability of the links, and the amount of energy that will be used. The connection intervals control the frequency of the communication events and the peripheral latency enables eligible peripheral devices to bypass some events under defined conditions. Frequent intervals can provide better responsiveness, but can cause more radio use, and long intervals can cause less radio use, but longer communication delays. The Bluetooth specification provides the rules for negotiating and changing connection parameters as dictated by the protocol and capabilities of the peer device. Thus, adaptive connection-management algorithms need to work in this context and take into account the performance requirements of the application. Traditional static parameter setting can be used for fixed communication loads, but when the signal quality or traffic rate of the communication channel, or the mobility of the equipment, changes then the use of traditional static parameter setting can become inefficient. These restrictions drive predictive connection management which proactively predicts link degradation and suggests appropriate parameter changes in advance of a significant performance drop.

2.2. Wireless Link Prediction in the Context of Machine Learning

The use of machine learning methods for wireless link prediction involves recognizing patterns in the data collected over time and predicting future traffic conditions. Such methods can be used in link-quality classification, mobility estimation, anomaly detection, and network resource management, for making informed decisions in dynamically changing wireless environments. Linear models are simple to calculate and easy to interpret, but fail to model nonlinear relationships between communication parameters. But more complex patterns can be captured in Decision trees and Random forests, and Neuro networks can be used to learn temporal dependencies, but may require more memory and processing resources. Lightweight models can evaluate features like the trends of the received signal strength (RSSI), Packet Delivery Ratios, retransmission frequency, and the recent number of connection failures for BLE connection management. Embedded devices are able to estimate connection quality and determine if there is a potential risk of disconnection by using these features without relying on the heavy computational processing. When dealing with scenarios where the models have never seen before, however, variations in hardware, environmental interference, and deployment conditions can decrease the accuracy of predictions. Thus, the proposed model is focused on compact feature extraction, efficient inference and evaluation under various operating conditions to better suit its practical deployment.

2.3. Wireless Communication: Energy-aware and adaptive communication.

The goal of energy-aware wireless communication is to reduce radio energy usage without compromising the reliability of wireless communication and the application performance. This goal is especially critical for battery-powered BLE devices in various wearable healthcare, environmental monitoring and industrial sensing applications. The right communication configuration is determined by workload characteristics and application requirements. Various applications may demand different interactive control systems with low latency and regular data exchange, while some sensing applications allow for more delay in communication, which can save energy. Taking snapshots of the signals and reacting to the immediate situation can result in the unnecessary changing of parameters when the signal quality varies around certain thresholds. This can lead to greater control overheads and to the loss of stable communication performance when facing changing environmental conditions. A predictive energy-aware control can overcome these limitations by integrating a knowledge of past trends, confidence estimates and considering constraints on the frequency of parameter updates. The goal is to achieve a stable, context-aware adaptation between energy consumption, communication latency and link reliability.

2.4. Research Gap and Comparative Analysis

Standardized procedures for setting communication parameters exist in the form of BLE connection-management. These can be used to configure the link in a standardized way. The prediction of future link conditions is possible using machine learning. But, embedding such capabilities into an energy efficient and protocol compliant embedded control system is a significant research challenge. In a conventional static approach, the methods do not adequately meet the needs of fast-changing communication circumstances, while reactive threshold-based methods may only be

able to detect degradation when it has occurred. Complex predictive models can also lead to excessive energy consumption, computational complexity, and memory usage for resource-constrained devices.

The proposed research aims to overcome these limitations through an integrated solution, incorporating compact feature extraction, light-weight machine learning, and adaptive connection control. It focuses on prediction accuracy, computational efficiency and conformance with the protocol limitations of Bluetooth. Additionally, the framework seeks to integrate the confidence of the prediction and stable decision-making rules to avoid unnecessary changes in parameters. The effectiveness will be measured in terms of reliability, latency, energy cost and computational overhead, compared to traditional connection management methods.

3. METHODOLOGY

3.1. Proposed System Architecture

The proposed Lightweight Predictive BLE Connection Management (LPBCM) framework is divided into five integrated steps: telemetry acquisition, feature engineering, lightweight prediction, risk-aware decision making, and protocol compliant parameter adaptation. The information from connection is passed through each stage to see if there is any possible degradation in performance and to decide on corrective measures. The architecture runs locally on a host processor, embedded gateway or capable microcontroller, lessening reliance on remote computing resources and constant cloud connections. Feedback process assesses the results of the implemented adjustments, and relies on newly gathered measurements to inform future predictions for strengthening adaptation action.

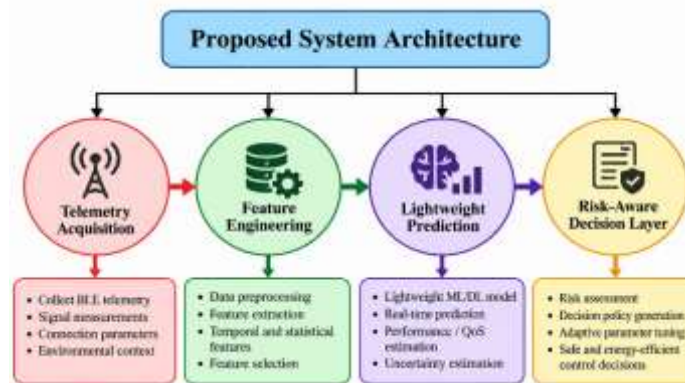


Fig 2 - Proposed System Architecture

3.1.1. Telemetry Acquisition

This telemetry acquisition layer captures measurements of BLE connections over a given observation period with timestamps to observe communication behavior. Parameters that are relevant are received signal strength indication (RSSI), number of packets received successfully, number of packets received unsuccessfully, packet delivery ratio, traffic rate, disconnection events and negotiated connection settings. Data collect is based on supported Bluetooth APIs, controller

statistics and application-level instrumentation, based on the capabilities of the protocol stack and the hardware. Available measurements are available, but for some BLE implementations, no measurement value is available or the detailed link-layer information is not exposed, in which case no measurement value or documented proxy links are included.

3.1.2. Feature Engineering

Feature engineering is the process of converting the raw telemetry data into a numerical representation that is small enough for efficient use by lightweight machine learning models. Packets delivery variations in the short time, short-term variations in traffic, moving averages, standard deviations and temporal differences are statistical features used to detect early symptoms of connection degradation. A sliding-window mechanism has been developed which captures recent communication behaviour while minimizing memory consumption and computational overhead. Feature normalization and proper treatment of missing values makes the model more reliable, and parameters for preprocessing are calculated from the training set only to avoid information leakage when testing.

3.1.3. Lightweight Prediction

The lightweight prediction stage utilizes computationally efficient machine learning algorithms to predict the future communication state of BLE and the probability of BLE communication degradation. Candidates: Decision Trees, Quantized Logistic Regression, and Compact Random Forests are used, depending on the predictive power and deployment needs. The prediction model is used to process the engineered feature vector and produce an output for use in proactive connection management. The choice of model takes into account the latency of inference, memory requirements, energy consumption and prediction error, ensuring that the solution chosen is adequate for the embedded devices that are resource constrained.

3.1.4. Risk-Aware Decision Layer

The risk-aware decision layer transforms predicted probability of connection degradation to the right control decision depending on the application requirements and real communication conditions. It takes into account the level of confidence in the prediction, traffic volume, link quality, current connection parameters, and ranges of permitted connections to suggest an adjustment.

Unwanted updates due to noisy measurements or rapidly changing predictions are avoided by the use of hysteresis thresholds and minimum intervals between parameter changes. It is a strategy that facilitates stable adaptation, while still ensuring the quality of communication, the response time, energy efficiency and application-specific quality of service requirements.

3.2. Mathematical Formulation

A mathematical modeling of the proposed Lightweight Predictive BLE Connection Management (LPBCM) framework unifies temporal feature extraction, degradation probability estimation, and risk-sensitive connection-parameter selection into a single optimization process. Let

the observation vector at time t be $\mathbf{x}_t = [r_t, p_t, v_t, q_t, b_t, c_t]$, where r_t are the statistics for RSSI received, p_t is the packet delivery ratio (PDR), v_t are the statistics for RSSI variability, q_t are available retransmission or failure indicators, b_t is a traffic demand, and c_t is the current connection configuration. The temporal features are computed over a window of length W for the observation time t , so that the moving average of RSSI is the following, which is denoted by RSSIbar : $\text{RSSIbar} = \frac{1}{W} \sum_{i=0}^{W-1} r_{t-i}$, and the moving standard deviation of RSSI is the following, which is denoted by RSSIstd : $\text{RSSIstd} = \sqrt{\frac{1}{W} \sum_{i=0}^{W-1} (r_{t-i} - \text{RSSIbar})^2}$. These statistics measure recent signal strength and variability, and PDR is computed as $\text{PDR}_t = S_t / N_t$, with S_t and N_t the number of successfully delivered and observed packets, respectively, for $N_t > 0$. The proposed light weight predictive model uses these features to predict the probability of connection degradation given a short-term time horizon h in the future, i.e. $\hat{p}_t = P(y_{t+h}=1 \mid \mathbf{x}_t)$, where $y_{t+h}=1$ denotes a predefined event of connection degradation or an unexpected loss of connection. Model can be trained with binary cross-entropy loss, so that its prediction probabilities can closely simulate the occurrence of degradation events, and the probability calibration can be tested separately. The objective function is then defined as $a_t^* = \arg \min_{a \in \mathcal{A}_t} [\lambda_{EE}(a) + \lambda_{LL}(a) + \lambda_{DD}(a) + \lambda_{CC}(a)]$, where $\mathcal{A}_t$ is only the set of possible connection configurations supported by the host stack, controller, peer device, and applicable Bluetooth protocol constraints, and the weighting factors are application specific priorities. Last but not least, a loop of observed connection behavior allows for ongoing performance evaluation and refinement of decisions, which allows LPBCM to maintain the reliability of the prediction while keeping the response to communication close and saving energy in changing operational conditions.

3.3. Learning and Adaptive Control Procedure

The proposed Lightweight Predictive BLE Connection Management (LPBCM) framework is based on four design principles: (1) Learning and Adaptive Control: Offline learning and Real-time Degradation Prediction, (2) Risk-aware Action Selection, (3) Protocol-compliant Parameter Adaptation, and (4) Feedback-based Performance Monitoring. Offline training is conducted in a variety of device movement, traffic, mobility, and device configuration scenarios, to gather BLE connection traces. The dataset is gathered and contains relevant features: received signal strength indication (RSSI), packet delivery ratio (PDR), signal variability, connection failures, and traffic statistics, as well as labels indicating the occurrence of pre-defined degradation events within a given prediction horizon. The data is split into a training, a validation and a testing set, whenever possible, to allow for the reduction of data leakage and to yield a more realistic idea of the data's ability to generalize. The embedded controller stores connection telemetry continuously while the system is being deployed, and applies the same preprocessing steps at deployment as at training to each observation window, creating a compact feature vector. The lightweight prediction model subsequently predicts the likelihood of future connection degradation, and the probability is compared to calibrated decision thresholds to decide whether corrective measures are needed. If the predicted risk is above the threshold, and prediction confidence is high enough, the controller

considers feasible connection configurations based on the estimated energy consumption, communication latency, reliability, and adaptation overhead. Each submitted configuration is transferred via facilitated Bluetooth connection-management process, considering protocol requirements, host-stack limitations, controller capabilities, and peer-device constraints. The negotiation process supported may be one of accept, reject or modify the requested update. After an accepted change, the framework monitors the connection performance for a second monitoring period and compares the measured results to the expected benefits. If the adjustment makes the relevant performance indicators better, and does not violate application requirements, then the controller can keep the same configuration; if it violates application requirements, the controller can restore a previously validated configuration or take another configuration action that is feasible. Excessive parameter changes and long periods of degraded performance are prevented with hysteresis, minimum update intervals and fallback policies. LPBCM enables proactive, stable and resource-efficient BLE connection management under dynamically changing communication conditions via feedback.

4. RESULT AND DISCUSSION

4.1. Evaluation Design and Performance Metrics

Lightweight Predictive BLE Connection Management (LPBCM) framework should be investigated by systematic experimental design for test performance of prediction accuracy, communication reliability, energy efficiency and resource-constrained embedded devices. The evaluation should be done by comparing the proposed tree-based controller with three reference strategies: the fixed connection parameters and the reactive RSSI-threshold based adaptation and a lightweight prediction model based on statistics. As far as computational resources allow, a more sophisticated machine learning model should be added as well to explore the model predictive performance-versus-overhead trade-off. Experimental scenarios should include stations that are stationary and mobile, different distances between stations, partial radio obstructions, other 2.4 GHz wireless traffic, low and high rate application workloads, and multiple connection attempts. Multiple independent runs should be performed for each configuration, and the results should be reported as means, standard deviations and confidence intervals (where appropriate) to show consistency and statistical significance between runs. When evaluating prediction performance, precision, recall, the F1 score, and the area under the receiver operating characteristic curve (AUROC) should be used together to assess classification accuracy and the ability to predict impending connection degradation. The reliability of the connections should be measured in terms of unexpected disconnection frequency, packet delivery ratio (PDR) and recovery time after the disruption of the communication. In assessing the responsiveness, application-level latency and application deadline miss-rate should be used, and for energy efficiency, average power consumption and energy cost to successfully receive an application payload should be used. The following embedded implementation overhead measures should be considered: Model Inference Latency, Flash Memory Requirements, RAM Utilization, Model Update Cost. In addition, the number of change(s) of connection parameter, rejected requests and ineffective adaptations should be measured during each experiment to evaluate the control stability.

4.2. Illustrative Performance Targets

Performance targets of the proposed Lightweight Predictive BLE Connection Management (LPBCM) framework are set to guide experiment and compare the benefits of the LPBCM framework with traditional fixed-parameter connection management. These values are used as an example of research goals and not as experimental results as they are not based on experimental data or hardware measurements.

Table 1: Illustrative Performance Targets

Evaluation Metric	Fixed-Parameter Baseline	Illustrative Target For LPBCM
Unexpected disconnection rate	100% reference	20% lower
Mean application latency	100% reference	10% lower
Energy per delivered payload	100% reference	12% lower
Degradation-detection F1-score	To be measured	At least 90%
Unnecessary parameter updates	100% reference	25% lower
Inference latency	To be measured	Within the device-specific real-time budget

4.2.1. Unexpected Disconnection Rate

The goal of the framework is to lower the unexpected disconnection rate by 20% compared to the fixed-parameter baseline, under similar operating conditions. If these link conditions are identified at an early stage, the controller can suggest appropriate changes to the links before communication is lost. This goal shall be tested by repeated experiments with device mobility, interference and physical obstructions.

4.2.2. Mean Application Latency

The proposed framework aims to reduce the mean application-level latency by 10% with respect to the fixed-parameter baseline. Predictive adaptation can help to increase responsiveness by choosing suitable connection configuration in order to better meet traffic demand and application deadlines. Improvements in real latency should take into consideration parameter negotiation delays, processing overhead and workload characteristics.

4.2.3. Energy per Delivered Payload

The goal of the framework is to reduce energy consumption per application payload successfully delivered, by 12% compared to the baseline. Reducing unnecessary radio activity and choosing connection parameters suitable for the communication load this improvement may be achieved. In order to draw a fair comparison, relevant costs of sensing, processing, communicating and adapting to energy should also be factored into energy measurements.

4.2.4. Degradation-Detection F1-Score

The proposed predictive model is aimed at achieving an F1 score of at least 0.90 when detecting pre-defined BLE connection-degradation events. The F1-score is a combination of precision and recall, providing a metric to assess the model's performance in detecting true degradation while

minimizing false alarms. The assessment should be based on independent test data, and defined degradation labels, prediction horizons and classification thresholds.

4.2.5. Unnecessary Parameter Updates

The framework aims to achieve 25% less than the baseline adaptive policy in connection-parameter updates that are unnecessary. Confidence intervals in the predictions, hysteresis thresholds, and the minimum time between updates can reduce the number of switches made due to noise in the signals. The evaluation ought to be able to consistently say that an unnecessary update is one that does not lead to a meaningful improvement in the selected performance objectives, for example.

4.2.6. Inference Latency

The prediction model should be able to infer within the real-time processing budget defined for the target embedded device. This need makes it possible to have degradation predictions helpful for timely decisions on connection management without adding unnecessary delays to the calculations. Actual deployment hardware should be used for measuring the inference latency, RAM usage, flash usage and processing energy.

4.3. Interpretation, Limitations, and Deployment Considerations

The assessment of the proposed Lightweight Predictive BLE Connection Management (LPBCM) framework should aim to identify potential benefits of predictive modeling and temporal feature extraction over traditional connection-management methods. Results from experiments will indicate that a better understanding of the situation of communication degradation can lead to better timing of connection-management decisions and better overall system efficiency if the performance targets are satisfied. A decrease in the number of unexpected disconnections would suggest that connections are more stable, while a decrease in energy use per successfully delivered payload would suggest that the adaptive communication settings can decrease the overall cost of radio activity, failed radio transmissions and unnecessary control operations. But all the system goals can't be optimized in all the individual measures of performance at the same time. For instance, shorter connection intervals can make the system more responsive but use more energy; or more conservative adaptation policies can save on the number of unnecessary changes but not be able to react to sudden interference. Likewise, sophisticated machine learning models can consume more memory and compute power to make predictions and may not result in significant improvements in prediction accuracy on new devices. Generalization, therefore, is a fundamental research challenge due to the variety of RSSI distributions, packet delivery behavior, antenna characteristics, chipsets, operating systems and environmental conditions across the deployment scenarios. To overcome this, training and testing sets should be split by session, device or environment (whenever possible) and performance should be reported over multiple independent experimental conditions. Class imbalance should also be taken into account since, when connection-degradation events are less common than normal communication events, misleading accuracy estimates could be generated. Moreover, the applicability of LPBCM heavily relies on the connection-management functionality

presented by the Bluetooth host stack and controller. The controller must not assume that any requested configuration will be granted due to protocol procedures, roles of devices, peer capabilities and negotiation outcomes. Some platforms may also have limited access to retransmission counters and detailed link-layer diagnostics. Other deployment concerns are: probability calibration, worst case inference execution time, memory usage, processing energy, and being reliable when the telemetry is lost or an unexpected operating condition occurs. If measurements are unavailable or if predictions exceed validated operating conditions, the controller should fall back to a conservative policy that is compliant with standards. Such safeguards, coupled with regular hardware testing and clear reporting of the limits, are vital for demonstrating the reliability, scalability and usability of LPBCM in production Internet of Things applications.

5. CONCLUSION

This paper introduced a new framework, called Lightweight Predictive Bluetooth Low Energy Connection Management (LPBCM), to enhance the communication reliability and energy efficiency in the IoT applications with limited resource. The proposed architecture combines connection telemetry acquisition, temporal feature engineering, lightweight machine learning inference, risk-aware decision making and feedback driven adaptation to proactively predict connection deterioration and provide guidance for timely management. The framework uses received signal strength indication (RSSI) statistics, packet delivery ratio, available retransmission/failure indicators, application traffic classification, and current connection parameters to build up a compact description of the recently observed communication behavior. The lightweight predictive model estimates the probability of future link degradation and the adaptive controller determines the set of acceptable connection-management actions based on the evaluated energy consumption, communication latency, reliability and adaptation overhead. The proposed approach is to focus on the validity of the predictive aspects only, so that a practical benefit under realistic operating conditions must be measurable. Thus, the following features are included to ensure stable operation: confidence-sensitive decisions, hysteresis mechanisms, protocol-compliant parameter updates and conservative fallback policies. However, the performance improvements achieved in the real world have not yet been recorded in experiments, and the experimental hardware has yet to be developed. Thus, the percentage enhancements that are mentioned in the assessment portion of this study are targets of future research and not actual results. Future research needs to be done using representative BLE development platforms and compare the performance of LPBCM across a variety of device mobility, physical obstructions, wireless interference, traffic workloads, and heterogeneous hardware configurations. Prediction accuracy is one of the metrics that should be compared in a comparative investigation, in addition to inference latency, memory usage, energy consumption, and generalization capability in the cases of decision trees, logistic regression, quantized neural networks and compact ensemble models. Other possible research avenues are online learning, online probability calibration, explainable control decisions, device specific adaptation, and coordinated management of multiple BLE connections in dense IoT environments. In conclusion, light nature and predictive connection management has a potential future role in smart wireless communication at the network edge. The practical value will depend on repeatable experimentation, a thorough

comparison to baseline technologies, and certification to Bluetooth protocol specifications. If successful, it could help facilitate more reliable, responsive, and energy-efficient BLE applications, while maintaining the computational simplicity needed for battery-powered embedded devices.

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