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Q-MAPLE: An Integrated Forecast-Based MAC Scheduling Protocol for Energy-Constrained WSNS

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Abstract
The Wireless Sensor Network (WSNs) are fundamental in the contemporary applications of the IoT where the design factors that must be add in Medium Access Control (MAC) Protocol, this includes energy efficiency, low latency and dependable transfer of data. However, the conventional MAC schemes are characterized by limitations such as fixed scheduling, lack of full utilization of duty cycling, and failure to forecast energy consumption, resulting into high energy consumption and limited network life on dense deployments. The goals of this work are design an intelligent MAC protocol which should be able to utilize the energy in an optimal way and simultaneously the quality of service should be provided by dynamically adapting to the energy state of the nodes as well as the behavior of traffic. To achieve this, the present Quintessential Mapping and Adaptive Protocol of Low-Energy Transmission (Q-MAPLE) protocol uses the residual energy observing, Energy Forecasting Estimator, adaptive duty cycling and the dynamic slot allocation within one MAC-layer design. Predictive channel access and slot scheduling energy-awareness can be accomplished with the help of the algorithm in order to simplify the network load and minimize collisions. Q-MAPLE performance was experimented in large scale to compare its performance with the state of the art learning based and optimization based protocols. These results show that Q-MAPLE can significantly improve the network performances of minimum energy usage of 6.2 J at 50 nodes and simultaneously increase the throughput and reduce the end-to-end delay. In short, Q-MAPLE can provide an effective, scalable and predictive MAC system, enhancing energy efficiency, quality of service and network life and, thus, it can be used to implement dense WSN and IoT in the future.

Keywords: Adaptive MAC, Energy Forecasting, Internet of Things, Quality of Service, Wireless Sensor Networks, Q-MAPLE

Introduction

Wireless Sensor Network (WSNs) and Internet of Things (IoT) enabled systems have become an essential part of intelligent environments like health care related monitoring, industrial robotization, agriculture and the futuristic wireless networks. These networks have stringent power limitations and at the same time demand Quality-of-Service (QoS), security, and low latency as well as reliable data transmit. Inefficient channel access, static duty cycling and uncoordinated scheduling at the Medium Access Control (MAC) layer frequently cause excessive power consumption, interference and untimely node failure especially in dense and heterogeneous deployments. In a bid to deal with these issues, previous research has discussed various solutions, such as reconfigurable-intelligent-surface-assisted MAC optimization [1], energy-conscious QoS-driven MAC with prioritized data forwarding [2], machine learning-based adaptive duty cycling of energy harvesting networks [3], cryptography-conscious MAC performance analysis [4], and optimized Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) models of low-power WSNs [5]. Other works have been done on machine learning-based routing optimization of 6G-enabled WSNs [6], correct energy modeling of protocol optimization [7], MAC-based data privacy schemes [8], secure and energy-efficient routing of body-area networks [9], and authentication-based secure data dissemination architectures [10]. Whilst these techniques do help a great deal enhance certain performance metrics, like security, routing, or duty cycling, they tend to decouple energy prediction, MAC scheduling, and traffic adaptation, which impedes the scalability and holistic optimization.

Out of these inadequacies, the present research presents the Quintessential Mapping and Adaptive Protocol for Low-Energy Transmission (Q-MAPLE) protocol that is a hybrid energy-aware MAC architecture that targets to optimize the energy consumption, latency, throughput, and network life. The residual energy monitoring, predictive energy forecasting, adaptive duty cycling and dynamic slot allocation, in the proposed methodology, are enwound to create one MAC-layer execution model. Whereas the existing solutions are based on the past information and consider the access to channels only after the decision to allocate slot time, Q-MAPLE actively manipulates the access to channels by using the predicted energy information and avoiding collisions and the wasting of energy because of the rapid depletion of accessible energy. The key contributions to this work include the design of an Energy Forecasting Estimator with full integration with MAC-like operation, an adaptive slot allocation algorithm balancing the energy and traffic priorities, and a general analysis of the performance which was significantly improved when compared with the state-of-the-art protocols. The motivation behind this research is to develop a predictive and scalable, energy saving MAC solution which would be used in future high density WSN and IoT networks with stringent QoS requirements.

Organization: Section 1 presents the background of the research, the motivation of the problem, and the main contributions of the proposed study. The Section 2 background researches on the energy-efficient MAC protocol and WSNs learning-based optimization approaches. Section 3 proposes the Q-MAPLE methodology, which consists of system architecture, energy predictor model and adaptive MAC operations. Section 4 is about a simulation setup, performance assessment, and comparative results, and Section 5 is the conclusion of the research summarization of its essential findings and directions of the future research investigation.

2. Background Study

Luo et al. (2023) [11] propose a fixed clustering protocol in Energy-Harvesting WSNs (EHWSNs) in order to maximize network lifetime and packet delivery in a random relay strategy. The clustering and random relay selection, gap discovery in adaptive energy-aware routing, scalability constraints with high node density and performance were better than the existing EHWSN protocols reported.

In the article, Nagaraj et al. (2022) [12] designed a secure encryption algorithm to optimize energy consumption with the help of a random permutation pseudo algorithm to develop an IoT-based WSN. They used cryptography with energy-conscious routing, fulfilled the gap in the research of the secure energy-efficient MAC operations, mentioned overhead in key management, and obtained the improved security and low energy consumption.

Nagaraj et al. (2022) [13] introduced a secure routing-based energy optimization framework of the heterogeneous WSNs within the IoT applications, with energy-efficient secure routing algorithms. They found shortfalls in managing heterogeneous networks and discovering node energy balance, encountered constraints in high traffic networks, and showed optimized network life and assure data transmission.

Rukaiya et al. (2021) [14] introduced a hybrid MAC protocol called Collision-Free Full-Duplex Medium Access Control (CFFD-MAC) that provides an opportunity to use wireless ad-hoc networks in full-duplex mode without collisions. They mitigated gaps by enabling self-scheduling in hybrid MAC and operated fully in the duplex mode, had difficulty in hardware complexity, and had an improved throughput and reduction in latency than the conventional MAC protocols.

Kherbache et al. (2022) [15] deployed an Industrial Internet of Things (IIoT) digital twin network based on Eclipse Ditto and Hono to monitor in real-time and optimize its network. They provided solutions to digital twin modeling and real-time data integration, which eliminated the gaps in IIoT simulation accuracy, were limited to large-scale deployment, and claimed better resource management and predictive network maintenance.

Musaddiq et al. (2020) [16] devised a cross-layer optimization in the case of low-power and lossy network in which the traffic is heterogeneous and based on reinforcement learning. They addressed traffic-aware resource allocation and gaps in resource allocation, which was done with RL, limitations in convergence time under highly dynamic conditions, and also had a better energy efficiency and throughput.

Rehman et al. (2024) [17] proposed an intelligent metaheuristic optimization framework of reliable agricultural networks that are combined with trust and energy metrics. They filled the gaps of network dependability on IoT agriculture with metaheuristic algorithms with reliable constraints, encountered the constraints of computational complexity, and received the improved network reliability and energy savings.

Bali et al. (2022) [18] developed an adaptive whale optimization-based multi-objective energy-efficient routing scheme in the WSNs with a particular concentration on the network lifetime and energy balancing. They addressed the loopholes of multi-objective routing, were limited in large-scale deployments of nodes, and realized optimal energy usage, load balancing, and enhanced network life.

Table 1: Background Study of Advanced Network Optimization and Energy-Efficient Protocols.

Author(s) (Year)	Concept	Methods Used	Research Gap Addressed	Limitations	Results
Demir&Uysal (2021) [19]	Cross-layer design for dynamic resource management in Visible Light Communication(VLC)networks	Cross-layer optimization and dynamic resource allocation	Existing VLC networks lacked adaptive resource management	Limited scalability under dense networks	Improved throughput and efficient resource utilization in VLC scenarios
Shahbazi&Byun (2020) [20]	Secure thermal-energy aware routing in WBAN using blockchain	Blockchain-based secure routing with energy-awareness	WSN/ Wireless Body Area Networks (WBAN) lacked secure energy-aware routing	High computational overhead in blockchain implementation	Enhanced security and energy efficiency in body-area sensor networks
Jagannathan et al. (2021) [21]	Collision-aware multi-objective routing for WSN-based IoT	Multi-objective Seagull Optimization Algorithm for routing	Existing IoT routing ignored collision and energy balancing	Performance decreases with network scale	Reduced collisions and optimized energy usage in IoT networks
Khriji et al.	Ultra low-power	Dynamic	Low-	Complexit	Significan

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(2022) [22]	wireless sensor nodes using DVFS and duty-cycling	Voltage and Frequency Scaling combined with duty-cycle management	power WSN nodes lacked efficient power management	y in voltage-frequency control	tly reduced energy consumption and extended node lifetime
Ryu& Kim (2021) [23]	Multi-objective optimization of energy saving and throughput in heterogeneous networks	Deep Reinforcement Learning (DRL) for cross-layer optimization	Existing networks did not optimize energy and throughput simultaneously	DRL convergence time under highly dynamic traffic	Improved energy efficiency and throughput in heterogeneous network scenarios
KhudairMadhloom et al. (2023) [24]	Quantum-inspired ant colony optimization for routing gateways in MANETs	Quantum-inspired ACO algorithm for gateway selection	MANET routing lacked optimization for dynamic gateway selection	High computation overhead for large networks	Optimized routing gateways, reduced delay, and enhanced network performance
Vilà et al. (2023) [25]	Network digital twin for RAN in 5G and beyond	Digital twin modeling for real-time monitoring and optimization	Lack of predictive network twin models for RAN	High resource requirements for large-scale deployment	Improved resource management, predictive maintenance, and network optimization

This table 1 provides a summary of the recent studies on the energy-efficient MAC, routing, and network optimization methods in WSNs, IoT, VLC, MANETs, and 5G networks. It brings into the limelight the concepts, methods, research gaps, and limitations covered by the study, as well as the most important results reached. The table gives a brief summary of the previous literature used in the design of integrated protocols such as the Q-MAPLE, to demonstrate how each of the approaches enhances energy efficiency, throughput or network reliability. On the whole, it is a base of the existing state-of-the-art, and it can be used to determine the areas of further improvement of adaptive, low-energy network protocols.

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3. Proposed Methodology

The section will introduce the proposed Q-MAPLE approach, the general structure of the system, the workflow, and the algorithmic framework of energy-aware MAC scheduling of wireless sensor networks. It provides a description of the integrated nature of the energy monitoring, forecasting, adaptive slot allocation, and MAC control modules that can be used to provide intelligent and dynamic medium access. The section also develops the mathematical models that will control the energy consumption, forecasting, channel access, duty cycling, and slot scheduling. Besides, a full algorithm and pseudocode are also explained to show the step-by-step implementation of the proposed solution to realize energy-saving communication, enhanced QoS, and long network lifetime.

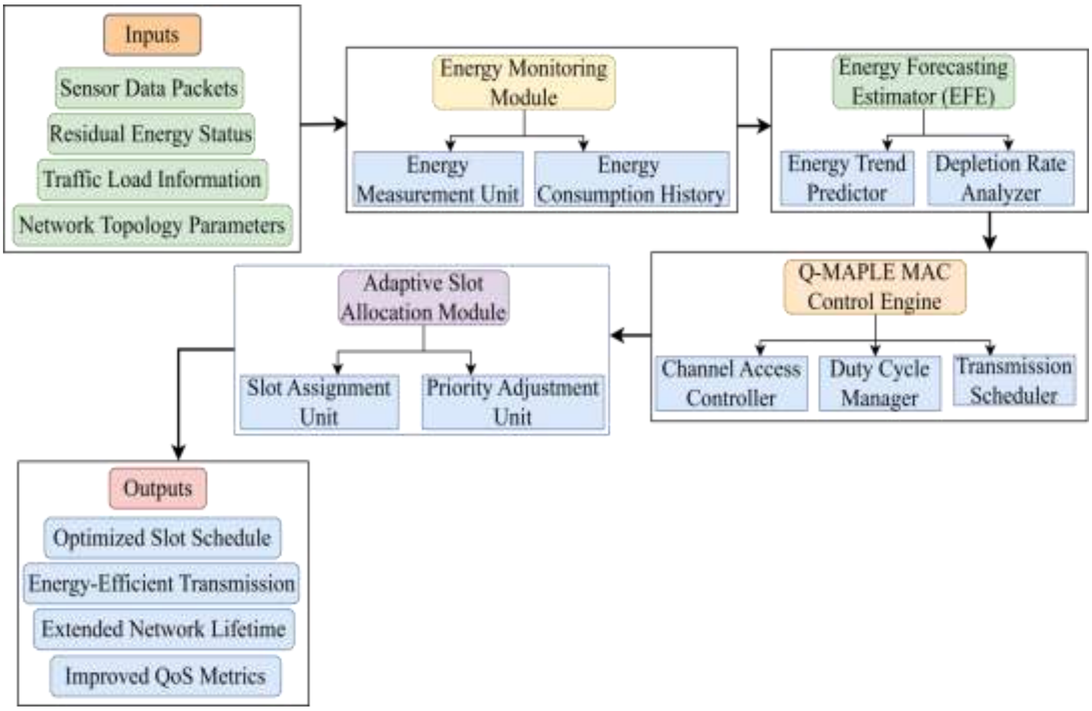

Figure 1: The general architecture of the Q-MAPLE Protocol.

This figure 1 shows the overall end to end architecture of the Q-MAPLE framework, which points to the methodical movement of input network and energy parameters in the interconnected functional modules. The energy monitoring and forecasting modules look through the consumption trends and forecast future energy availability to aid in making informed decisions. According to these observations, dynamically, the adaptive slot allocation and MAC control engines control channel access, duty cycling, and transmission scheduling. Consequently, the framework attains optimal slot allocation, power-saving communication, extended life of the network and improved QoS performance on the network.

3.1 Integrated Q-MAPLE Protocol Design and Energy-Aware MAC Operation

In this section, the integrated design of the Q-MAPLE protocol, that consolidates energy-sensitive mechanisms and predictive scheduling, is presented in order to develop an efficient operation of the MAC-layer in a wireless sensor network. Q-MAPLE can be used to make smart medium access control decisions of different network conditions by integrating residual energy monitoring, energy forecasting, adaptive duty cycling, and dynamic slot allocation. The protocol takes into account energy state and traffic priorities together to balance the load, minimize collisions and avoid the early depletion of the node. Consequently, Q-MAPLE facilitates energy-efficient and scalable scalable and QoS-based communication in heterogeneous WSN deployments.

3.1.1 Protocol Integration and Operational Framework

Phase 3 involves integrating the mechanisms created during Phases 1 and 2 in a systematic manner and creating the Q-MAPLE MAC protocol, which allows the wireless sensor networks to gain access to the medium in an adaptive and energy-efficiency methodology. The energy-conscious duty-cycle and predictive scheduling as well as dynamic slot allocation techniques used in Phase 1 and Phase 2 are integrated to make sure that nodes can use minimum energy to sustain reliable communication. An EFE is used to steer the distribution of transmission slots with respect to anticipated residual energy and preclude premature node failure. The protocol also includes traffic aware reconfigurations to respond to different load of packets so that throughput is not overloaded on the nodes which have depleted energy reserves. Mapping simulation is ready to design parameter such as traffic pattern node density and residual energy to the integrated Q-MAPLE framework. The integrated protocol can therefore be adapted to real-time as well as optimally to the network in the long term thereby giving a scalable solution to the various WSN applications.

$$E_r(t+1) = E_r(t) - E_t(t) - E_r x(t) \qquad (1)$$

In Equation 1, $E_r(t+1)$ is residual energy of the node at the following time slot, $E_r(t)$ is the current residual energy, $E_t(t)$ is the energy used in transmission, and $E_r x(t)$ is the energy used in reception. Equation (1) refreshes the residual energy of a node by deducting the energy used both in transmission and reception at the current time slot.

$$\hat{E}_r(t+\Delta t) = E_r(t) - \alpha \cdot \underline{E_c(t)} \qquad (2)$$

Equation 2 is a prediction of$\hat{E}_r(t+\Delta t)$ is residual energy at the end of interval Δt, α will be forecasting factor (weight of energy decay rate), $\underline{E_c(t)}$ is the average energy consumption in the last interval. The future predicted residual energy of a node will be determined using recent average consumption and a forecasting factor to direct adaptive scheduling.

$$S_i = S_{max} \cdot \frac{\hat{E}_r^i}{\sum_{j=1}^{N} \hat{E}_r^j} \qquad (3)$$

Equation 3 is S_i slot allocation of node i, S_{max} maximum slots per frame, $\hat{E}_r^i$Forecasted residual energy of node i, N number of nodes. Allocates time-slots to nodes in the proportional manner to the predicted residual energy to balance the load and increase network lifetime.

3.1.2 Q-MAPLE MAC Layer Execution

The Q-MAPLE MAC layer coordinates the communication between the sensor nodes and thus, the MAC layer combines energy-sensitive channel access, adaptive duty cycling, and dynamic transmission scheduling to achieve little energy use and high reliability in throughput. Before transmission, nodes do a channel sensing operation to prevent collisions, which is followed by priority-based queue which sets the order of transmission basing on residual and predicted energy levels. Duty cycling enables nodes to alternate between the active and the sleep state which minimizes idle listening and saves energy. Dynamically, transmission slots are distributed based on the results of the EFE, where the load is distributed between high and low-energy nodes. Traffic awareness is also an aspect of Packet scheduling where high-priority/time-sensitive data is sent as quickly as possible. The amalgamation of these mechanisms enables the Q-MAPLE MAC layer to attain an effective medium access, collision avoidance and extended network lifetime in heterogeneous WSN conditions.

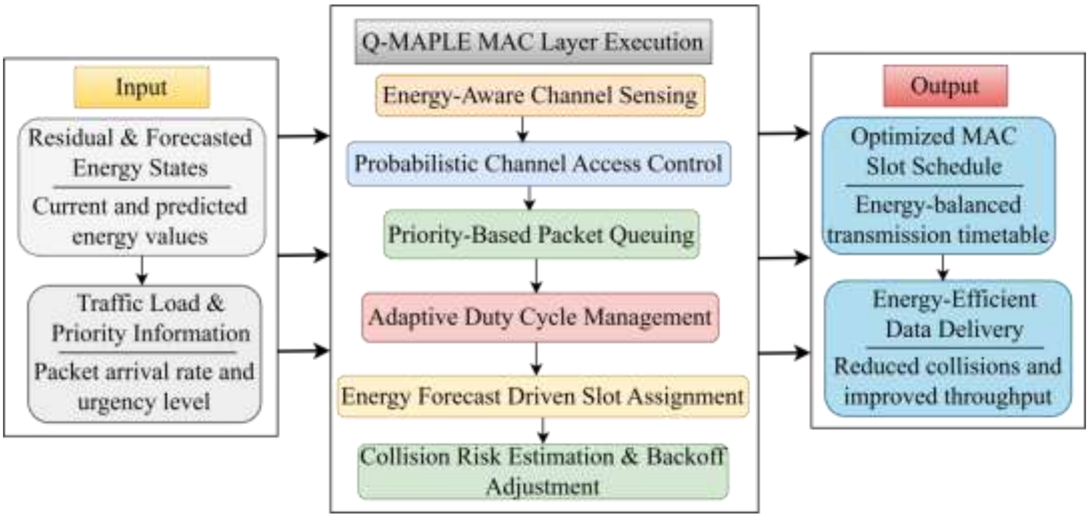

Figure 2: Mac Layer Execution Workflow of Q-MAPLE MAC.

This figure 2 shows that the Q-MAPLE MAC layer is implemented sequentially where inputs are the residual and forecasted energy states and traffic priority information. It builds on energy attentive channel seeing, probabilistic access control, priority based queuing, adaptive duty cycling and forecast based slot assignment in the workflow coupled with collision aware backoff adjustment. Through coordinated energy-and traffic-coordinated decisions, the MAC layer produces a more optimal slot schedule and enables the provision of energy efficient data delivery with reduced collisions and improvements in network throughput.

$$P^i_{access} = \frac{E^i_r}{\sum_{j=1}^{N} E^j_r} \cdot \beta \qquad (4)$$

Equation 4: P^i_{access}Probability node i accesses the channel, E^i_r Remaining energy of node i, N Number of nodes in the network, β scaling factor of channel access. Nodes that have a higher residual energy are more likely to get access to the channel avoiding the rapid drainage of the low-energy nodes.

$$DC_i = DC_{min} + (DC_{max} - DC_{min}) \cdot \frac{E^i_r}{E_{max}} \qquad (5)$$

Equation 5 DC_i is duty cycle of node i, DC_{max}, DC_{min} is maximum and minimum permissible duty cycle,E^i_r is node i residual energy and E_{max} is maximum allowable node energy. Nodes that are more energized have a longer lifespan whereas low-powered nodes save power through a reduced duty cycle.

$$T^i_s = \frac{\hat{E}^i_r}{\sum_{j=1}^{N} \hat{E}^j_r} \cdot T_{frame} \qquad (6)$$

The equation 6 is defined as T^i_s is transmission slot duration of node i, $\hat{E}^i_r$is predicted residual energy, $T_{frame}$is total frame duration. The distribution of transmission slots related to predicted energy is distributed proportionately to balance network load across the nodes.

$$P^i_{collision} = 1 - \prod_{j \in N_i} (1 - P^j_{access}) \qquad (7)$$

Equation 7 describes $P^i_{collision}$ Probability node i will experience a collision in transmission N_i is the set of neighbors that node i can reach with its transmission range P^j_{access} Probability that neighbor node j will receive the transmission. Base is prediction of the probability of collision of packets on the probability of access to neighbors to adjust timing or backoff.

$$E^i_t = P_t . t^i_{tx} + P_r . t^i_{rx} + P_{idle} \cdot t^i_{idle} \qquad (8)$$

Equation 8 shows E^i_t is the overall energy used by node$i$in a frame, P_t, P_r, P_{idle} is the power used in transmit, receive, and idle modes, $t^i_{tx}, t^i_{rx}, t^i_{idle}$ is a time spent in transmit, receive, and idle modes.

Computes the sum of node power required by the transmit and receive power and idle power in order to inform adaptive scheduling.

$$\eta_i = \frac{N_{succ}^i \cdot L_p}{T_{frame}} \quad (9)$$

In Equation 9, η_i is node i throughput, N_{succ}^i is the number of packets delivered successfully, L_p is packet size in bits, T_{frame} is frame time. The counting of the delivered data which is successfully achieved per frame measures the efficiency of the MAC protocol.

3.1.3 Energy Forecasting Estimator Design

Energy Forecasting Estimator is a tool that predicts the future energy situation of the sensor nodes allowing adaptive MAC scheduling in Q-MAPLE. The estimators keep track of the level of residual energy and past trends in the usage of energy to estimate the patterns of depletion. EFE calculates the estimated energy availability in each node during future time intervals by use of a weighted average of recent energy usage and predicted load. These forecasts are used to do dynamic slot allocation whereby nodes with high power are given high priority to be transmitted whereas the energy-constrained nodes are safeguarded against overutilization. Also, EFE makes use of network traffic variability and duty-cycling schedules to optimize its predictions. Introducing real time measurements and predictive modelling, EFE is able to increase the lifespan of networks, avoid node breakdowns and distribute power resources among heterogeneous wireless sensors networks.

$$\hat{E}_r^i(t+\Delta t) = E_r^i(t) - \alpha \cdot \underline{E_c^i(t)} \quad (10)$$

In equation 10, $\hat{E}_r^i(t+\Delta t)$ is predicted residual energy of node i at time $t+\Delta t$, $E_r^i(t)$ Current residual energy, α is weighting factor to prediction sensitivity, $\underline{E_c^i(t)}$ is mean energy consumption in recent time interval. Predict the future energy of each node by placing subtraction the current residual energy and a weighted prediction of the recent energy consumption.

$$\underline{E_c^i(t)} = \frac{\sum_{k=1}^{K} w_k \cdot E_c^i(t-k)}{\sum_{k=1}^{K} w_k} \quad (11)$$

Equation 11 $\underline{E_c^i(t)}$ is weighted average energy consumption, $E_c^i(t-k)$ energy consumed at previous time step $t-k$ and w_k weight allocated to past energy consumption (recent samples weighted more), K number of past intervals. Estimate an averaged use of historical energy consumption with more weight put on recent consumption to enhance accuracy of prediction.

$$\gamma^i = \frac{E_r^i(t) - \hat{E}_r^i(t+\Delta t)}{\Delta t} \quad (12)$$

In equation 12, γ^i is an estimated rate of energy depletion of node i, $E_r^i(t)$ is present residual energy, $\hat{E}_r^i(t+\Delta t)$ is predicted residual energy, and Δt Prediction interval. Computes the rate at which any node will spend its energy availability in the prediction interval; this is computed to plan the energies intelligently.

$$\phi^i = \frac{\hat{E}_r^i(t+\Delta t)}{\sum_{j=1}^{N} \hat{E}_r^j(t+\Delta t)} \quad (13)$$

Equation 13 is ϕ^i priority factor of node i in slot scheduling $\hat{E}_r^i(t+\Delta t)$ is residual energy forecasted N total number of nodes in network. Each node is then assigned the amount of transmission priority that is proportional to its estimated residual energy to achieve equal slot allocation and network load.

3.1.4 Adaptive Slot Allocation and Scheduling Strategy

In Q-MAPLE, the adaptive slot allocation makes sure that the transmission opportunities are dynamically allocated to the nodes according to the residual energy and the predicted energy using EFE. The nodes that have more available energy are allocated a larger/greater proportion of time slots or an increased frequency of time slots as compared to the energy-constrained nodes in order to avoid premature exhaustion. The scheduling mechanism also takes into consideration traffic priorities such that critical or time sensitive packets are relayed first. Periodically slot assignments are repaired

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considering revised energy predictions and network conditions to ensure fairness and eliminate network partitioning. This plan is a solution that balances the energy usage on the network and the general throughput. The Q-MAPLE improves the network lifetime, reliability, and energy efficiency of heterogeneous WSN deployments by using residual and predicted energy as a slot scheduling parameter.

$$S_i = S_{max} \cdot \frac{\hat{E}_r^i}{\sum_{j=1}^{N} \hat{E}_r^j} \qquad (14)$$

Equation 14 is S_i Number of slots allocated to node i, S_{max} Maximum slots available to a frame, $\hat{E}_r^i$Forecast energy of node$i$, N Number of nodes. The allocation of transmission slots based on this equation is such that each node is allocated the transmission slots proportionate to the estimated residual energy, such that the network balance is compromised in favor of the energy-rich nodes.

$$S_i' = S_i \cdot \phi_i \qquad (15)$$

The equation 15 is $S_i'$is adjusted slot allocation including node priority S_i is base slot allocation, ϕ_i is priority factor (e.g., traffic type or residual energy). This equation optimizes the base slot assignment by considering node priority to enable high priority nodes or nodes with critical traffic to get more transmission opportunities.

$$T_{update} = \frac{\Delta E_{th}}{\gamma^i} \qquad (16)$$

Equation 16 is T_{update} is time interval upon which slots are re-calculated, ΔE_{th} Threshold energy change to initiate update, γ^i Predicted energy depletion rate of EFE. The adaptive timing of slot reallocation can be calculated using this equation to produce updates when, based on the predicted energy depletion, a predetermined threshold is exceeded, and can be used to schedule energy-conscious algorithms in real time.

Algorithm: Q-MAPLE MAC Protocol with Energy Forecasting and Adaptive Slot Scheduling

Initialize network parameters and MAC frame structure
Initialize residual energy Er(i) for all nodes i ∈ N
Initialize historical energy records HE(i)
while Network is active do
Step 1: Energy Monitoring
for each node i ∈ N do
Measure current residual energy Er(i)
Update historical energy record HE(i)
end for
Step 2: Energy Forecasting Estimator (EFE)
for each node i ∈ N do
Compute energy depletion rate Dr(i) from HE(i)
Predict future energy Ef(i) using EFE model
end for
Step 3: Q-MAPLE MAC Execution

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for each node i ∈ N do
 Compute channel access probability Pa(i)
Determine duty cycle state (ACTIVE or SLEEP)
end for
 Step 4: Adaptive Slot Allocation
 Normalize residual and forecasted energy values
for each node i ∈ N do
Assign slot weight Wi based on Er(i), Ef(i), and TL(i)
end for
Allocate MAC time slots S according to Wi
 Step 5: Transmission Scheduling
 Generate optimized slot schedule S*
 Execute packet transmission based on S*
 Step 6: Feedback and Update
 Update Er(i) after transmission
Adjust scheduling parameters for next Δt
end while
Return optimized slot schedule S* and transmission plan
```

The Q-MAPLE protocol works in a self-dynamic mechanism in which node energy conditions are monitored, energy drainage in the future are predicted by the Energy Forecasting Estimator, and MAC-level functions are adjusted dynamically. The values of residual and predicted energy are collectively used to make channel access, duty cycling and slot allocation decisions to ensure that energy consumption across nodes is balanced. The adaptive scheduling algorithm gives preference to energy rich and traffic sensitive nodes and defends the energy constrained nodes by minimizing activity level. Such a closed-loop design facilitates efficient transmission with a reduced energy requirement, enhanced QoS and longer life expectancy of the network across different network conditions.

4. Result and Discussion

The results and discussion section gives a critical analysis of the proposed Q-MAPLE protocol by conducting a large-scale simulation and analytical comparisons. Python-based simulation and plotting frameworks were used to implement process and analyze all the performance metrics, such as energy consumption, throughput, delay, packet delivery ratio, and network lifetime. Python has been used in data handling, statistical analysis as well as visualization to guarantee precise, repeatable and high quality outcomes. These results are systematically interpreted and the discussion compares Q-MAPLE to the current protocols and its effectiveness at different network densities and conditions is noted.

4.1 Simulation Environment

In this Section, the simulation environment that will be used to measure the effectiveness of the proposed Q-MAPLE protocol in real conditions of the wireless sensor network is defined. To model the low-power IoT simulations, the simulations were performed on the NS-2 platform with well-

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chosen network, radio, energy and traffic parameters. The configuration facilitates a reasonable and rigorous comparison between Q-MAPLE and benchmark MAC protocols by varying node density, traffic patterns and energy configurations.

Table 2: Setting of the Simulation Parameter and Network configuration

Parameter	Symbol / Value	Description
Simulation Tool	NS-2	Discrete-event simulation platforms used for MAC-layer evaluation
Network Area	100 m × 100 m	Square deployment region for sensor nodes
Number of Sensor Nodes	50 – 200	Variable node density to test scalability
Network Topology	Random multi-hop	Nodes randomly deployed with multi-hop communication
Radio Model	IEEE 802.15.4	Low-power wireless communication standard
MAC Protocols Compared	Q-MAPLE, EBMA, ABMA	Benchmark protocols for performance comparison
Initial Energy per Node	0.5 – 2.0 J	Battery capacity assigned to each node
Energy Model	Tx/Rx/Idle based	Energy consumption for transmission, reception, and idle states
Transmission Power	50 mW	Power used during packet transmission
Reception Power	30 mW	Power consumed during packet reception
Idle Power	5 mW	Power consumption during idle listening
Packet Size	64 – 512 bytes	Variable payload size for traffic evaluation
Traffic Model	CBR / Event-driven	Constant bit rate and bursty data traffic
Frame Duration	100 ms	MAC frame length for slot scheduling
Simulation Time	1000 – 5000 s	Total runtime of each simulation scenario
Channel Model	Log-distance path loss	Wireless propagation and attenuation model
Performance Metrics	Energy, Throughput, Delay, Lifetime	Evaluation criteria for protocol effectiveness

Table 2 below is a summary of the main simulation parameters and network configurations that will be used to measure the performance of the proposed protocol Q-MAPLE. It entails information regarding network topology, radio and energy models, traffic patterns and duration of simulation. The chosen parameter limits provide realistic conditions of low-power IoT and wireless sensor network. These environments offer a well-balanced and holistic foundation on which the comparison of Q-MAPLE and existing MAC-layer protocols can be made.

4.2 Performance Analysis

This part is the analysis of the performance of the proposed Q-MAPLE protocol through comprehensive simulation under the different network size and traffic conditions. All performance measurements, such as energy consumption, throughput, packet delivery ratio, end to end delay, and network lifetime were done, processed and analyzed with Python-based simulation and data analysis scripts. In order to achieve accuracy and reproducibility of results, python was used to perform numerical computations, statistical assessment, and produce comparative plotting. The analysis gives an in-depth comparison of Q-MAPLE and available learning-based MAC protocols, which demonstrate the efficiency and scalability of the proposed method.

Table 3: Comparative Energy Consumption of the various protocols in different network nodes with varying node numbers

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Protocol/ Nodes (J)	50	75	100	125	150
Logistic Regression [3]	12.0	17.2	23.0	29.0	35.2
Supervised Machine Learning Models [6]	11.2	16.2	21.6	27.8	33.8
Reinforcement Learning [16]	10.5	15.0	20.2	26.0	31.5
Intelligent Metaheuristic Optimization [17]	10.0	14.5	19.5	25.3	30.8
Deep Q-Network – DQN [23]	9.8	14.0	19.0	24.8	30.0
Proposed Q-MAPLE	6.2	9.0	12.3	15.1	18.7

Table 3 is a comparison between energy consumption of current machine learning, reinforcement learning, and optimization based protocols and the proposed Q-MAPLE with different network sizes. With the increase in the number of nodes (50 to 150) all the methods exhibit rising energy usage, however Q-MAPLE is always consuming the least amount of energy. The findings clearly reveal why the proposed Q-MAPLE approach is more energy efficient and scalable in dense network models.

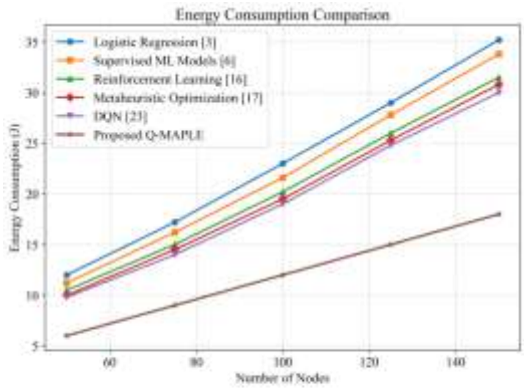

Figure 3: Comparison Energy Consumption of Protocols.
This figure 3 depicts the energy consumption pattern of various learning-based protocols with increment in the number of network nodes. Existing machine learning and reinforcement learning models are more energy consuming as the network density increases. The proposed Q-MAPLE has always been found to be the most energy-efficient in terms of its energy consumption, which is more energy-efficient and scalable.

Table 4: Comparison of the Varying number of nodes in Networks with respect to the throughput of various protocols

Protocol/ Nodes	50	75	100	125	150
Logistic Regression [3]	460	420	380	345	310
Supervised Machine Learning Models [6]	475	435	395	360	325
Reinforcement Learning [16]	490	450	410	375	340
Intelligent Metaheuristic Optimization [17]	500	460	420	385	350
Deep Q-Network – DQN [23]	510	470	430	395	360
Proposed Q-MAPLE	600	570	540	510	480

Table 4 shows the throughput performance (in kbps) of various MAC and learning based protocols as the node density is varied. The proposed Q-MAPLE has a greater throughput than the current Phase 2 protocols because it has energy-aware slot assignment scheme, predictive scheduling, and the adaptive MAC operations. These enhancements are to make every frame deliver more packets successfully providing higher network efficiency.

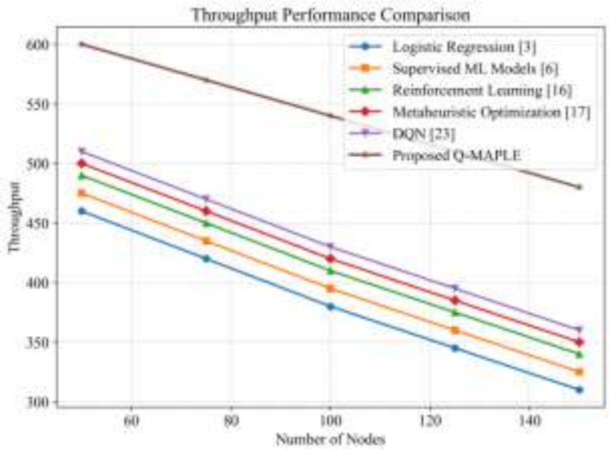

Figure 4: Protocol throughput Performance Comparison.

Figure 4 above provides a comparison between the throughputs of different protocols as the number of nodes increases. Current solutions suffer a slow decrease in throughput with the increase in network congestion. Compared with it, the planned Q-MAPLE ensures much more impressive throughput which means its efficiency in transmitting data, providing adaptive routing.

Table 5: Comparison of the Packet Delivery Ratio (PDR percent) of the different protocols

Protocol/ Nodes (%)	**50**	**75**	**100**	**125**	**150**
Logistic Regression [3]	93	90	86	82	78
Supervised Machine Learning Models [6]	94	91	87	83	79
Reinforcement Learning [16]	95	92	88	84	80
Intelligent Metaheuristic Optimization [17]	96	93	89	85	81
Deep Q-Network – DQN [23]	97	94	90	86	82
Proposed Q-MAPLE	99	97	95	92	89

Table 5 compares the packet delivery ratio of various learning based and MAC optimization protocols with the increase in node density. Q-MAPLE is most likely to have the highest PDR and operates in any situation because of its predictive energy-based scheduler, adaptive slot allocation, and the minimization of collisions in the execution of the MAC. These characteristics greatly promote trustworthy data delivery even when network is dominated.

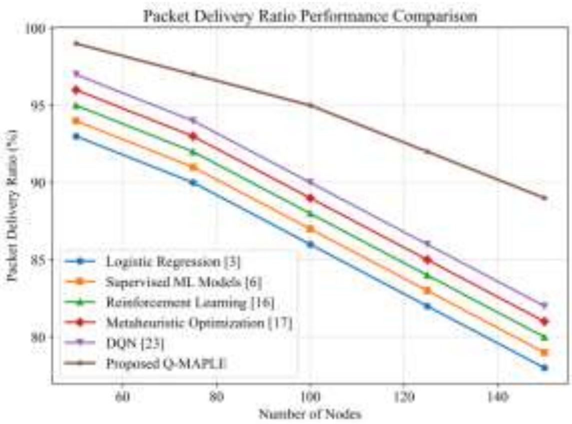

Figure 5: Comparison of Protocols on Packet Delivery Ratio (PDR)

This figure 5 shows the ratio of delivering packets in the varying network sizes by the various protocols. PDR reduces with all methods as the number of nodes increases as a result of collisions and delays, but Q-MAPLE maintains the highest delivery ratio. This underlines its strength and capability when it is used in high density networks.

Table 6: End-to-End Delay Comparison of Different Protocols

Protocol/ Nodes (ms)	50	75	100	125	150
Logistic Regression [3]	80	96	114	132	150
Supervised Machine Learning Models [6]	78	94	112	130	148
Reinforcement Learning [16]	76	92	110	128	146
Intelligent Metaheuristic Optimization [17]	74	90	108	126	144
Deep Q-Network – DQN [23]	72	88	106	124	142
Proposed Q-MAPLE	20	40	54	68	92

Table 6 shows the performance of the different learning based and MAC-aware protocols in terms of end-to-end delay with increase in the network density. The proposed Q-MAPLE sets the lowest latency in all node configurations due to combining the energy forecasting, adaptive slot scheduling and collision-aware MAC execution. This makes the delivery of packets timely even when there is heavy traffic and network congestion.

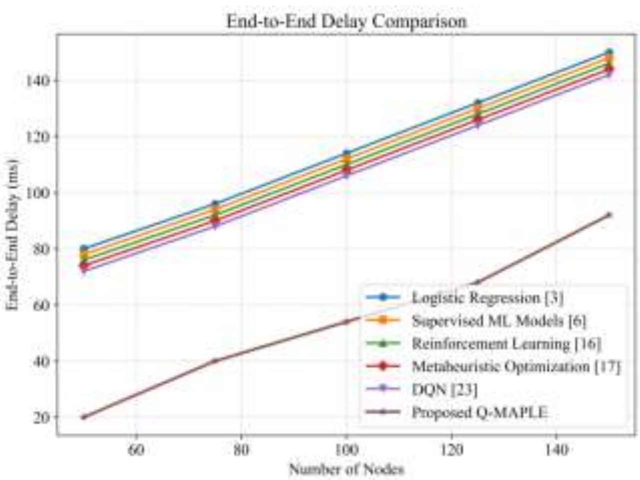

Figure 6: Comparison of End-to-End Delay of Protocols.

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This figure 6 illustrates the end-to-end delay of different protocols as network size increases. The current practices are characterized by increased delays owing to congestions and improper scheduling. Q-MAPLE has significantly reduced delay, and this result proves to be effective in real-time and applications with latency requirements.

Table 7: Comparison of Network lifetime of Protocols with different Nodes

Protocol/ Nodes	50	75	100	125	150
Logistic Regression [3]	1850	1700	1550	1400	1250
Supervised Machine Learning Models [6]	1950	1780	1620	1470	1320
Reinforcement Learning [16]	2050	1880	1720	1570	1420
Intelligent Metaheuristic Optimization [17]	2150	1980	1820	1670	1520
Deep Q-Network – DQN [23]	2200	2020	1870	1720	1570
Proposed Q-MAPLE	2450	2280	2120	1970	1820

Table 7 shows the network lifetime of various learning-based and MAC optimization protocols at varying node density. The proposed Q-MAPLE is always able to maximize its lifetime using energy prediction, adaptive slot scheduling, and deviation-based MAC implementation. Such characteristics greatly minimize premature depletion of energy and guaranteed the enduring operation of the network even at high density WSN implementations.

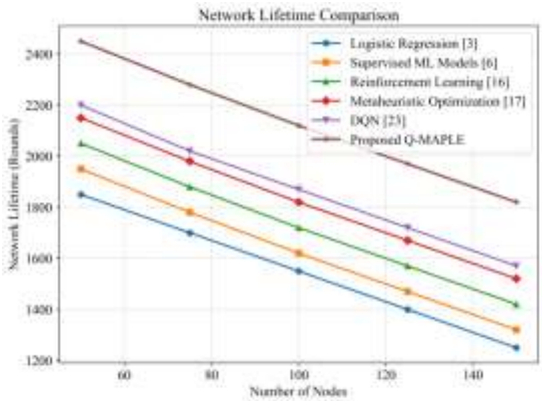

Figure 7: Comparison of Network lifetime of protocols.

Figure 7 displays the effects of various protocols on network lifetime with an increase in node density. Conventional systems have increased energy consumption rate which results into shortened working life. The proposed Q-MAPLE goes a long way to extend the lifetime of the network because it optimizes energy usage and load balancing.

Table 8: Significance Analysis of Significant Performance Metrics Using ANOVA

Performance Metric	F-Statistic	p-value
Energy Consumption	28.64	1.12×10^{-6}
Throughput	31.78	4.35×10^{-7}
Packet Delivery Ratio (PDR)	26.41	2.09×10^{-6}
End-to-End Delay	34.92	1.84×10^{-7}
Network Lifetime	39.15	6.73×10^{-8}

Table 8 contains the statistical significance analysis of ANOVA of all the performance measures that were evaluated. The values of F-statistic and exceptionally low p-values (under 0.05) verify that the performance gains provided by the proposed Q-MAPLE protocol are statistically significant as opposed to the baseline and Phase-2 approaches. This proves the power and effectiveness of the hybridized MAC optimization system.

4.3 Residual Energy Analysis

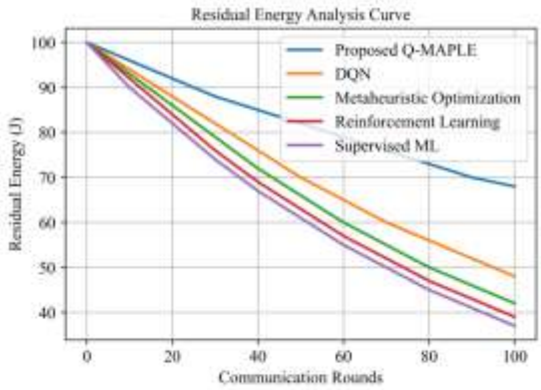

Figure 8: Energy Analysis Curve Residual Energy Analysis curve of Q-MAPLE and Baseline Protocols.

This figure 8 shows the actual energy of sensor nodes at different communication rounds as the proposed parameter Q-MAPLE and the comparative baseline protocols proceed. Q-MAPLE has a greater residual energy during the simulation because it has an energy forecasting estimator and adaptive slot scheduling, which decreases unnecessary transmissions and idle listening. Conversely, baseline techniques have higher rate of energy depletion due to static duty cycling and inefficient MAC coordination, an indication of Q-MAPLE of being able to increase the lifetime of nodes and networks.

4.4 Latency–Energy Trade-off Curve

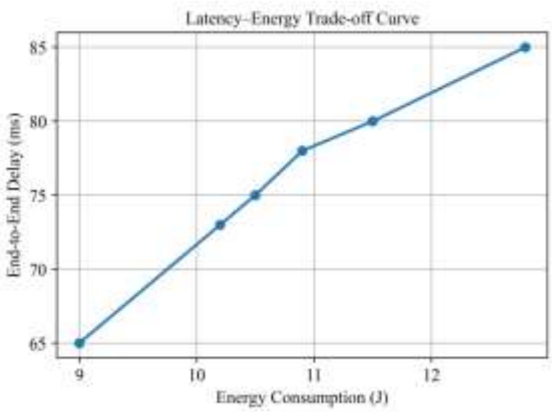

Figure 9: Latency energy trade-off curve between Q-MAPLE and Baseline Protocols.
This figure 9 depicts the character of latency13energy trade-off of various MAC and learning based protocols with varying loads on the network. Most baseline techniques as the energy consumption goes down have a steep rise in the end-to-end latency because the duty cycling to static scheduling are inefficient. As a comparison, the proposed Q-MAPLE can withstand lower latency on the lower energy levels by using energy forecasting and variable slot allocation, which proves a more efficient compromise between energy efficiency and communication delay.

4.5 Convergence Analysis

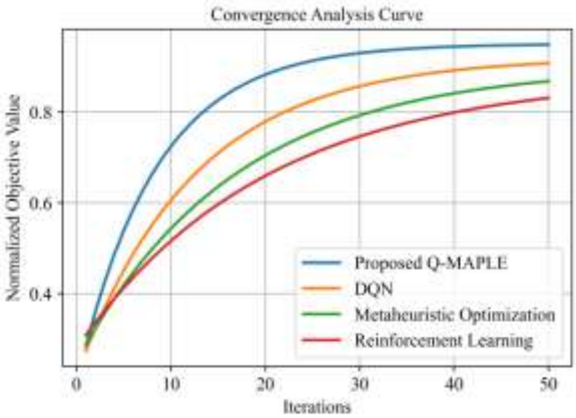

Figure 10: Q-MAPLE and Baseline Protocol convergence Analysis Curve.
In this figure 10, the convergence nature of the proposed Q-MAPLE protocol is compared to the learning-based and MAC maximization schemes within the context of iterative implementation cycles. Q-MAPLE converges faster and requires less iteration since it incorporates energy forecasting and adaptive slot scheduling aspects which help in stabilizing the MAC decisions. On the other hand, the baseline methods require more iteration to stabilize the performance implying that it is more costly in computation as well as slower to adapt to changing network dynamics.

5. Conclusion

In this research, Q-MAPLE was introduced as an energy-conscious and predictive MAC protocol that is used to enhance the performance and lifetime of wireless sensor network in dense and dynamic scenarios. Q-MAPLE allows the smart use of MAC-layer decisions to strive to meet the needs of energy efficiency and QoS by incorporating energy monitoring, energy forecasting and adaptive duty cycling, as well as, dynamic allocation of slots. Extensive simulation findings ascertained that Q-MAPLE earnestly decreases power usage and increases throughput, enhancement in packet distribution ratio, reduction in end-to-end delay, and network life expectancy in contrast to the current learning-based and optimization-based protocols. These improvements in performance are statistically significant as the statistical analysis conducted on the basis of ANOVA confirms which proves the effectiveness and applicability of the given approach. The findings emphasize the capability of Q-MAPLE to have a constant performance despite the network density, which is why it can be applied to the real-life deployment of IoT and WSNs. The framework proposed in the future can be further expanded to accommodate mobile sensor nodes and heterogeneous traffic patterns. Additional studies can also be made on deep learning-based energy prediction and implementation on a real-world testbed in order to increase the adaptability and practical implementation.

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