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Analysis of Quality of Experience Evaluation Framework for RPL Protocol in Mobile IoT Environments under Manhattan Grid Mobility

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Abstract— This research paper introduces a novel and advanced framework for assessing the Quality of Experience (QoE) implications associated with the utilization of the Routing protocol for low power and lossy networks (RPL) in the context of the Internet of Things (IoT). The study undertakes a thorough investigation into RPL's performance under the influence of Manhattan grid (MG) mobility scenarios, addressing a notable gap in current research. By meticulously incorporating essential Quality of Service (QoS) metrics like average packet delivery ratio (PDR), average power consumption (Avg_P), and average inter-packet time (Avg_IPT), the framework enables an in-depth evaluation of QoE. The uniqueness of this work lies in its incorporation of a comprehensive dependency matrix (DM) and the subsequent application of a dependency function (DF) that comprehensively captures the multifaceted aspects of the system's perceived quality.

Beyond its methodological innovation, this research enhances our comprehension of RPL's adaptability through the shift from static to dynamic environments. Furthermore, the study systematically explores various scalability levels, contributing novel insights into how RPL performs across diverse IoT scenarios.Based on the Quality of Experience (QoE) analysis, it can be deduced that the network effectively maintains the performance of a static model even under conditions of MG scenarios. In the static model, the RPL's performance was measured at 67.73%. However, when exposed to the MG mobility model, its performance decreased to 42.93%. Given that RPL is primarily optimized for static models and considering its static model performance as a reference benchmark, it manages to retain approximately 63.38% of the static model's performance when subjected to the MG mobility model.

Keywords- Quality of Service (QoS), Quality of Experience (QoE), average packet delivery ratio, average inter-packet time, average power consumption, dependency matrix (DM), dependency function (DF), RPL protocol, Manhattan grid mobility, IoT scalability.

I. INTRODUCTION

The Internet of Things (IoT) comprises a network of specialized smart devices like sensors, processors, actuators, and controllers designed for specific purposes. These devices enable information exchange through single-hop or multi-hop communication, where efficient routing protocols are vital due to resource limitations. The designated protocol, RPL (Routing Protocol for Low-Power and Lossy Networks), defined by RFC 6550, uses a Destination Oriented Directed Acyclic Graph (DODAG) for routing. However, as real-world IoT networks often exhibit mobility, assessing RPL's performance in such scenarios is crucial. Traditional network performance evaluation relies on Quality of Service (QoS) parameters like bandwidth, throughput, delay, packet loss, and jitter, posing challenges due to trade-offs between these parameters. A more subjective but essential approach is to measure user satisfaction, considering the varying expectations of different users. Adaptable QoS values aligned with user perceptions enable a balance between QoS parameters without compromising perceived quality.

This research presents a groundbreaking approach to IoT network evaluation by prioritizing user satisfaction as the ultimate metric. It introduces adaptive QoS values based on user expectations, recognizes interdependencies among QoS parameters, and offers a data-driven approach to optimize network design. Furthermore, it addresses the mobility challenge in IoT networks and presents a customizable evaluation model, enhancing its applicability. This work's focus on subjective evaluation contributes to the expanding field of Quality of

Experience (QoE) research, enriching our understanding of network performance in a dynamic technological landscape. The subsequent sections discuss related research in QoE measurement, the proposed QoE evaluation model, simulation results, and future directions.

II. RELATED WORKS

Wherever This section delves into various scenarios and applications where Quality of Experience (QoE) is explored and used as an evaluative measure. The subsequent works present distinct approaches leveraging QoE for assessment.

In the context of software-defined multi-tier LTE-A networks, an approach involving Device-to-Device (D2D) communications is employed to amplify QoE enhancement [1]. This strategy enhances the success probability of uplink (UL) and downlink (DL) transmissions for internet access. However, this proposed algorithm encounters several challenges, encompassing network management, stability of D2D links, incentive stimulation, and privacy preservation, which must be addressed before its application.

Isaias Martinez and collaborators introduce a QoE measurement technique considering different networking layers' influence on QoE [2]. They devise a Functional Benchmarking Framework (FBM) that structures the comparison of QoE proposals. This framework delineates an environment and workload definition across layers, specifying output parameters to gauge proposal efficiency and cost. The FBM enhances the organization of parameters for QoE measurement.

Mario Siller and John Woods propose a framework for QoE evaluation employing QoS metrics, network feedback, and dynamic user requirements [3]. By ensuring close interaction between QoS and network/application layers, improved QoE is achieved. This framework includes network arbitration mechanisms driven by feedback from agent software, employing weighting factors and RT tables for QoS management, considering metrics like delay, jitter, and packet loss.

Jeevan Pokhrel explores the correlation between QoS and QoE for estimation purposes [4]. Using a dataset linking QoS parameters and QoE, various machine learning algorithms like fuzzy expert system and random neural network are trained for QoE prediction. This approach examines the impact of network conditions on services such as Video on Demand (VoD) and analyzes the effect of MAC layer QoS parameters on VoD over wireless networks.

Alessandro Floris and Luigi Atzori tackle QoE evaluation for IoT applications, particularly multimedia content [5]. A layered QoE model centered on Multimedia IoT (MIoT) assesses contributing factors to MIoT application QoE. However, challenges arise due to the lack of a reference IoT architecture and undefined Quality of Data (QoD) for video signals.

Quantitative assessment of wireless network QoE involves two methods [6]. Statistical sampling assesses service performance, while a Network Management System (NMS) leverages QoS parameters. In video streaming, network path quality impacts QoE [7]. This is resolved by dividing the issue into two sub-problems: correlating network/application QoS and application QoS/QoE. The improvement of QoE through network or application QoS management is highlighted.

Efficient QoE measurement employs a pentagram model, replacing subjective surveys [8]. Comprising factors like integrality, retainability, availability, usability, and instantaneousness, this model aids VoIP service providers in QoE evaluation and enhancement.

The OneClick framework captures user perceptions in network applications using quality assessment methods [9]. This lightweight, time-aware framework employs PESQ and VQM methods to assess audio and video quality. Its applicability is tested in different environments, although reliability and efficiency remain potential concerns.

Prometheus estimates mobile app QoE through passive network measurements and machine learning [10]. A prototype system correlates QoE and passive measurements via machine learning. Challenges include accuracy improvement, user interaction, and benchmark automation.

Antonio et al. develop software modules to predict QoE in real-time multimedia delivery streams [11]. Utilizing decision trees, these modules suggest QoE remedies and improvements. The e-Health sector employs fuzzy logic for QoE estimation [14]. A framework evaluates the relationship between technology and human factors in e-Health, albeit challenges remain in defining QoD and application.

Quantitative and qualitative QoE assessment in wireless multimedia is conducted using Rough Set Theory and user opinions [15]. QoS parameters' impact on QoE is explored, highlighting variations in network QoS parameters affecting user opinions.

Machine learning facilitates QoE evaluation in commercial mobile TV [16]. Accurate QoE prediction is achieved with minimal dataset through machine learning, enabling QoE estimation based on real-time data.

QoE's significance in cloud computing applications is emphasized [17]. Optimizing QoE for economic gains while ensuring resource efficiency and standardized interfaces is pivotal.

QoE management for multimedia cloud services, particularly YouTube videos, relies on QoE models, monitoring, and optimization [18]. Initial delay and stalling effects are analyzed, and QoE monitoring approaches are explored.

The VLQoE tool extends VLC media player for smartphone-based video QoE tests [19]. Metrics from user interface, network layer, and sensors are captured, with the goal of minimizing perceived quality degradation.

In-smartphone passive traffic measurements and QoE crowd-sourced feedback inform QoE monitoring in cellular networks [20]. Machine learning techniques are applied to estimate QoE, utilizing a decision trees classifier algorithm.

A general system for IP network QoE evaluation is introduced [21]. This architecture emulates multi-agent networks and dynamic systems, showcasing its utility through web browsing QoE experiments.

QoE-driven emulation explores cross-layer dependencies in DASH [22]. This approach highlights dependencies between network conditions and configurations, shedding light on adaptive video streaming intricacies.

Enrico Bocchi presents metrics for WebQoE assessment [23], introducing generalized indices for QoE evaluation. Wi-Fi quality's impact on WebQoE is also examined [24], demonstrating a predictive model's accuracy.

Mapping QoS metrics to QoE metrics via decision trees is proposed [25], serving traffic management and QoE estimation. This work fills a gap in QoE estimation by providing a generic framework.In summary, this work encompasses a wide spectrum of QoE evaluation techniques, addressing challenges, and fostering a comprehensive understanding of QoE in various networking scenarios.

III. PROPOSED SYSTEM

The proposed system aims to comprehensively evaluate the Quality of Experience (QoE) of the RPL protocol in varying scalability levels within the context of the Manhattan grid mobility scenario. Despite its original design for static node environments, this study addresses the increasing mobility of IoT nodes and investigates RPL's performance in dynamic settings. The research involves data collection through simulations and subsequent analysis of critical evaluation parameters, namely Average Power Consumption (Avg_P), Packet Delivery Ratio (PDR), and Average Inter-Packet Time (Avg_IPT), known for their substantial impact on RPL's overall performance.

Utilizing Karl's Pearson Correlation method, relationships between QoS parameters are established, revealing their significance within the study. An Ishikawa Fishbone diagram visually depicts the underlying sub-parameters influencing main QoS parameters. Coefficient of correlation visualizations provide insights into the strength of relationships. A Dependency Matrix (DM) and Dependency Function (DF) illustrate interdependencies and weighted relationships. QoE is calculated based on DF, with user-perceived quality-based weights, and compared between static and mobile scenarios. A generic weight allocation process enhances flexibility, and the entire process is summarized algorithmically, facilitating a comprehensive assessment of RPL's QoE performance in dynamic IoT environments .The proposed system encompasses the following steps to thoroughly evaluate the Quality of Experience (QoE) of the RPL protocol in a dynamic IoT environment:

Step 1 : Initial Setup :

The research aims to evaluate the Quality of Experience (QoE) associated with the RPL protocol across different scalability levels in the context of the Manhattan grid mobility scenario. While the RPL protocol was initially designed for static node environments, the prevalent mobility of IoT nodes necessitates an assessment of its performance in dynamic settings. To achieve this, critical evaluation parameters are chosen, including Average Power Consumption (Avg_P), Packet Delivery Ratio (PDR), and Average Inter-Packet Time (Avg_IPT), known to significantly influence the overall RPL performance.

The architecture of the proposed system is depicted in Figure 1, providing a comprehensive overview of its structural framework. This design encompasses all essential components and their interconnections, forming the foundation for the system's functionality and performance.

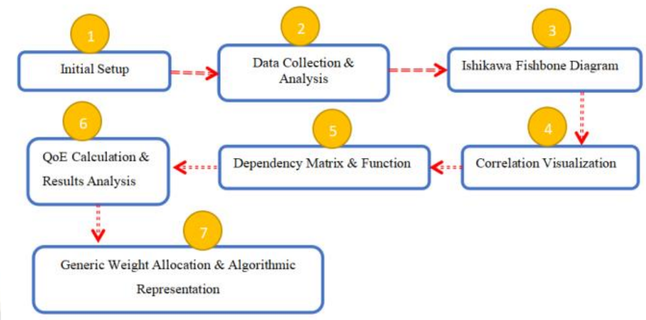

Figure 1 : Architecture of the Proposed System

Step 2: Data Collection & Analysis :

Using the Contiki and Cooja simulator, simulations are set up to collect QoS parameters in both static and mobility scenarios. This collected data forms the basis for subsequent analysis. To understand the relationships between QoS parameters, Karl's Pearson Correlation analysis is applied. This statistical method quantifies the extent of correlation between selected variables, revealing their significance within the study's context.

Step 3: Ishikawa Fishbone Diagram :

The sub-parameters that influence the main QoS parameters (Avg_P, PDR, Avg_IPT) are identified and visualized in an Ishikawa Fishbone diagram. This diagram highlights the underlying factors contributing to the performance of the chosen QoS parameters.

Step 4: Correlation Visualization :

The coefficient of correlation for PDR (Packet Delivery Ratio), Avg_IPT (Average Inter-Packet Time), and Avg_P (Average Power Consumption) are visualized in separate diagrams (Figure 2, Figure 3, and Figure 4). These visualizations provide insights into the strength and direction of the correlations between the QoS parameters.

Step 5: Dependency Matrix & Function :

A Dependency Matrix (DM) is constructed, showcasing the interdependencies among the QoS parameters. The Dependency Function (DF) is calculated based on the matrix, representing the weighted relationships between the parameters.

Step 6: QoE Calculation & Results Analysis :

The QoE is calculated using the Dependency Function (DF) as the base value. Comparisons are drawn between the QoE values obtained from simulations in both non-mobile and mobility scenarios. The QoE values are assigned weighted values based on user perceptions of quality, which are outlined in a predefined table.

Step 7: Generic Weight Allocation & Algorithmic Representation

To provide flexibility, a generic weight allocation process is introduced. The allocation of weighted values for QoS parameters is based on the simulation results obtained in non-mobile scenarios. These weights can be adjusted to cater to specific user requirements and perceptions of quality. The entire

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process is summarized in an algorithmic representation for clear understanding.

3.1 Comprehensive Explanation of Every Step in the Proposed System

A thorough explanation of each and every step of the proposed system is provided here. This work is dedicated to examining the holistic quality of experience (QoE) associated with the RPL protocol across varying scalability levels within the context of the Manhattan grid mobility scenario. Despite the original design of the RPL protocol for static node environments, it's essential to address the prevalent mobility of IoT nodes. Consequently, we've taken the opportunity to assess the operational effectiveness of RPL within this dynamic framework. To accomplish this, we've selected crucial evaluation parameters, namely average power consumption, average packet delivery ratio, and average inter-packet time. These parameters were chosen based on their considerable impact on the overall performance of the RPL protocol, and their significance was quantified through the application of Karl's Pearson correlation method. Karl's Pearson coefficient, a statistical tool [26], was employed to discern the extent of the relationships between the selected variables, further informing their significance in the study's context. Equation 1 depicts Karl's Pearson correlation coefficient: X with respect to Y.

$$r = \frac{\sum(X-\bar{X})\,(Y-\bar{Y})}{\sqrt{\sum(X-\bar{X})^2}\,\sqrt{(Y-\bar{Y})^2}} \qquad (1)$$

In the given equations, X and Y denote two interdependent variables being studied. The correlation coefficient, denoted as "r," quantifies the degree of dependency between X and Y. The value of "r" falls within the range of -1 to +1. A value closer to the negative end signifies a robust inverse relationship, while a value closer to the positive end indicates a strong direct relationship. An "r" value of zero implies the absence of correlation. This established approach was employed to identify secondary QoS parameters that exhibit a substantial correlation with primary QoS parameters. The primary and secondary QoS parameters were visually presented in the form of an Ishikawa fishbone diagram [27].

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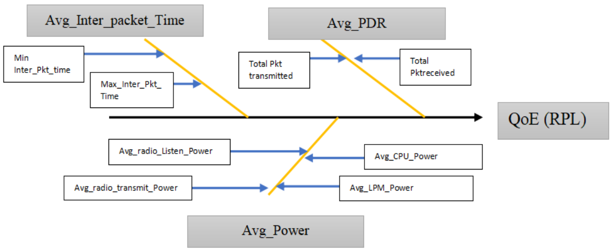

Figure 2 Ishikawa Fishbone diagram - QoS dependencies

From this explanation, it's evident that the average power (Avg_P) is obtained from factors like radio listen power, radio transmission power, low power mode power (LPM), and CPU power utilization. Similarly, the packet delivery ratio (PDR) is calculated by dividing the total transmitted packets by the total received packets. Additionally, the average inter-packet time (Avg_IPT) is determined by finding the difference between the maximum and minimum inter-packet times. These sub-parameters exhibit strong correlations with the main parameters under investigation. The significance of these correlations is illustrated in Figures 3, 4, and 5, which showcase the relationships between QoS and sub-QoS parameters.

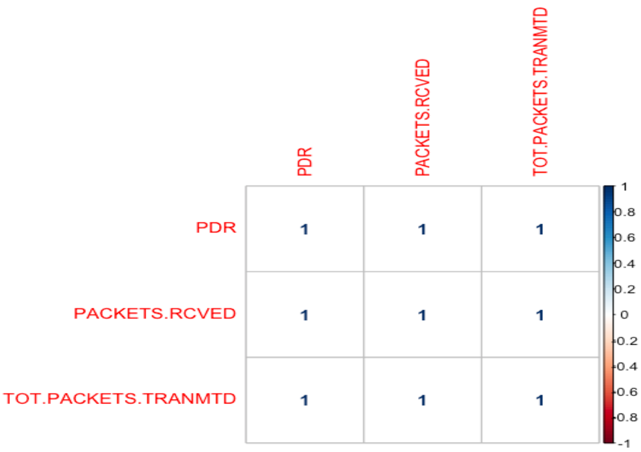

Figure 3 Co-efficient of correlation for PDR

To assess the overall Quality of Experience (QoE) of RPL, it's crucial to identify the interdependencies among the QoS parameters. This information is crucial for understanding how different parameters relate to each other. Figure 7 provides a visual representation of the correlation coefficients between various QoS parameters, offering insights into their relationships.

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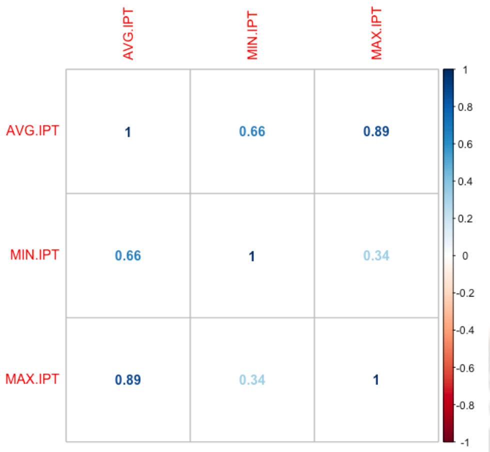

Figure 4 Co-efficient of correlation for Average _IPT

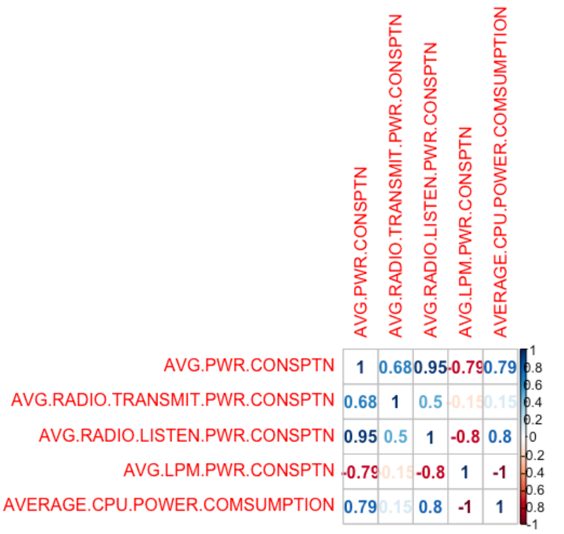

Figure 5 Co-efficient of correlation for Average_Power

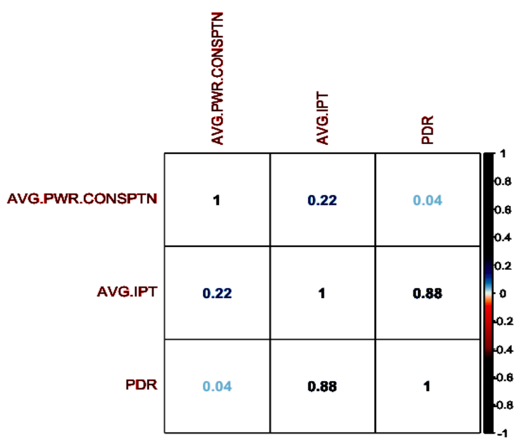

Figure 6 Co-efficient of correlation of Interdependency amongst QoS variables

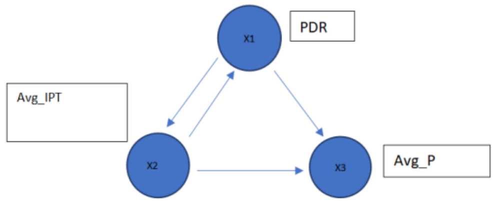

Figure 7 Directed graph of Parameters

To assess the overall Quality of Experience (QoE) of RPL, it's crucial to identify the interdependencies among the QoS parameters. This information is crucial for understanding how different parameters relate to each other. Figure 7 provides a visual representation of the correlation coefficients between various QoS parameters, offering insights into their relationships.

Figure 7 provides a clear depiction of the relationships between the parameters. Notably, the Packet Delivery Ratio (PDR) and Average Inter-Packet Time (Avg_IPT) exhibit mutual dependence. Specifically, changes in PDR influence Average Power Consumption (Avg_P), and variations in Avg_IPT significantly impact Avg_P. However, alterations in Avg_P do not notably affect PDR and Avg_IPT. This pattern is evident in figure 7, where there are no arrows connecting Avg_P to PDR and Avg_IPT. This dynamic is represented as a dependency matrix as illustrated below.

$$DM = \begin{bmatrix} X1 & X12 & X13 \\ X21 & X2 & X23 \\ X31 & X32 & X3 \end{bmatrix} \qquad (2)$$

The values of X in the matrix above are adjusted to the weighted values as outlined in Table 1. The diagonal elements reflect the weighted Quality of Service (QoS) parameters, taking into account users' quality perception from the application standpoint. On the other hand, the off-diagonal elements symbolize the scaled weighted values representing the level of correlation significance between QoS parameters. The scaling follows the guidelines presented in Table 2.

Table 1.Weight distribution based on perceived quality

Weight	Quality
1	Poor
2	Average
3	Good
4	Very Good
5	Excellent

3.1.1 Generic weight allocation for the framework :

Since RPL was originally designed for a non-mobile IoT environment [28], which serves as a benchmark for evaluating the performance of the mobile IoT environment, we use it as a reference. From Table 2, weighted values ranging from 1 to 6 are assigned based on the simulation values for each parameter.

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These values are derived from the static simulation model, where the range of each QoS parameter is calculated and divided into five equal slots. Lower range values are assigned a weight of 1, indicating poorer perceived quality, while higher ranges receive progressively higher weight values. This uniform weight assignment approach forms a foundational representation of the framework, which can be customized based on user preferences and application requirements to adjust the range of each QoS parameter value according to their needs and perceptions.

Table 3: Weights used for correlation levels

Correlation Range	Weight
0.0 – 0.20	**1**
0.21 – 0.40	**2**
0.41 – 0.60	**3**
0.61 – 0.80	**4**
0.81 – 1.00	**5**

3.1.2 Calculation of QoE for Manhattan mobility model

The weight allocation process for each QoS parameter, initially observed under a non-mobile simulation model, is determined. Subsequently, the corresponding average QoS values derived from simulations involving the Manhattan mobility model [29] are compared and adjusted to match the weighted values of the non-mobile environment. This mapping to the non-mobile environment allows us to assess how well the RPL protocol maintains its original functionality in the presence of mobility. This procedure is repeated for various scalability levels of nodes, such as 20, 40, and 60. The simulations are conducted using the Contiki-based Cooja simulator. The resulting weighted values are then arranged in a dependency matrix (DM), where elements X1, X2, and X3 form the diagonal. Off-diagonal DM elements represent the weighted correlation values of QoS parameters, as specified in Table 3. Specifically, elements like X12, X13, X21, X23, X31, and X32 denote positive correlations, representing relationships such as X1's correlation with X2, X1's correlation with X3, X2's correlation with X1, and so forth.

By observing Figure 3, it becomes clear from the directed graph that establishing a relationship between X1 and X2 through X3 is not feasible. As a result, matrix elements X31 and X32 are assigned null values, indicated as zeros. To ascertain the overall Quality of Experience (QoE) of RPL in the context of the Manhattan mobility model, it becomes crucial to determine the positive determinant of the dependency matrix (DM). This positive determinant is calculated using the dependency function (DF) presented as follows:

$$DF = \{(X_1 * X_2 * X_3) + (X_3 * X_{21} * X_{12}) + (X_2 * X_{31} * X_{13}) + (X_1 * X_{23} * X_{32}) + (X_{12} * X_{23} * X_{31}) + (X_{13} * X_{21} * X_{32}) + (X_{21} * X_{32} * X_{13}) + (X_{23} * X_{31} * X_{12}) + (X_{31} * X_{12} * X23) + (X_{32} * X_{13} * X_{21})\} \quad (3)$$

The Quality of Experience (QoE) values are expressed in percentage format as follows. In the ideal operational scenario, both the diagonal and off-diagonal elements are assigned the maximum weights from tables 1 and 2, which are then used to calculate the dependency function (DF). This resulting value serves as the base for representing the QoE of both the static and mobile environments in percentage using equation 5.

$$QoE\ in\ percentage = \frac{DF\ static\ or\ mobile}{DF\ Ideal} \times 100 \quad (4)$$

In the ideal case scenario, the dependency function yields a value of 250. Using this ideal value, the QoE for both the static and Manhattan mobility models across various scalability levels is computed in percentage using equation 5, and the results are shown in tables 4 and 5.

IV. Simulations, Results and Inference

The RPL protocol undergoes simulation using the Contiki Cooja 2.1 simulator[29]. Within the simulation environment, the chosen node is the "sky mote." The scalability spectrum encompasses 20 to 60 nodes. The simulation's time span is consistently set at 10 minutes across all population categories.
Two simulation models are executed for experimentation. Initially, the simulation focuses on stationary nodes, evaluating scalability levels of 20, 40, and 60. The outcomes of this immobile simulation are established as the baseline since RPL is tailored for static contexts. The metrics of Packet Delivery Ratio (PDR), Interpacket Time, and Power are segmented into five equal intervals. These intervals are assigned weights referenced from table 1 in section 3. Employing a dependency function (DF) tied to their respective weights, the Quality of Experience (QoE) values are computed and outlined in the ensuing table 5.

Table 5: QoE values for non-mobile environment

Number of Nodes	PDR in percentage	Interpacket Time in seconds	Avg_power in milli watts	QoE
20	95.23	42.25	1.0933	200
40	98.18	45.987	1.4672	144
60	100	43.854	2.0295	164
Average QoE :169.333				

Table 6 quantifies the QoE values numerically. Examining the data reveals QoE scores of 200, 144, and 164 for 20, 40, and 60 nodes respectively in a non-mobile environment. The mean QoE value for the static RPL context calculates to 169.333. Notably, a decline in QoE accompanies higher scalability levels. This trend could be attributed to heightened inter-node communication and an increased occurrence of packet loss.

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Within the same simulation context, the Manhattan mobility pattern is employed via the Bonnmotion simulator. The QoS outcomes for matching scalability levels are documented. The Manhattan grid model, as demonstrated in previous research [29], emerges as the most fitting mobility model for RPL when compared to alternatives like the Gaussian and Randomway point models. RPL's performance remained at its best under the influence of the Manhattan grid mobility scenario [29]. The ensuing table outlines the findings from the mobility model.

Table .6. QoE values for mobile environment – Manhattan Grid

Number of Nodes	PDR in percentage	Interpacket Time in seconds	Avg_power in milli watts	QoE
20	95.23	45.75	1.3438	50
40	97.56	45.713	1.7163	108
60	98.36	44.076	2.0051	164
			Average QoE : 107.333	

The above findings indicate a significant deterioration in the performance of RPL. For a network involving 20 nodes, the Packet Delivery Ratio (PDR) registers at 95.23%, the Interpacket Time measures 45.75 seconds, and the average power loss stands at 1.34 milliwatts. As scalability expands to 40 and 60 nodes, the calculated PDR figures rise to 97.56% and 98.36% respectively. Moreover, the Interpacket Time is observed as 45.71 seconds and 44.07 seconds respectively. Correspondingly, the average power loss escalates to 1.71 milliwatts for 40 nodes and 2 milliwatts for 60 nodes.

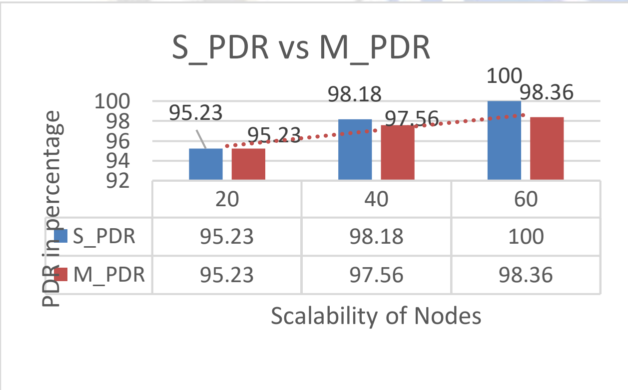

Figure 8 S_PDR vs M_PDR

On average, in mobile scenarios, the PDR stabilizes at 97.05%. Similarly, the Interpacket Time averages around 45.179 seconds. However, the average power consumption increases to 0.15 milliwatts in mobile environments. This could be attributed to the mobility pattern of the nodes within the network. Clearly, as nodes move farther apart, a noticeable decline in performance occurs due to link disruptions and the ensuing delays in route reconstruction.The following graphs compares the performance of RPL under static and mobile environment.

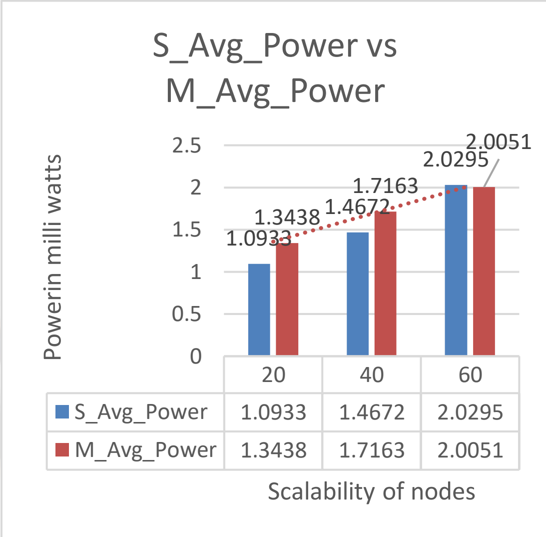

Figure 9 S_Avg_Power vs M_Avg_Power

V. Conclusions

Based on the conducted experiments, the Quality of Experience (QoE) for the RPL protocol is computed at 131.333 under static conditions and 169.333 under mobile scenarios. In an ideal scenario, the QoE reaches a computed value of 250, representing the highest achievable level. By applying equation 5 to express this as a percentage, the overall QoE under non-mobile conditions is determined to be 67.73%. This value serves as the actual performance benchmark for RPL, given its design for static IoT models. Transitioning this network scenario to a Manhattan grid mobility pattern yields a computed QoE value of 42.93%, showcasing RPL's performance at 63.38% relative to the Manhattan mobility model. This discrepancy highlights that while RPL's evaluation based solely on Quality of Service (QoS) metrics indicates a substantial performance drop, an evaluation based on QoE demonstrates a more favorable performance in terms of perceived quality. An added advantage of the QoE-centric performance analysis from the proposed framework is its consideration of interdependencies among the studied QoS variables. In contrast, traditional QoS-based analysis ignores these interdependent factors, focusing solely on the outcomes of QoS parameters for evaluation. Consequently, such QoS-based evaluation overlooks critical dependency details. The decline in perceived QoE from the aforementioned simulations can be attributed to factors like mobility-induced disconnections among neighboring nodes and increased power consumption. Frequent disconnections among IoT nodes prompt RPL to reconstruct the Destination Oriented Directed Acyclic Graph (DODAG), introducing delays and reducing throughput. Active participation of nodes in the route reconstruction process further elevates power consumption. As a future avenue, the proposed QoE evaluation framework can be extended to gauge the performance of Vehicular Ad-Hoc Networks (VANETs). Given the similarity between the mobile patterns of VANETs and the Manhattan Grid, the proposed QoE framework can be effectively employed. As this work introduces QoE evaluation as a generic framework, it holds potential for assessing the user-perceived quality of any service provided by products or technology.

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