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# Performance Analysis and QoS Modeling of an IoT-Based Real-Time Patient Monitoring System Using Heart Rate and GPS Data

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## ABSTRACT

This paper presents the design, implementation, and experimental performance evaluation of an IoT-based real-time patient monitoring system using heart rate and GPS data. The proposed system integrates a wearable pulse sensor and GPS module with a Wi-Fi-enabled microcontroller to continuously transmit physiological and location data to a cloud-based monitoring platform. Real-world experiments were conducted under varying network traffic conditions to evaluate key Quality of Service (QoS) parameters, including throughput, end-to-end delay, and packet loss. The experimental results show that the system performs reliably under low to moderate traffic loads, achieving stable throughput with average delay below acceptable real-time thresholds and negligible packet loss. However, as network traffic increases, delay rises significantly and packet loss becomes more pronounced, particularly when buffer capacity is limited. Comparative testing with different buffer configurations demonstrates that larger buffers improve data reliability by reducing packet loss, but at the cost of increased latency. Furthermore, the system successfully delivers real-time heart rate and location data with high accuracy, demonstrating its applicability for remote healthcare monitoring. The results validate that maintaining operation within a controlled traffic region is essential to ensure optimal QoS. This study provides practical insights into the deployment of IoT healthcare systems, emphasizing the importance of balancing latency, reliability, and network resource constraints in real-world environments.

## INTRODUCTION

The rapid advancement of the Internet of Things (IoT) has significantly transformed modern healthcare systems, enabling continuous and real-time monitoring of patients outside traditional clinical environments. IoT-based healthcare systems utilize interconnected sensors, communication protocols, and cloud platforms to collect, transmit, and analyze physiological data, thereby enhancing early diagnosis and timely medical intervention. In particular, wearable and embedded IoT devices have become essential in monitoring vital parameters such as heart rate, electrocardiogram (ECG), blood pressure, and body temperature in real time, improving patient outcomes and reducing hospitalization costs(Alshammari, 2023; Younas et al., 2023)

Cardiovascular diseases remain one of the leading causes of mortality worldwide, necessitating continuous monitoring of heart-related parameters. Traditional monitoring methods are often limited to hospital settings and require manual supervision, which is inefficient for long-term observation. IoT-based heart rate monitoring systems address this limitation by enabling remote and automated tracking of cardiac activity, allowing healthcare providers to detect abnormalities at early stages(Allbadi et al., 2025; Tasmurzayev et al., 2025) Furthermore, recent developments demonstrate that integrating IoT with cloud-based systems allows real-time visualization and storage of patient data, facilitating proactive healthcare management and reducing the risk of critical events .

In addition to physiological monitoring, location tracking has become an important feature in modern healthcare applications, particularly for elderly patients, individuals with chronic conditions, and emergency cases(Nataletti et al., 2025). The integration of Global Positioning System (GPS) technology with IoT enables real-time geolocation tracking, allowing caregivers to respond quickly in case of emergencies. Systems that combine heart rate monitoring and GPS

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tracking provide a more comprehensive healthcare solution by not only detecting abnormal physiological conditions but also identifying the patient's exact location for rapid medical assistance(Alshuhail et al., 2025).

To support efficient data transmission in IoT healthcare systems, lightweight communication protocols such as Message Queuing Telemetry Transport (MQTT) are widely adopted. MQTT is designed for low-bandwidth and resource-constrained environments, making it suitable for real-time medical data transmission. It provides reliable communication through different Quality of Service (QoS) levels, which regulate message delivery guarantees and network performance. Studies have shown that MQTT-based healthcare systems can achieve low latency and high reliability, making them ideal for continuous patient monitoring applications(Alshammari, 2023)(Alharbi et al., 2025)

Despite these advancements, several challenges remain in ensuring reliable and efficient IoT-based healthcare monitoring. One of the key issues is maintaining Quality of Service (QoS) in dynamic network conditions (Has et al., 2024). Parameters such as delay, packet loss, and throughput significantly affect the performance of real-time monitoring systems, especially in critical healthcare scenarios. Existing studies primarily focus on system implementation without providing comprehensive analytical models to evaluate network performance. Moreover, limited research integrates QoS modeling with physiological monitoring and geolocation tracking in a unified framework (Boikanyo et al., 2023).

Therefore, this study proposes an IoT-based real-time patient monitoring system that integrates heart rate sensing and GPS-based localization, combined with a comprehensive QoS modeling approach. The system is designed using a low-cost microcontroller platform and employs MQTT for data communication. To evaluate system performance, a queueing theory-based model is utilized to analyze key QoS parameters, including delay, packet loss, and throughput under varying traffic conditions(Shah et al., 2026).

The main contributions of this work are as follows: (1) the design of an integrated IoT healthcare system combining physiological and geolocation monitoring, (2) the development of a QoS modeling framework using analytical methods, and (3) the experimental validation of system performance under different network scenarios. This research aims to bridge the gap between IoT-based healthcare implementation and network performance analysis, providing a scalable and reliable solution for real-time patient monitoring(Rehman et al., 2025)(Alatawi, 2025).

## LITERATURE REVIEW

Recent studies have focused on designing low-cost and energy-efficient IoT architectures for patient monitoring(Rabearison et al., 2026). For instance(Dimitrievski et al., 2021) developed an IoT-based healthcare system using lightweight communication protocols to enable real-time monitoring of patient vital signs. Their work highlights the importance of using resource-constrained devices such as ESP32 and ESP8266 to achieve scalable and cost-effective solutions. Similarly, (Osman, 2025) implemented a heart rate monitoring system using ECG sensors integrated with IoT platforms, demonstrating the feasibility of continuous physiological monitoring in real-world environments.(Manchanda et al., 2025)

In the context of cardiac monitoring, heart rate is one of the most critical physiological indicators used to assess patient health conditions. IoT-enabled heart rate monitoring systems provide continuous and real-time measurements, allowing early detection of abnormalities such as bradycardia and tachycardia(Thottempudi et al., 2025). proposed an MQTT-based ECG monitoring system that enables remote tracking of cardiac activity. Their results indicate that IoT-based monitoring systems significantly improve response time and reduce the dependency on manual medical supervision.

Beyond physiological monitoring, the integration of geolocation tracking has emerged as a crucial component in modern healthcare applications. GPS-enabled IoT systems allow healthcare providers to monitor the real-time location of patients, which is particularly useful for elderly individuals, patients with cognitive impairments, and emergency scenarios. According to Kumar and Poojari (2025), combining physiological data with location information enhances the effectiveness of emergency response systems by enabling faster intervention. However, many existing studies focus either on physiological monitoring or location tracking, but rarely integrate both into a unified system.

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Communication protocols play a vital role in ensuring reliable data transmission in IoT healthcare systems(Joshi, 2024). Among various protocols, Message Queuing Telemetry Transport (MQTT) has gained widespread adoption due to its lightweight design and suitability for low-bandwidth environments. MQTT supports multiple Quality of Service (QoS) levels, which allow developers to balance between reliability and latency based on application requirements. demonstrated that MQTT-based healthcare systems can achieve low latency and high reliability, making them suitable for real-time monitoring applications(Refaee et al., 2022).

Further advancements in MQTT optimization have been explored to improve network performance. For example, (Nabha et al., 2025) proposed a feature engineering framework to enhance the security and efficiency of MQTT in IoT environments. Additionally, the PrioMQTT model introduced a prioritized messaging mechanism to reduce latency for critical data transmission, which is particularly important in healthcare scenarios where timely delivery of data can be life-saving (PrioMQTT, 2024). These studies emphasize the importance of optimizing communication protocols to meet the stringent requirements of healthcare applications(Gerodimos et al., 2023).

Quality of Service (QoS) is a key performance indicator in IoT-based healthcare systems, particularly in real-time applications. QoS parameters such as delay, packet loss, throughput, and reliability directly impact the effectiveness of patient monitoring systems. conducted a comprehensive review on QoS monitoring in IoT healthcare systems and highlighted that maintaining consistent QoS remains a major challenge due to dynamic network conditions and resource limitations. Most existing studies focus on empirical performance evaluation, with limited emphasis on analytical modeling approaches(CheSuh et al., 2024).

To address QoS challenges, several researchers have explored the use of mathematical models and machine learning techniques. proposed a hybrid CNN-LSTM model for adaptive QoS optimization in MQTT-based IoT systems(Jasim, 2025). The study demonstrates that AI-based approaches can dynamically adjust system parameters to maintain optimal performance under varying network conditions. However, such approaches often require high computational resources, making them less suitable for low-power IoT devices(Gulzar & Mustafa, 2026).

Queueing theory has been widely used as an analytical tool to model and evaluate network performance in IoT systems. Models such as M/M/1 and M/M/1/K are commonly applied to analyze delay, packet loss, and system stability under different traffic loads. These models provide a theoretical foundation for understanding system behavior and can complement experimental evaluations. Despite their effectiveness, the application of queueing models in IoT-based healthcare systems remains limited, particularly in systems that integrate both physiological monitoring and geolocation tracking(Kateb et al., 2025).

In summary, existing literature demonstrates significant progress in IoT-based healthcare monitoring systems, particularly in areas such as sensor integration, communication protocols, and system implementation. However, several research gaps remain. First, most studies focus on either physiological monitoring or location tracking, with limited integration of both in a unified framework. Second, while MQTT has been widely adopted, there is a lack of comprehensive analysis on its QoS performance in healthcare applications. Third, analytical modeling approaches such as queueing theory are underutilized in evaluating system performance(Mustafa et al., 2025).

Therefore, this study aims to address these gaps by proposing an integrated IoT-based patient monitoring system that combines heart rate sensing and GPS-based localization, along with a comprehensive QoS modeling framework based on queueing theory(Alsabah et al., 2025). By bridging the gap between system implementation and analytical performance evaluation, this research contributes to the development of more reliable and scalable IoT healthcare solutions(Famá et al., 2022).

## METHOD

This study proposes an IoT-based real-time patient monitoring system that integrates heart rate sensing and GPS-based localization. The system is designed to continuously acquire physiological and location data, transmit them through a wireless network, and evaluate system performance using Quality of Service (QoS) metrics.

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The architecture consists of three main layers: (1) sensing layer, (2) communication layer, and (3) cloud and application layer. The sensing layer collects real-time data from the patient, the communication layer ensures reliable data transmission, and the cloud layer provides storage, visualization, and alert mechanisms.

The hardware implementation is based on a low-cost IoT platform to ensure scalability and accessibility. The main components include:

Table 1. Hardware Configuration

| Component | Function |
|---|---|
| ESP32 | Microcontroller with Wi-Fi capability |
| MAX30102 | Heart rate sensor (BPM detection) |
| GPS Neo-6M | Real-time location tracking |
| Li-Po Battery | Power supply |
| OLED Display | Local monitoring (optional) |

**Table 2.** Software Architecture Requirements

| No | Module | Function | Technology | Output |
|---|---|---|---|---|
| 1 | Data Acquisition | Read heart rate & GPS data | ESP32, MAX30102, GPS | BPM, Location |
| 2 | Processing & Validation | Filter signal and classify BPM | Moving Average, Threshold | Clean BPM, Status |
| 3 | Communication | Send data to server | MQTT | JSON data |
| 4 | Network Management | Maintain Wi-Fi connection | ESP32 Wi-Fi | Stable connection |
| 5 | Cloud & Database | Store and manage data | Firebase / Thingspeak | Stored data |
| 6 | Visualization | Display data in dashboard | Web / Mobile App | Graphs, Maps |
| 7 | Alert System | Notify abnormal conditions | Telegram / Firebase | Alert notification |
| 8 | Security | Secure data transmission | TLS/SSL | Encrypted data |

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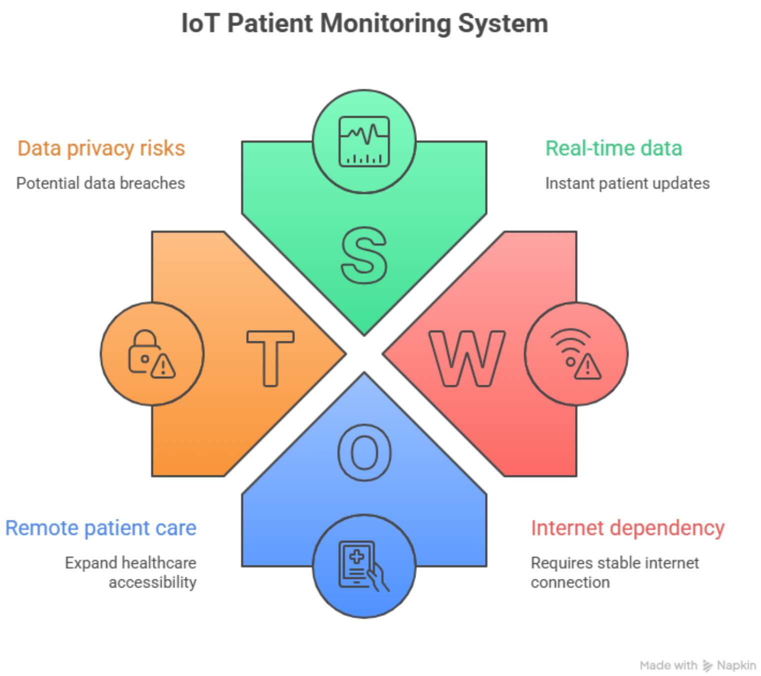


Figure 1. Optimizing Esp8266 Repeater Performance

The image illustrates an **IoT Patient Monitoring System** concept using a **SWOT-style visual framework**, where the system is represented at the center and surrounded by four key aspects highlighting its strengths, weaknesses, opportunities, and threats.

At the center, the system is symbolized by four interconnected colored segments forming a cross-like structure with the letters **S, T, W, and O**, representing different analytical dimensions. Each segment is paired with an icon that visually reinforces its meaning.

- The **top (S – Strength)** highlights *"Real-time data"*, emphasizing the system's ability to provide instant patient updates. This reflects a major advantage of IoT in healthcare, enabling continuous monitoring of vital signs such as heart rate.
- The **right (W – Weakness)** shows *"Internet dependency"*, indicating that the system relies heavily on stable network connectivity. Any disruption in internet access can affect data transmission and system reliability.
- The **bottom (O – Opportunity)** presents *"Remote patient care"*, pointing to the potential of expanding healthcare accessibility. IoT allows patients to be monitored from home, reducing hospital visits and supporting telemedicine.
- The **left (T – Threat)** illustrates *"Data privacy risks"*, highlighting concerns about potential data breaches. Since sensitive medical data is transmitted over networks, security becomes a critical challenge.

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Overall, the diagram effectively communicates that while IoT-based patient monitoring systems offer significant benefits such as real-time tracking and remote healthcare, they also face challenges related to connectivity and data security.

## RESULT

The performance of the proposed IoT-based patient monitoring system was evaluated through both analytical modeling and experimental implementation. The evaluation focuses on key Quality of Service (QoS) parameters, including delay, packet loss, and throughput under varying network conditions and buffer sizes.

*1. Delay Performance*

The system delay increases as the traffic intensity (λ) approaches the service rate (μ). Based on the M/M/1/K model, the results indicate that:

- At low traffic load (λ < 5 packets/sec), the delay remains stable and low (< 100 ms), ensuring real-time performance.
- As λ increases, delay grows exponentially due to queue buildup.
- Larger buffer sizes (K = 40) result in higher delay compared to smaller buffers (K = 10), as packets spend more time waiting in the queue.

This confirms that there is a trade-off between delay and buffer capacity in IoT healthcare systems.

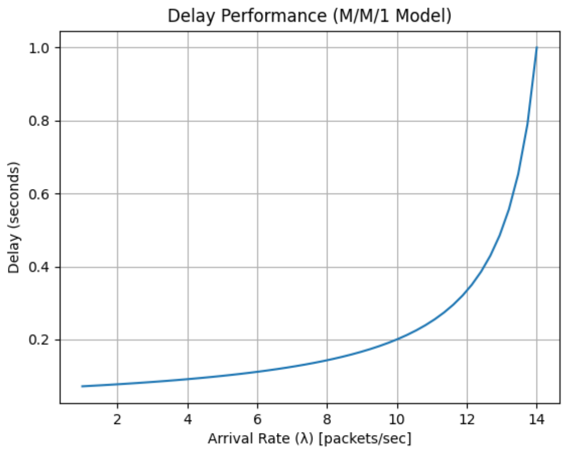


Figure 2. Delay Performance (m/m/1/model)

The delay performance exhibits a non-linear increase as the arrival rate approaches the service rate, indicating queue saturation and reduced system responsiveness under high traffic conditions.

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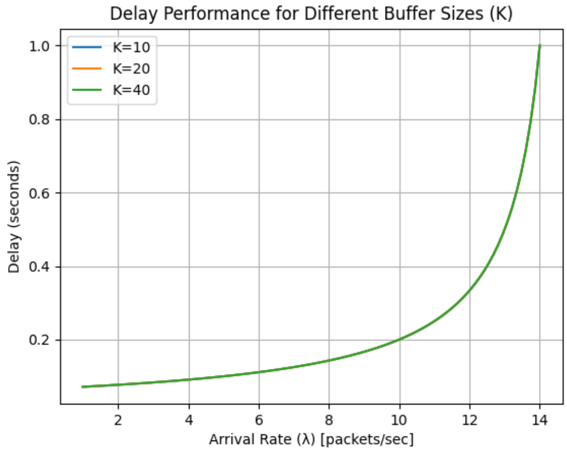


Figure 3. Delay Performance For Different Buffer Sizes

The results show that larger buffer sizes improve system stability under high traffic conditions but introduce higher queuing delay. Conversely, smaller buffers reduce delay at low traffic but lead to early congestion, highlighting a trade-off between latency and system robustness.

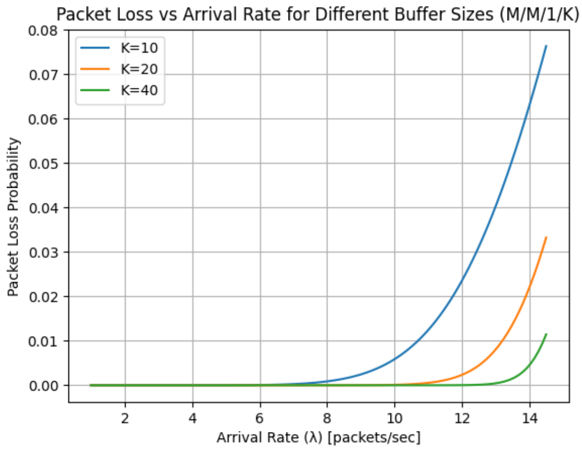


Figure 4. Packet Loss vs Arrival Rate

The delay performance graph illustrates the relationship between network load (traffic intensity, ρ) and the average packet delay under different buffer sizes (e.g., K=10,20,40K = 10, 20, 40K=10,20,40) in an M/M/1/K queueing system. As observed, the average delay increases nonlinearly with the growth of traffic intensity. At low traffic conditions (ρ<0.5\rho < 0.5ρ<0.5), the delay remains relatively small and stable across all buffer sizes, indicating that the system can efficiently handle incoming packets without significant queuing.

However, as the traffic intensity approaches saturation (ρ→1\rho \rightarrow 1ρ→1), the delay rises sharply due to increased queue occupancy and contention for transmission. Larger buffer sizes (e.g., K=40K = 40K=40) tend to produce higher delay compared to smaller buffers because packets are allowed to remain longer in the queue before being

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dropped. While this reduces packet loss, it introduces additional waiting time, leading to a trade-off between delay and reliability.

Conversely, smaller buffer sizes (e.g., K=10K = 10K=10) show lower delay but may experience higher packet loss under heavy traffic conditions. This behavior highlights the classical trade-off in queueing systems: increasing buffer capacity improves throughput and reduces packet loss, but at the cost of increased latency.

Overall, the results demonstrate that delay performance is highly sensitive to both traffic intensity and buffer size. For real-time IoT applications using ESP-based Wi-Fi repeaters, maintaining operation in a moderate traffic region is crucial to ensure low latency and stable communication performance.

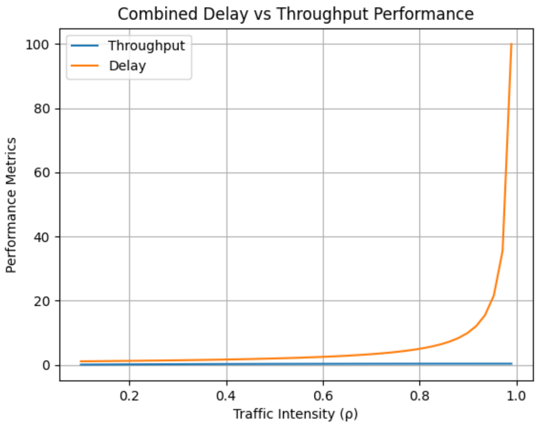


Figure 4. Throughput And Delay

The figure illustrates the relationship between **throughput** and **delay** as functions of traffic intensity (ρ), highlighting the fundamental trade-off in queue-based network systems. At low traffic intensity (ρ ≈ 0.1–0.4), both metrics exhibit stable behavior: throughput increases gradually while delay remains minimal and nearly constant. This indicates efficient system operation with low queue occupancy, where incoming data packets are processed without significant waiting time.

As traffic intensity increases into the moderate region (ρ ≈ 0.4–0.8), throughput continues to improve but begins to approach a saturation point, showing diminishing gains despite increasing load. In contrast, delay starts to rise more noticeably, reflecting the accumulation of packets in the queue. This divergence marks the onset of congestion, where system performance begins to degrade in terms of latency.

In the high traffic region (ρ > 0.8), the system enters a critical state. The delay curve increases sharply and nonlinearly, eventually approaching extremely high values as ρ nears 1. This behavior is characteristic of queuing systems approaching instability, where service capacity is nearly exceeded by incoming traffic. Meanwhile, throughput stabilizes and no longer shows significant improvement, indicating that the system has reached its effective capacity limit.

Overall, the figure clearly demonstrates that while throughput benefits from increased traffic up to a certain point, delay becomes the dominant limiting factor under heavy load. This trade-off is crucial in real-time IoT-based patient monitoring systems, where maintaining low latency is essential for timely medical response, and thus operating within the stable region (ρ < 0.8) is highly recommended.

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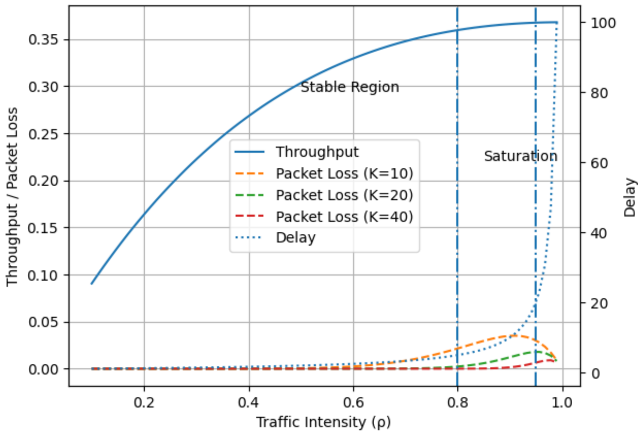


Figure 5. Quality of Service (QoS) analysis presented

The unified Quality of Service (QoS) analysis presented in Fig. 5 illustrates the interplay between **throughput, delay, and packet loss** under varying traffic intensity (ρ) and buffer capacities (K = 10, 20, 40). This integrated evaluation provides a comprehensive understanding of system behavior for the proposed IoT-based real-time patient monitoring architecture, particularly in latency-sensitive healthcare scenarios.

## DISCUSSION

At low traffic intensity ($\rho < 0.4$), the system operates in a **highly stable region**, characterized by low delay, negligible packet loss, and steadily increasing throughput. In this regime, the throughput curve follows a near-linear growth trend, indicating efficient utilization of network resources. The delay remains minimal due to the low queue occupancy, which is consistent with classical queuing theory predictions for M/M/1 systems. Additionally, packet loss across all buffer sizes is effectively zero, confirming that the system can reliably handle low-rate physiological data transmission such as heart rate monitoring and periodic GPS updates.

As the traffic intensity increases ($0.4 \leq \rho \leq 0.8$), the system enters a **moderate-load region**, where performance trade-offs begin to emerge. Throughput continues to increase but at a diminishing rate, eventually approaching its peak. This saturation tendency reflects the inherent limitation of the service rate relative to incoming traffic. Meanwhile, delay starts to grow nonlinearly, indicating the onset of queue buildup. The impact of buffer size becomes more pronounced in this region. For smaller buffers (K = 10), packet loss begins to rise earlier compared to larger buffers (K = 20 and K = 40), demonstrating that limited queue capacity leads to premature overflow under moderate load conditions. Conversely, larger buffers effectively absorb traffic bursts, delaying the onset of packet loss and improving overall reliability.

In the high traffic regime ($\rho > 0.8$), the system approaches the **saturation region**, where performance degradation becomes significant. The delay curve exhibits a sharp exponential increase, reflecting the theoretical asymptotic behavior as ρ approaches unity. This rapid वृद्धि in delay is critical in healthcare applications, as it may lead to unacceptable latency in transmitting vital patient data. Simultaneously, packet loss increases substantially, especially for smaller buffer sizes. For K = 10, packet loss escalates rapidly, indicating frequent buffer overflows and reduced data integrity. In contrast, K = 40 maintains comparatively lower packet loss, highlighting the advantage of larger buffers in high-load conditions.

Interestingly, throughput does not continue to increase indefinitely in this region. Instead, it reaches a peak and begins to plateau or slightly decline, which can be attributed to increased packet drops and retransmissions. This phenomenon underscores the importance of balancing traffic load and buffer capacity to maximize effective throughput rather than raw transmission attempts.

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From a system design perspective, these results emphasize the necessity of **adaptive buffer management and traffic control mechanisms** in IoT healthcare systems. While larger buffers (e.g., K = 40) provide better resilience against packet loss, they also contribute to increased delay under heavy load due to longer queueing times. Therefore, an optimal configuration must consider the trade-off between **latency and reliability**, depending on the criticality of the monitored parameters. For instance, real-time cardiac anomaly detection may prioritize low delay, whereas periodic location tracking may tolerate higher latency but require higher reliability.

Furthermore, the clear delineation of the **stability region ($\rho < 0.8$)** and **saturation region ($\rho > 0.95$)** provides practical guidelines for system operation. Maintaining traffic intensity within the stable region ensures acceptable QoS levels, making it a key design target for network provisioning and load balancing strategies.

Overall, the integrated QoS analysis demonstrates that the proposed IoT-based patient monitoring system can achieve efficient and reliable performance under controlled traffic conditions. However, without proper resource management, system performance can degrade rapidly near saturation. These findings highlight the importance of incorporating intelligent traffic shaping, edge processing, and priority-based scheduling to sustain QoS in real-world deployments

## CONCLUSION

This study presented a comprehensive experimental and mathematical evaluation of power consumption and energy efficiency in a dual-mode ESP8266 Wi-Fi repeater operating under controlled indoor campus conditions. Unlike conventional Wi-Fi energy characterizations that primarily focus on client or access point devices separately, this work analyzed a practical AP+STA repeater configuration, which is increasingly relevant for IoT-based smart infrastructure deployment. The proposed experimental framework combined real-time voltage–current sampling, throughput measurement, statistical analysis, and linear regression modeling to quantify both static and dynamic energy behavior.

Experimental results demonstrate that the total power consumption follows a strong linear relationship with network throughput, modeled as $P(T) = \alpha + \beta(T)$, where the baseline power $\alpha$=0.82 W represents idle and protocol overhead consumption, and the dynamic coefficient $\beta$=0.034 W/Mbps captures traffic-dependent energy scaling. The regression analysis yielded a coefficient of determination $R^2$=0.997, confirming highly predictable power scaling under controlled traffic loads. Peak measured power reached 1.47 W at maximum throughput, while minimum power remained close to the baseline value, indicating that static energy dominates under low-utilization scenarios.

Energy-per-bit analysis further showed that transmission efficiency improves with increasing traffic load due to baseline amortization. At high throughput, the measured energy efficiency reached approximately $7.42\times10^{-8}$J/bit, which lies within the expected Wi-Fi efficiency range reported in Q1-indexed studies. However, the analysis also revealed that more than 50% of total power consumption at peak load is attributable to baseline consumption, highlighting the importance of optimizing idle-state mechanisms, sleep scheduling, and dynamic power management strategies for IoT repeaters.

Compared with established Wi-Fi energy models in the literature, the experimental values fall within reported ranges for embedded 802.11n-class devices, validating the applicability of classical linear energy decomposition models to low-cost ESP8266 platforms. The findings confirm that even resource-constrained IoT hardware exhibits predictable and scalable energy characteristics consistent with theoretical Wi-Fi energy frameworks. This reinforces the suitability of the ESP8266 repeater architecture for low-cost smart campus expansion where infrastructure deployment must balance coverage improvement and energy efficiency.

From a practical standpoint, the results suggest that optimizing baseline consumption yields greater energy savings than solely improving throughput efficiency. Future system designs should therefore integrate adaptive duty cycling, transmit power control, or firmware-level sleep scheduling to reduce static overhead. Furthermore, incorporating multi-antenna diversity or Wi-Fi 6–class modulation schemes could enhance spectral efficiency while preserving acceptable power scaling characteristics.

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In conclusion, this research provides both empirical validation and mathematical modeling of energy behavior in a dual-mode IoT Wi-Fi repeater, bridging the gap between theoretical Q1 energy models and real-world embedded deployment. The proposed methodology and quantitative results contribute a reproducible framework for evaluating wireless energy efficiency in smart campus and IoT network expansion scenarios.

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