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# A new hybrid model based on machine learning and fuzzy logic for QoS enhancing in IoT

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**ABSTRACT**

The fast expansion of internet of things (IoT) devices presents a more complicated scenario for maintaining a stable quality of service (QoS), which would guarantee the network's dependable operation. The emergence of increasingly complex applications that call for additional devices makes this even more crucial. Adaptive intelligence solutions that guarantee optimal network behavior are therefore required. This paper presents a hybrid optimized solution for a three-layer IoT network that models the application, network, and perception layers of an IoT network using machine learning and fuzzy logic (FL). This method guarantees optimal QoS prediction with improved network adaptability by using fuzzy membership parameters. When the number of devices increases from 100 to 1,500, FLGA maintains an average QoS of 95% to 87%, while FL maintains 84% and RANDOM maintains 79%. At the application level, genetic algorithm (GA) continues to outperform RANDOM by 15.57% and FL by 6.32%. The goal of this paper is to provide a solid network solution that could enhance the consistency of QoS performance in order to combat the increasingly complex scenario of an IoT network.



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## 1. INTRODUCTION

The internet of things (IoT) is a rapidly evolving technological paradigm built on interconnected devices—such as sensors, smartphones, and radio-frequency identification (RFID) tags that communicate via the Internet. Ensuring high quality of service (QoS) is essential in critical application domains such as agriculture, transportation, healthcare, and manufacturing [1], [2]. However, maintaining QoS in IoT environments remains a significant challenge. These systems operate across multiple layers perception (sensors), network, and application each introducing distinct complexities [3], [4]. As the number of IoT devices increases, ensuring smooth and reliable communication becomes increasingly difficult. Key challenges include heterogeneous standards, network congestion, and signal degradation, all of which can impede optimal system performance [5]. Recent studies suggest that hybrid metaheuristic methods typically outperform single-method approaches in optimizing IoT system performance [6], [7]. Traditional cloud-based architectures, where computation is centralized, often fail to meet the stringent real-time requirements of delay-sensitive applications. Multi-access edge computing (MEC), which processes data closer to its source, mitigates latency issues [8], maintaining real-time

QoS under dynamic network conditions is challenging. Different IoT domains have varied requirements; for example, smart healthcare and urban monitoring prioritize low network-layer latency for timely critical signals [9], [10], while smart transportation and city management require fast data processing to support safety, emergency response, and traffic control, necessitating a holistic QoS strategy [11]-[13]. Security-aware QoS metrics (e.g., encryption overhead, authentication delay) are not considered here, but the proposed fuzzy framework could accommodate them in future extensions.

Fuzzy logic (FL) and metaheuristic hybrids show strong potential for addressing the complexities of modern IoT environments. Approaches such as fuzzy-based multi-criteria decision-making and metaheuristic optimization dynamically balance QoS metrics, including execution time, energy consumption, and communication delays, in IoT and fog–cloud systems [14], [15]. Metaheuristic-based techniques, including ant colony optimization and improved seagull optimization, enable adaptive task scheduling and controller placement to enhance load balancing and energy efficiency across heterogeneous IoT layers [16], [17]. In wireless sensor networks (WSNs), interval Type-2 fuzzy clustering combined with heuristic sleep scheduling extends network lifetime by managing uncertainties in node energy levels and fluctuating workloads [18], [19]. Furthermore, hybrid metaheuristic frameworks, such as the combination of genetic algorithms (GA) with particle swarm optimization (PSO), improve routing reliability and throughput in dynamic IoT networks [20], [21]. Integrating software-defined networking (SDN) with heuristic feature selection enhances traffic classification and real-time flow management by optimizing the placement of controllers [22], [23]. Finally, hybrid fuzzy-metaheuristic scheduling methods optimize task allocation, reducing latency and maintaining QoS in latency-sensitive edge computing scenarios by effectively navigating the trade-off between computational cost and accuracy [24], [25]. Despite advances, most existing methods focus on single QoS metrics or individual layers, with limited attention to multi-layer optimization under high device density, highlighting the need for scalable IoT QoS strategies.

To address this, we propose a holistic, multi-layer framework that simultaneously evaluates and tunes QoS parameters across perception, network, and application layers. By integrating FL interpretability with GA-based membership function tuning, the framework improves adaptability and reduces root mean square error (RMSE) under varying IoT loads. The GA adjusts fuzzy system parameters based on observed performance, acting as a learning mechanism that enables adaptation to complex network dynamics. This approach addresses high device density and cross-layer dependencies, providing a comprehensive solution for end-to-end QoS enhancement in scalable IoT systems. The paper is organized as follows: section 2 presents the system model, section 3 details the proposed approach, section 4 presents the results, and section 5 concludes the study.

## 2. THE PROPOSED SYSTEM MODEL AND PROBLEM FORMULATION

The IoT architecture, depicted in Figure 1, is structured into three primary layers. The perception layer is responsible for data acquisition from physical devices, including sensors, RFID tags, and actuators. The network Layer facilitates data transmission through various communication protocols such as Wi-Fi, Ethernet, ZigBee, and cellular networks (4G/5G). The application layer processes the transmitted data to deliver specific services to end-users.

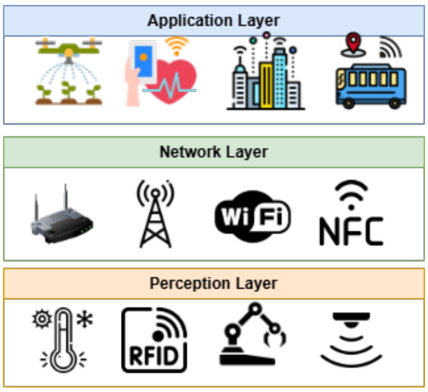


Figure 1. IoT three-layer architecture

High QoS is critical in a three-layer IoT system. Each layer has specific requirements: the perception layer must ensure accurate and timely data acquisition; the network layer should maintain low latency and minimal packet loss; and the application layer must deliver reliable, scalable services. The heterogeneous and dynamic nature of IoT environments introduces uncertainty, resulting in a complex multi-objective optimization problem under stochastic conditions. To address this, a fuzzy inference system aggregates layer-specific metrics—such as latency, throughput, and accuracy—into a unified QoS score, normalized from 0% to 100%.

$$\text{QoS} = \frac{\sum_i x_i \cdot \mu(x_i)}{\sum_i \mu(x_i)} \tag{1}$$

Here, $x_i$ denotes possible QoS outcomes and $\mu(x_i)$ represents the degree of membership for each outcome. This approach consolidates multiple performance metrics into a single score. Maintaining high QoS across all layers therefore requires an adaptive and flexible optimization framework, making the integration of FL with GA a suitable solution.

## 3. METHOD

The proposed system, illustrated in Figure 2, is designed to enhance QoS across the application, network, and perception layers of an IoT environment. Each layer is evaluated using a dedicated set of QoS metrics to ensure reliability, efficient communication, and scalable performance under increasing device density and data traffic.

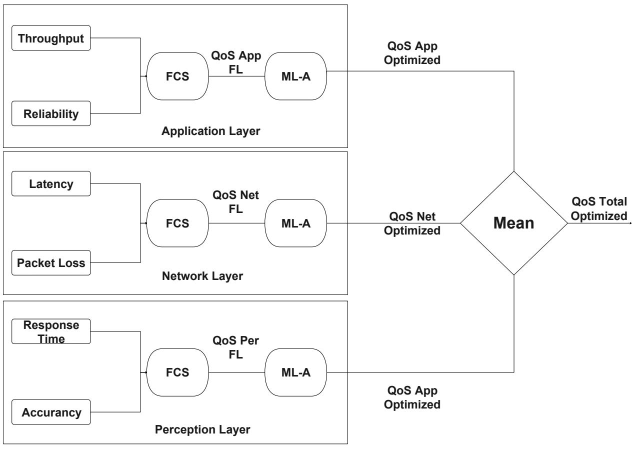


Figure 2. Multi-layer QoS optimization model

The overall QoS is formulated as a weighted aggregation of the application, network, and perception layer QoS values,

$$Q_{\text{total}} = w_1 Q_{\text{app}} + w_2 Q_{\text{net}} + w_3 Q_{\text{perc}} \tag{2}$$

where equal importance is assumed for all layers, i.e., $w_1 = w_2 = w_3 = \frac{1}{3}$. A hybrid fuzzy–genetic optimization framework is adopted, in which the GA is guided by the RMSE, to improve the aggregated QoS across all IoT layers.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

From a computational standpoint, let $P$ represent the population size, $G$ the number of generations, $n$ the number of training samples, and $R$ the number of fuzzy rules or membership function parameters. The evaluation of a single chromosome requires executing the fuzzy inference mechanism over all $n$ samples, leading to a computational complexity of $O(n \times R)$. As the GA evaluates $P$ individuals in each generation, the resulting per-generation computational cost is $O(P \times n \times R)$. Consequently, after $G$ generations, the overall optimization complexity can be expressed as $O(P \times G \times n \times R)$. In practical deployments, this tuning procedure is performed offline or at scheduled update intervals on gateway or server-level nodes, whereas the online fuzzy inference process incurs an approximately constant execution time per request. As a result, the proposed GA–fuzzy framework remains computationally efficient and scalable for large-scale IoT systems. Based on the RMSE-based fitness function defined in (3), a genetic algorithm is employed to tune the fuzzy QoS parameters. The complete optimization procedure is described in Algorithm 1.

**Algorithm 1. Genetic algorithm for fuzzy QoS tuning**

**Require:** IoT Architecture, $N = 50$, $G = 100$, $P_c = 0.8$, $P_m = 0.01$
**Ensure:** Optimized Fuzzy Parameters (Best Chromosome)
Initialize population $P$ with 50 random chromosomes
**for** generation $g = 1$ to 100 **do**
  **Fitness:** Evaluate $RMSE$ for each $C_i \in P$ via PureEdgeSim
  Calculate Fitness($C_i$) $\leftarrow 1/(1 + RMSE)$
  **Selection:** Perform **Tournament Selection** for elite parents
  **Crossover:** Apply **Multi-point Crossover** ($P_c = 0.8$)
  **Mutation:** Mutate offspring chromosomes ($P_m = 0.01$)
  **Update:** Replace low-performing individuals with offspring
  Retain elite chromosomes to maintain population integrity
  **if** QoS convergence reached **OR** $g = 100$ **then**
    **break** and identify best chromosome
  **end if**
**end for**
**return** Best Chromosome (Optimized QoS Parameters)

## 4. RESULTS AND DISCUSSION

The GA–fuzzy QoS optimization framework was evaluated using PureEdgeSim [26] in a three-layer IoT architecture with a high-density scale of up to 1,500 devices. Layer-wise QoS values were optimized via a GA configured with a population size of 50 and 100 generations. To ensure robust global search while maintaining the integrity of heuristic rules, we utilized a crossover probability of 0.8 and a mutation probability of 0.01. Selection was performed via tournament selection. These parameters were specifically chosen to maximize QoS convergence in complex, high-density scenarios, where local optima are frequent. Tables 1 and 2 summarize the fuzzy input and output parameters employed to assess QoS in each layer.

Table 1. IoT fuzzy parameters by layer

| Layer | Input parameter | Fuzzy sets | Range/UoD |
|---|---|---|---|
| App. | Throughput/Reliability | Low, Med, High | 0–100 % |
| | No. of devices | Few, Mod, Many | 100–1500 |
| Net. | Latency/Packet loss | Fast, Med, Slow | 0–1 / 0–3 (s) |
| | Device load | Low, Med, High | 0–100 % |
| Perc. | Accuracy | Low, Med, High | 0–100 % |
| | Response time | Fast, Med, Slow | 0–3 (s) |
| | Active devices | Few, Mod, Many | 100–1500 |

Table 2. Fuzzy logic output parameters

| Parameters | Fuzzy set | Range (%) |
|---|---|---|
| App_QoS, Nw_QoS, Perc_QoS | Bad, Medium, Good | 0–100 |

### 4.1. Application layer QoS analysis

Figure 3 shows how QoS changes at the application layer as the number of IoT devices increases, while comparing the different approaches. The GA approach consistently achieves the strongest performance, starting at nearly 95% QoS for 100 devices and slowly decreasing to around 87% when the number reaches 1,500 devices, which indicates both reliability and scalability. PSO follows this trend, maintaining QoS above 90% until close to 1,000 devices, after which a sharper decline appears. FL begins near 88% but decreases more rapidly as the device count grows, whereas the RANDOM approach performs the worst, starting around 80% and dropping quickly. Overall, GA delivers the most stable and effective QoS, demonstrating better adaptability as system demands continue to increase.

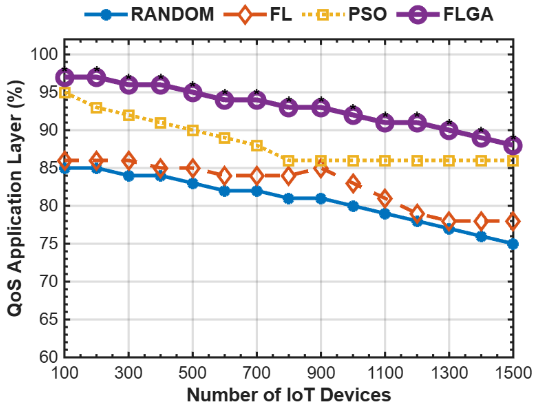


Figure 3. Application layer QoS for different approaches

### 4.2. Network layer QoS analysis

Figure 4 illustrates the performance of each method in maintaining network layer QoS as the number of devices increases. GA consistently achieves QoS above 95%, with only a slight decrease under higher congestion, demonstrating robust performance when latency and packet loss are critical. PSO performs comparably, maintaining QoS above 90%, indicating effective swarm-based optimization, though slightly less resilient than GA under stress. FL exhibits a faster decline in QoS, suggesting limited adaptability under heavy congestion. RANDOM shows significant fluctuations and lacks optimization. Overall, adaptive evolutionary strategies such as GA and PSO outperform both static FL and baseline RANDOM approaches in managing network complexity.

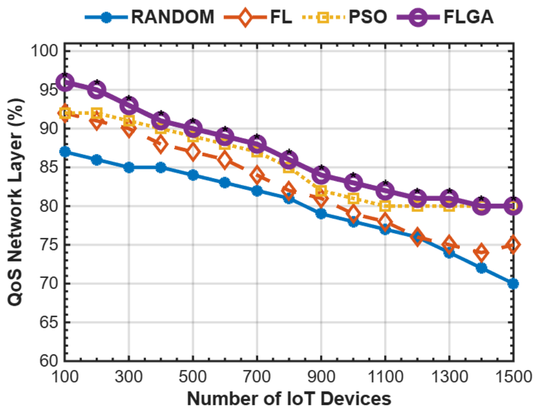


Figure 4. Network layer QoS for different approaches

### 4.3. Perception layer QoS analysis

Figure 5 shows how each approach handles QoS at the perception layer, looking at sensor accuracy, response time, and data consistency. The GA approach demonstrates superior performance, maintaining QoS near 95% with only a slight decline as device density increases. This indicates effective tuning of the fuzzy membership functions for sensory data conditions. PSO maintains a consistent but lower QoS, ranging between 88% and 90%. In contrast, FL exhibits a more pronounced performance degradation, revealing its limited adaptability to changing sensing conditions. The RANDOM strategy consistently yields the lowest QoS, highlighting significant challenges in stability and scalability. Collectively, these results underscore the adaptive robustness of the GA-based optimization, making it a suitable candidate for large-scale and unpredictable IoT environments.

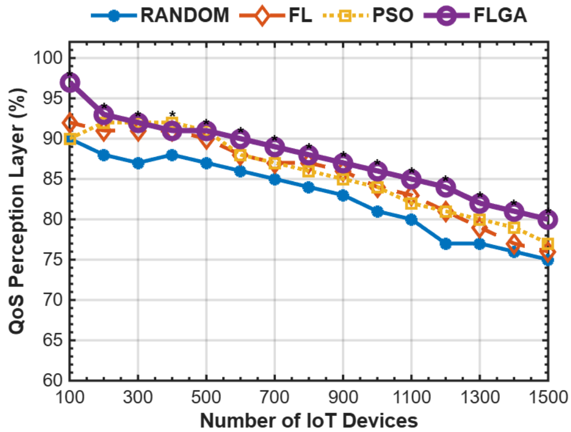


Figure 5. Perception layer QoS for different approaches

#### 4.3.1. Overall QoS performance

Table 3 shows the combined QoS for all three IoT layers, where GA consistently achieves the highest values, gradually decreasing from 95% to 87% as the number of devices increases from 100 to 1,500. PSO ranks second, followed by FL and RANDOM, highlighting GA's superior performance and reliability across varying system sizes.

Table 3. QoS performance (%) relative to the number of IoT devices

| Algorithm | 100 | 300 | 500 | 700 | 900 | 1100 | 1300 | 1500 |
|---|---|---|---|---|---|---|---|---|
| RANDOM | 87 | 85 | 84 | 83 | 82 | 81 | 80 | 79 |
| FL | 91 | 90 | 89 | 88 | 87 | 86 | 85 | 84 |
| PSO | 93 | 92 | 91 | 90 | 89 | 88 | 87 | 86 |
| **FL-GA** | **95** | **94** | **93** | **92** | **91** | **90** | **89** | **87** |

Table 4 shows the data suggests a clear trade-off: by allowing a longer offline optimization period, the FL-GA model achieves a 15.57% improvement in the application layer and a 6.03% gain in the Network layer compared to PSO. Because the GA is more resilient to local optima in high-density scenarios (1,500 devices), it manages the stochastic nature of the perception and network layers more effectively. Since this tuning process is decoupled from real-time operations, the superior QoS stability provided by the GA makes it the most robust solution for large-scale IoT deployments where performance quality is the ultimate metric of success.

Table 4. Percentage improvement of FL-GA vs. Baselines

| Comparison | App. | Net. | Perc. | Total QoS |
|---|---|---|---|---|
| FL-GA vs. RANDOM | 15.57% | 12.57% | 7.95% | 9.64% |
| FL-GA vs. FL | 6.32% | 2.50% | 2.97% | 4.00% |
| FL-GA vs. PSO | 3.33% | 6.03% | 6.38% | 1.68% |

### 4.4. Computational runtime and scalability analysis

Table 5 reports The mean runtime of the proposed FL-GA model for device densities up to 1,500 devices is evaluated using a GA (population = 50, generations = 100). This runtime corresponds to an offline training phase for tuning fuzzy parameters and does not affect online system operation. The optimization prioritizes QoS maximization over training time, as reliability is critical in dense IoT environments. During online validation, RANDOM-based tuning results in the highest latency, PSO achieves lower delays due to swarm-based adaptation, while the proposed FL-GA consistently delivers the lowest latency owing to globally optimized fuzzy parameters. To validate the offline optimization, an online latency comparison in Figure 6 among RANDOM, FL, PSO, and FL-GA is conducted, where FL-GA consistently achieves the lowest delay. The device scale reflects realistic dense IoT scenarios within PureEdgeSim and ensures stable, reproducible evaluation.

Table 5. Mean runtime performance

| Algorithm | Mean runtime (Seconds) | Latency (s) |
|---|---|---|
| RANDOM | 2,858.4 | High |
| PSO | 4,960.5 | Low |
| **FL-GA (Proposed)** | **6,928.2** | Very low |

Figure 6 show latency validation results, the proposed FL-GA approach consistently outperforms RANDOM, FL, and PSO across all device densities from 100 to 1,500 devices. As the number of IoT devices increases, all methods experience higher latency; however, FL-GA maintains the lowest delay, increasing from 0.89 s to 1.63 s, demonstrating superior scalability. This improvement is attributed to the offline genetic tuning of fuzzy parameters, which enables more efficient decision-making during online execution. Compared to PSO and classical FL, FL-GA achieves better load adaptation under dense network conditions, validating the effectiveness of the offline optimization process.

The simulation results demonstrate the reliability and effectiveness of the GA–Fuzzy approach for QoS optimization in IoT systems. GA–Fuzzy consistently maintains stable performance across all layers, even as the number of devices grows. The fuzzy system adapts dynamically, ensuring minimal performance degradation compared with PSO, FL, and RANDOM methods. Variability in FL and RANDOM highlights the challenges of static or non-adaptive approaches. GA–Fuzzy achieves high QoS while requiring careful parameter tuning and computational resources, indicating that it provides a scalable and robust solution, particularly suitable for large-scale or dynamic IoT deployments.

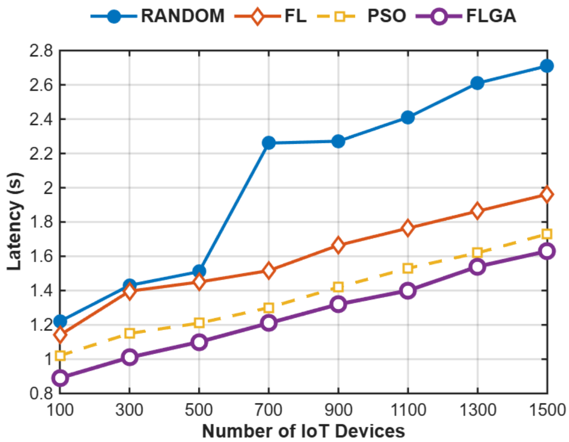


Figure 6. The latency of all approaches VS the number of IoT devices

## 5. CONCLUSION

This paper presents a multi-layer hybrid GA–FL framework for enhancing QoS across the perception, network, and application layers of IoT systems. By integrating the interpretability of FL with the adaptive optimization capability of GA, the proposed model enables effective QoS evaluation and optimization in dense IoT environments. Simulation results obtained using PureEdgeSim demonstrate the consistent superiority of the GA-based approach. When the number of IoT devices increases to 1,500, the proposed method maintains an overall QoS between 95% and 87%, outperforming both classical FL and RANDOM-based strategies. Significant improvements are also observed at the application layer, confirming the scalability and reliability of the proposed solution. Although the evaluation is limited to simulation-based experiments, real-world factors such as hardware constraints, protocol overheads, and environmental interference may influence performance. These aspects motivate future efforts toward real-world validation, extended scalability analysis, and the integration of security-aware QoS metrics into the proposed framework.

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**AUTHOR CONTRIBUTIONS STATEMENT**

The CRediT (Contributor Roles Taxonomy) authorship contribution statement for this study is summarized in the following Table, which details the specific roles and responsibilities of each author.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Oussama Lagnfdi | √ | √ | √ | √ | | √ | √ | √ | √ | √ | √ | | | |
| Marouane Myyara | √ | √ | | √ | | | | √ | | √ | √ | | | |
| Anouar Darifr | √ | √ | √ | √ | | √ | | √ | | √ | √ | √ | √ | |

| | | |
|---|---|---|
| C : **C**onceptualization | I : **I**nvestigation | Vi : **Vi**sualization |
| M : **M**ethodology | R : **R**esources | Su : **Su**pervision |
| So : **So**ftware | D : **D**ata Curation | P : **P**roject administration |
| Va : **Va**lidation | O : Writing - **O**riginal Draft | Fu : **Fu**nding acquisition |
| Fo : **Fo**rmal analysis | E : Writing - Review & **E**diting | |

**CONFLICT OF INTEREST STATEMENT**

The authors declare that they have no conflict of interest.

**DATA AVAILABILITY**

The data that support the findings of this study are not publicly available due to confidentiality restrictions.

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