A Modular Intelligent Resource Architecture: Optimizing QoS in Edge-Cloud Fusion Systems for Smart Agriculture

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ABSTRACT

Smart agriculture systems increasingly adopt edge–cloud fusion to improve the responsiveness and reduce the data overload. However, many existing models still depend on static or centralized transmission, resulting in high latency and inefficient communication. This paper proposes a Modular Intelligent Resource Architecture (MIRA) that integrates a three-layer fusion model to optimize Quality of Service (QoS) in greenhouse monitoring. The system applies Probabilistic Neural Networks (PNN) at the edge for anomaly filtering and Adaptive Neuro-Fuzzy Inference System (ANFIS) at the cloud for contextual aggregation. Using Network Simulator-3 (NS-3) simulations with 50–300 virtual sensor nodes, three transmission scenarios, namely serial, parallel, and modular, were evaluated. The results show that the modular model significantly reduces the end-to-end delay (35–54 ms), latency (32–50 ms), and improves the response time and Packet Delivery Ratio (PDR) (up to 95%) compared to conventional approaches. The proposed architecture demonstrates superior scalability and reliability under dense network conditions. Its modular design enables efficient, real-time data processing and selective communication, making it well-suited for precision agriculture in resource-constrained environments.

Keywords-smart agriculture; edge–cloud fusion; modular architecture; quality of service; PNN; ANFIS

I. INTRODUCTION

The rapid advancement of Information and Communication Technologies (ICT) has impacted modern agriculture, leading to the emergence of smart agriculture systems [1, 2]. These systems leverage the integration of Internet of Things (IoT) devices, real-time data analytics, and intelligent automation to address long-standing challenges in traditional farming, such as climate variability, limited labor, and inefficiencies in environmental monitoring and control [3, 4]. In controlled environments, like greenhouses, maintaining optimal growing conditions requires continuous data collection, timely analysis, and dynamic actuation [5, 6]. However, many existing automation systems rely on centralized architectures that are rigid, energy-intensive, and slow to adapt to the fluctuating micro-environmental changes [7, 8].

A key strategy to enhance the adaptability and efficiency in such systems lies in the adoption of edge–cloud computing models [9-11]. Edge computing enables localized data processing at or near the source of data generation, reducing the communication overhead and response times [12]. In contrast, cloud computing provides the computational power needed for large-scale inference and pattern recognition [13]. Together, edge-cloud fusion facilitates real-time responsiveness and scalability. Despite these advantages, distributed systems still face QoS challenges, such as maintaining low latency, reliable throughput, high packet delivery ratios, and efficient energy consumption [14-16].

To address these challenges, this study introduces a MIRA designed to operate across three abstraction layers: low-level fusion at edge nodes, mid-level inference at the cloud, and high-level control logic for actuation. The model employs PNN and ANFIS to filter, aggregate, and interpret environmental data [17-19]. It aims to minimize the redundant transmission by sending only context-aware information upstream [20, 21].

Unlike conventional systems that transmit raw data continuously to the cloud, wasting bandwidth and power, the proposed architecture sends only relevant, fused data. This selective transmission reduces the communication load, improves the reliability, and enhances the overall QoS. Its modular design supports the integration of new sensors, fusion models, or control mechanisms, allowing flexible deployment across different crop types and greenhouse layouts. The study compares three approaches, serial transmission, where data are forwarded sequentially to a central node, leading to delays and poor scalability; parallel transmission, which reduces the latency but causes packet collisions and channel contention; and the modular architecture, which combines hierarchical fusion with context-aware transmission to achieve a more efficient balance of autonomy and performance.

To evaluate the system performance, simulations were conducted using NS-3, a well-established network simulation tool. Real-world data from a greenhouse testbed were used to emulate the sensor behavior. The wireless communication layer was modeled using IEEE 802.15.4 (Zigbee) to simulate the low-power, short-range communication, incorporating realistic constraints, like interference and data rate limitations.

The key performance indicators assessed include end-to-end delay, latency, throughput, and PDR. Across all metrics, the modular architecture outperformed both serial and parallel models, demonstrating lower latency, higher delivery reliability, and improved responsiveness. These results confirm its applicability for real-time, resource constrained environments like greenhouses.

This research contributes to the development of context-aware, energy-efficient IoT systems suitable for deployment in regions with limited infrastructure. In developing countries, such as Indonesia, where the rural connectivity and access to advanced infrastructure are limited, the ability to perform localized processing using low-cost devices is a major advantage. The system's lightweight architecture, low energy demands, and minimal communication requirements make it practical for deployment at scale.

This research addresses three critical design goals for smart agriculture systems. It develops a scalable, modular architecture adaptable to the changing greenhouse conditions and employs multi-level data fusion to enhance the QoS and system efficiency. The simulations further demonstrate that the modular approach outperforms traditional models, confirming its value as a reliable and effective solution.

II. PROPOSED METHOD

The IoT with edge–cloud computing has become increasingly essential in the development of smart agriculture systems, particularly in greenhouse environments, where microclimate precision is critical. Numerous studies have investigated the use of edge or cloud architecture independently, but fewer have compared data transmission models or QoS challenges in heterogeneous environments.

In traditional serial transmission models, the sensor nodes forward data sequentially to a central node or cloud server. While simple to implement, these models are prone to high end to end delay and suffer from poor scalability, demonstrating that centralized cloud processing can lead to latency bottlenecks in precision agriculture, particularly under high node density [22]. Parallel transmission models attempt to reduce the latency by allowing simultaneous data forwarding from all nodes. This improves timeliness but increases the likelihood of packet collisions and channel contention. Authors in [23] highlighted how uncoordinated parallel transmissions in fog environments may lead to network instability and decreased reliability, especially when low power communication protocols like Zigbee are utilized.

To overcome the limitations of these two extremes, research has explored modular or hierarchical fusion approaches that distribute intelligence across the network layers. These architectures typically involve early-stage data processing at the edge to reduce the traffic volume before forwarding to the cloud for deeper analysis. Authors in [14] proposed an edge-cloud collaborative model for environmental sensing, which improved the latency and reduced the energy consumption through local pre-processing. However, many of these studies either lacked real-time anomaly filtering or did not integrate intelligent context-aware decision systems at the cloud layer.

This research proposes a MIRA that implements a three-layer fusion approach combining low-level fusion at the edge using PNN and mid-level contextual aggregation at the cloud using ANFIS. The architecture is designed to selectively transmit only significant or anomalous data, reducing the redundancy and communication load. This modular design is intended to enhance QoS across latency, throughput, and packet delivery, while maintaining the flexibility and scalability in diverse greenhouse deployments.

A. Modular System Architecture Design (MIRA)

The specific architecture is structured into three layers, physical, network, and application, each fully modeled in NS-3 simulation. At the physical layer, four types of sensors are virtually deployed: temperature and humidity (DHT22), CO_2 concentration (MH-Z19), and light intensity (LDR). These sensors are organized into clusters, with each cluster connected to an edge node. The sensor nodes generate environmental data at regular intervals, mimicking real-world agricultural dynamics. At the edge level, low-level fusion is performed using PNN. This layer classifies and filters the raw sensor readings to detect anomalies or significant environmental changes. If no anomaly is detected, the data remain local; otherwise, only filtered, relevant data are transmitted upstream. This approach reduces the bandwidth usage, conserves energy, and prevents unnecessary data flooding. As illustrated in Figure 1, the physical layer includes sensor clusters connected to edge nodes, which communicate upstream to a cloud server that performs mid-level fusion via ANFIS.

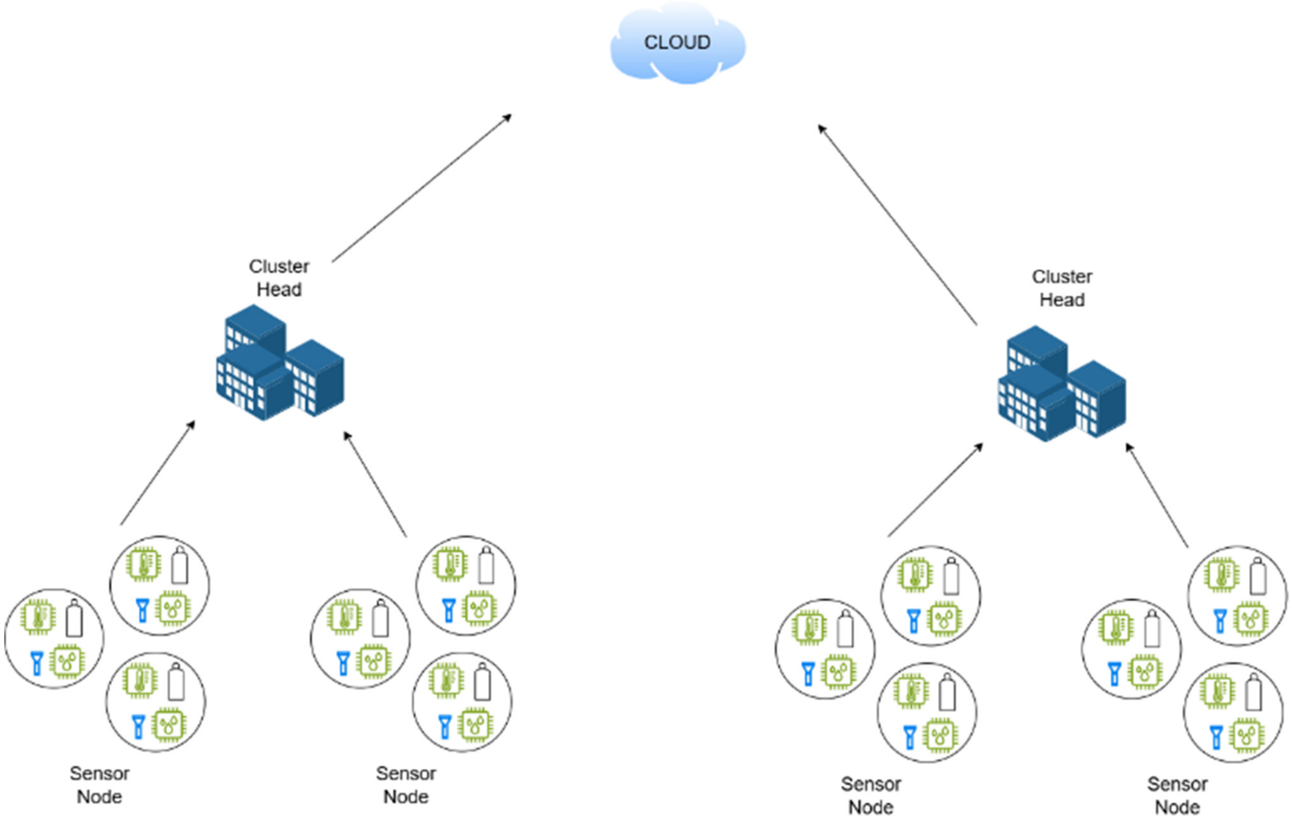

Fig. 1. Illustration of modular architecture.

At the network layer, the edge nodes forward the selected data to a simulated cloud server for mid-level fusion. Here, the ANFIS is employed to interpret sensor data patterns in a broader context. For example, slight increases in both humidity and temperature may individually seem normal but collectively indicate a potential malfunction in ventilation. ANFIS is suited to capture such fuzzy relationships, enhancing the interpretability and responsiveness. At the application layer, control decisions, such as activating virtual fans, lights, or CO_2 injectors are simulated using logical rules based on the cloud-level output. While actuators are not physically implemented, the simulation mimics their activation to represent closed-loop automation. This reflects real-world systems where sensing, decision-making, and actuation are tightly integrated for optimal crop growth. The layered architecture is modular by design. Additional sensors or fusion models can be integrated without overhauling the system. This flexibility supports deployment across different greenhouse layouts or crop types and enables future scalability.

B. Communication Protocols and Data Flow

The communication between the sensor nodes, edge devices, and the cloud is simulated using the IEEE 802.15.4 protocol, commonly deployed in IoT applications due to its low power consumption and mesh networking capabilities. This protocol accurately represents real-world constraints in smart agriculture systems, such as limited range, interference, and low data rate. The sensor nodes periodically transmit data to their respective edge nodes over the Zigbee protocol. Each edge node processes the data using PNN and determines whether the information is significant enough to be sent to the cloud. If a critical condition or anomaly is detected, the edge node activates its transmission module and sends only the essential, processed data [14-16].

Upon receiving these data, the cloud layer applies ANFIS-based aggregation to interpret broader environmental patterns. Based on this analysis, the application layer generates appropriate control actions and simulates actuator responses within NS-3. This selective and hierarchical data flow creates a context-aware communication structure that enhances the overall QoS. Compared to serial models that suffer from cumulative delay due to the sequential transmission and parallel models, which risk data collision and network congestion, the modular model demonstrates a better balance of latency, reliability, and energy efficiency.

The results from the simulation confirm that the proposed modular fusion system consistently achieves lower end-to-end delay and latency, while maintaining a high PDR, even at higher node densities. Although the throughput is slightly lower due to the data filtering, the trade-off is acceptable given the improved responsiveness and reduced energy usage. In summary, the communication strategy combines lightweight transmission at the edge with intelligent interpretation at the cloud, forming a scalable and reliable framework for real-time smart agriculture.

III. RESULTS AND DISCUSSION

A. Simulation Scenario and Metrics

The network simulation in this study was conducted using NS-3 to model a virtual smart greenhouse environment. NS-3 was chosen for its capabilities in accurately simulating the wireless communication and network protocol behaviour. The simulation scenario was designed to evaluate the performance of three different data transmission architectures, serial, parallel, and the proposed modular multilayer fusion architecture under varying network conditions. The detailed breakdown is presented in Table I.

TABLE I. NS-3 ENVIRONMENT

Simulation parameters	**Value**
Number of sensor nodes	50 – 300 nodes
Greenhouse scale	100 x 200
Packet size	1024 bytes
Cluster size	4 nodes per cluster
Initial node energy	2 joule

These parameters were selected to reflect both small-scale and large-scale smart agriculture deployments. For instance, increasing the number of sensor nodes from 50 to 300 allows for evaluation under different traffic loads, while the cluster size and limited node energy emulate realistic resource constraints in wireless sensor networks. To assess the system’s performance, four key QoS metrics were considered during the simulation. End-to-end delay refers to the total time required for a packet to travel from the source to the destination, including transmission, propagation, queueing, and processing delays. Throughput measures the amount of data successfully transferred over the network per unit of time, reflecting the effective transmission rate. Latency indicates the time needed for a single packet to travel from the source to the destination, considering only the basic physical or protocol level delays, such as transmission and propagation. Finally, the PDR represents the proportion of packets successfully received out of the total sent, serving as an indicator of the network reliability [12, 13]. Together, these metrics provide an understanding of each architecture's ability to support responsive and reliable data transmission in smart agriculture scenarios. The results derived from this simulation are analyzed in the following subsections.

B. Result Analysis

The performance of the proposed architecture was evaluated through simulation by comparing it with serial and parallel transmission models. The analysis of the key QoS metrics is presented to assess the system's efficiency, responsiveness, and reliability under varying network conditions.

As shown in Figure 2, the Edge-Fusion architecture consistently achieved the lowest end-to-end delay across all node densities (50–300 nodes), starting at just 35.00 ms, far outperforming the serial (175.02 ms) and parallel (152.27 ms) models. Even at 300 nodes, its delay remained low at 54.41 ms, while the other models experienced sharp increases to over 270 ms. These results highlight Edge-Fusion’s scalability and efficiency in managing the data transmission. The optimal performance was observed at 100–200 nodes, where the system maintained minimal delay, ensuring real-time responsiveness, critical for smart agriculture applications.

As depicted in Figure 3, the serial model achieves the highest peak throughput (9.17 units at 200 nodes), followed by the parallel model (7.98 units), though both suffer from increased delay and latency under higher loads. The Parallel model also shows fluctuating performance across the node densities. In contrast, Edge-Fusion delivers stable and gradually increasing throughput from 3.72 units at 50 nodes to 5.79 units at 300 nodes while maintaining low delay and high reliability. Its optimal performance occurs between 250–300 nodes, making it well-suited for scalable smart agriculture deployments.

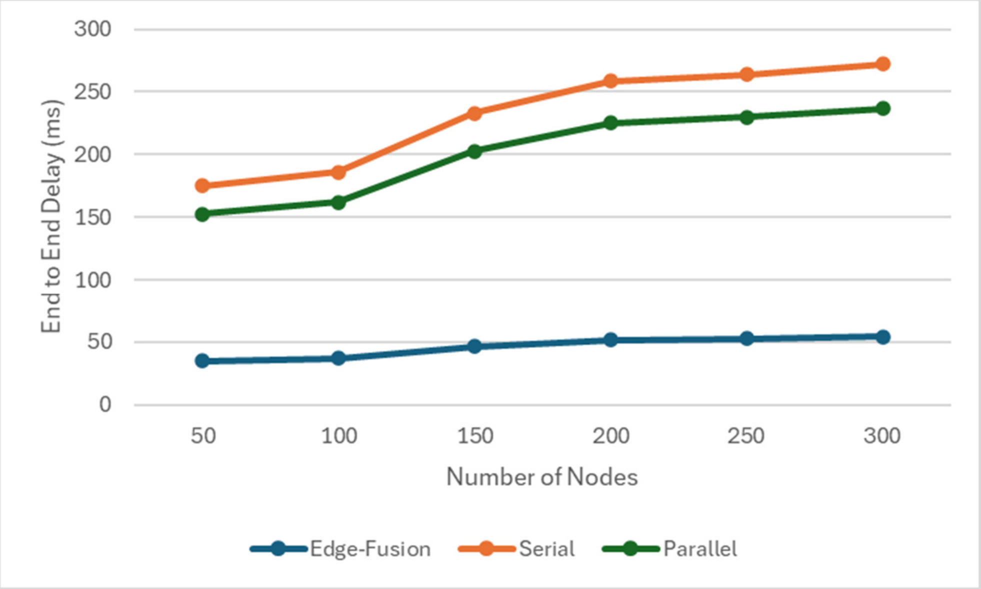

Fig. 2. Performance comparison on end-to-end delay.

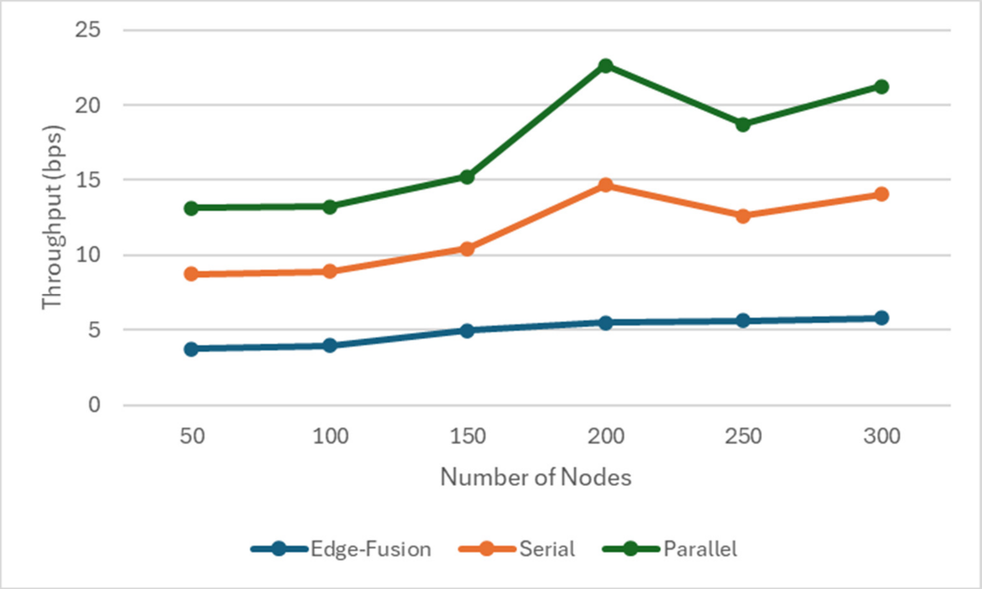

Fig. 3. Performance comparison on throughput.

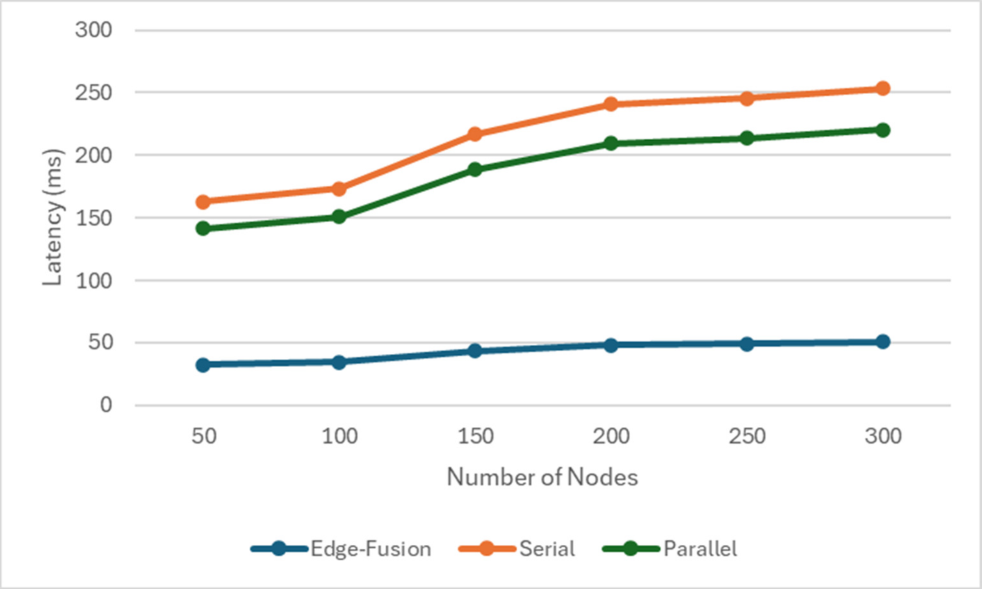

Fig. 4. Performance comparison on latency.

The Edge-Fusion architecture consistently achieves the lowest latency, as portrayed in Figure 4, across all node densities, starting at 32.59 ms with 50 nodes and rising modestly to 50.65 ms at 300 nodes. This gradual increase highlights its scalability and efficiency under growing network loads. In contrast, the Serial and Parallel models experience significantly higher latency, reaching 253.27 ms and 220.34 ms, respectively, at high node densities. These results align with the end-to-end delay trends and confirm Edge-Fusion's responsiveness, which is critical in smart agriculture, where the timely data transmission supports real-time control decisions. Notably, the most optimal latency performance occurs between 150–200 nodes, making the architecture well-suited for medium-scale greenhouse deployments.

The PDR results, as illustrated in Figure 5, exhibit that the Edge-Fusion architecture consistently delivers superior reliability across all levels of node density. At a low density of 50 nodes, Edge-Fusion achieves an outstanding PDR of 95.13%, indicating excellent data integrity and minimal packet loss. Although this value decreases gradually with an increased network load, reaching 73.4% at 300 nodes, it still significantly outperforms both the Serial and Parallel models under identical conditions. Specifically, the Serial model drops to a low of 55.78%, while the Parallel model falls to 58.72% at 300 nodes, highlighting their inability to handle congestion and transmission collisions effectively.

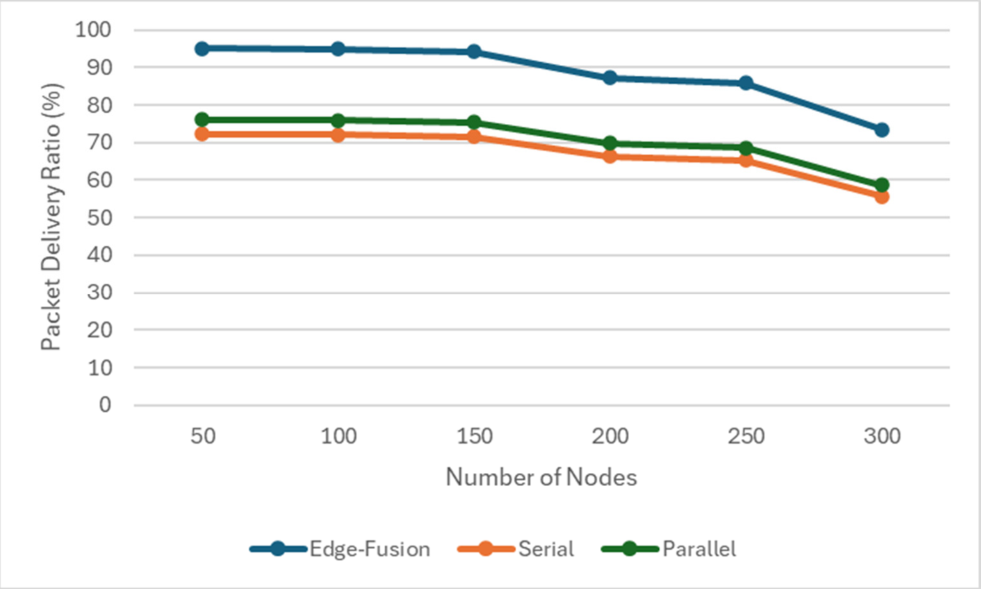

Fig. 5. Performance comparison on PDR.

This trend emphasizes the robustness of the modular Edge-Fusion model in maintaining consistent and reliable communication, even in scenarios with heavy traffic and dense sensor deployments. The hierarchical data fusion and selective transmission logic help minimize the unnecessary data flow, reducing the channel contention and improving the overall network stability. The most optimal PDR values are observed in the 50–150 node range, where Edge-Fusion maintains over 90% delivery success. This makes it especially suitable for small to medium-sized greenhouse environments where a reliable transmission of critical sensor data, such as temperature, humidity, and CO_2 levels, is essential for effective and timely decision-making in smart agriculture systems.

C. Comparative Analysis

To provide context, Table II compares the average performance of the three architectures across key metrics. Although Serial achieved a slightly better throughput, it performed poorly in all other metrics. The modular architecture demonstrated the best overall performance, especially in latency-sensitive and reliability-critical tasks, such as automated actuation. In Table II, the terms are abbreviated as Thr. for Throughput and Resp. T. for Response Time.

TABLE II. AVERAGE QOS PERFORMANCE SUMMARY

Model	Delay (ms)	Latency (ms)	PDR (%)	Thr.	Resp.T. (ms)
Serial	High	High	Low	Highest	Slowest
Parallel	Moderate	Moderate	Moderate	High	Moderate
Modular	Lowest	Lowest	Highest	Moderate	Fastest

IV. CONCLUSION

This study proposed a Modular Intelligent Resource Architecture (MIRA) to address the Quality of Service (QoS) challenges in edge–cloud fusion systems for smart agriculture. Based on Network Simulator-3 (NS-3) simulations, the proposed architecture consistently outperformed both serial and parallel transmission models across critical QoS metrics. Notably, the modular approach achieved substantial reductions in the end-to-end delay (up to 79% compared to serial and 73% compared to parallel) and latency (reduced by 81% and 77%, respectively). Although its throughput was approximately 12% lower than that of the serial model, it remained stable and consistent. In return, the modular model demonstrated superior responsiveness particularly at moderate node densities and maintained a higher Packet Delivery Ratio (PDR), reaching up to 95% at lower node counts, with an average improvement of 23% over the serial model.

A key strength of the proposed system lies in its context-aware, hierarchical fusion mechanism, which integrates fast edge-level anomaly filtering via Probabilistic Neural Networks (PNN) with intelligent cloud-level interpretation using Adaptive Neuro-Fuzzy Inference System (ANFIS). This layered approach minimizes the redundant transmissions and communication overhead while enhancing real-time decision-making, an essential capability for latency-sensitive and resource-constrained agricultural environments [19-21].

Beyond simulation, the architecture demonstrates promising scalability and flexibility, making it suitable for a range of agricultural applications, such as aquaponics, vertical farming, and remote environmental monitoring. Its modular structure allows for dynamic sensor integration and fusion logic reconfiguration without the need for complete system redesign. Future work will focus on implementing the architecture in a real-world setting to assess its robustness under physical constraints, including sensor variability, hardware limitations, and dynamic environmental conditions. Such deployments will further validate the architecture's practical viability and support enhancements in actuator integration, security, and fault tolerance.

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