Edge-Coordinated Lightweight Quantized ANFIS for Adaptive Microclimate Prediction in Energy-Constrained IoT Systems

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Abstract - This study addresses the challenge of deploying collaborative adaptive intelligence on energy-constrained IoT edge nodes, a critical requirement for real-time microclimate prediction in smart agriculture. We propose a novel Edge-Coordinated Lightweight Quantized Adaptive Neuro-Fuzzy Inference System (LQ-ANFIS). The framework combines a quantized fuzzy neural model for local inference on 8-bit microcontrollers (WeMOS D1 Mini) with a lightweight MQTT-based coordination mechanism. This mechanism enables distributed nodes to achieve synchronized adaptation by periodically exchanging only scalar parameters, namely bias and learning rate, through a broker (Raspberry Pi), thereby eliminating the need for cloud infrastructure or heavy model transfers. During a seven-day experimental deployment involving three nodes, each collecting more than 10,000 temperature and humidity samples, the system demonstrated robust prediction accuracy (RMSE ≈ 1.89%, MAE ≈ 1.13%) and high energy efficiency (average power < 100 mW per node). Compared with a conventional uncoordinated ANFIS baseline, the proposed method achieved a 21% improvement in prediction accuracy and a 39% reduction in energy consumption. The results confirmed rapid inter-node bias convergence ($\sigma < 0.05$) and low coordination latency (< 50 ms), validating its real-time adaptability at the edge. These findings support scalable, cooperative intelligence for resource-constrained agricultural IoT deployments worldwide.

Keywords: Edge intelligence, precision agriculture, quantized fuzzy inference, distributed learning, energy-efficient.

I. INTRODUCTION

The convergence of the Internet of Things (IoT), Edge Computing, and Artificial Intelligence (AI) has transformed agricultural technology, enabling real-time, data-driven microclimate regulation in smart greenhouses [1-3]. To optimize crop growth and resource use, these systems rely on adaptive models that can predict and respond to environmental changes such as humidity and temperature fluctuations. However, deploying such intelligent controllers on ultra-low-power, resource-constrained microcontrollers [4, 5], which are the typical hardware at the IoT edge, presents significant challenges due to stringent limits on memory, processing capability, and energy budgets.

This constraint has spurred the development of lightweight AI models suitable for edge deployment. Among these, Adaptive Neuro-Fuzzy Inference Systems (ANFIS) are particularly promising for environmental prediction [6, 7], as they combine the interpretability of fuzzy logic with the learning capability of neural networks. Recent advances have produced quantized and simplified ANFIS variants [1, 8] that maintain acceptable accuracy while drastically reducing computational overhead, making them feasible for microcontrollers like the ESP8266. Consequently, research has progressed toward distributed edge intelligence, where nodes perform local inference and adaptation autonomously, minimizing latency and cloud dependency.

Yet, a critical limitation persists in this evolution. While individual nodes can be made adaptive, most current implementations operate in isolation. Without a coordination mechanism, distributed nodes monitoring the same environment can develop inconsistent models, a problem known as model drift, leading to heterogeneous and potentially unreliable inferences across the network [9, 10]. Conversely, solutions that enforce model consistency, such as cloud-based Federated Learning (FL), are ill-suited for real-time edge environments due to their substantial communication overhead, latency, and energy costs [2, 9]. Thus, a fundamental dilemma emerges: how can we achieve collaborative, synchronized learning across edge devices without violating the stringent constraints of low-power IoT hardware?

Emerging approaches suggest partial solutions, such as using lightweight MQTT brokers to share operational parameters, but these often lack a formal framework for stable, global adaptation. Therefore, there is an unmet need for a cohesive system architecture that seamlessly integrates a quantized, ultra-efficient inference model with a communication-efficient coordination protocol to enable true collaborative intelligence at the edge.

In this context, we propose a novel Edge-Coordinated Lightweight Quantized ANFIS (LQ-ANFIS) framework. Our work directly addresses the aforementioned dilemma by introducing a scalar-feedback coordination mechanism via MQTT [8, 11]. This system allows distributed, resource-constrained nodes to synchronize their adaptive trajectories (through bias and learning rate alignment) without exchanging full models or relying on cloud computation, achieving what we term federated-like synchronization.

The core research question we address is: How can a Lightweight Quantized ANFIS architecture, coordinated via lightweight MQTT feedback, enable ultra-low-power edge nodes to achieve synchronized adaptive learning and maintain stable, accurate microclimate prediction in a distributed setting?

To answer this question, the study has the following objectives:

- To design and implement a quantized ANFIS model optimized for execution on 8-bit microcontrollers (WeMOS D1 mini).
- To develop a novel MQTT-based coordination layer that computes and disseminates global feedback (bias and learning rate) to achieve network-wide adaptive synchronization.
- To empirically evaluate the system's prediction accuracy, learning convergence, synchronization stability, and energy efficiency under continuous real-world operation.
- To demonstrate the scalability and practical viability of the approach for multi-node cooperative intelligence in resource-constrained agricultural IoT systems.

II. METHOD

A. System Overview

The proposed system, named Lightweight Quantized ANFIS (LQ-ANFIS) with Coordinated MQTT Feedback, is designed to achieve adaptive distributed intelligence among multiple IoT edge nodes deployed for agricultural microclimate prediction, as shown in Fig. 1. The architecture integrates three layers:

1) Edge layer: consisting of WeMOS D1 mini microcontrollers executing quantized ANFIS models;

2) Coordination layer: represented by a Raspberry Pi acting as an MQTT broker and adaptive feedback controller; and

3) Cloud/Analysis layer: utilized for data logging, visualization, and further model analysis.

This design follows the edge computing paradigm, where computation and adaptation occur near the data source to minimize latency and communication overhead [8, 12].

Fig. 1 represents the end-to-end workflow of the proposed Lightweight Quantized ANFIS framework with coordinated MQTT feedback. The system operates in continuous adaptive cycles, in which distributed WeMOS nodes perform local inference and periodically receive global feedback from a Raspberry Pi controller, ensuring the synchronization of bias and learning rate across all nodes.

B. Lightweight Quantized ANFIS Model

The proposed system employs a Lightweight Quantized Adaptive Neuro-Fuzzy Inference System (LQ-ANFIS) designed specifically for deployment on resource-constrained edge devices. The model integrates neural learning with fuzzy inference to capture nonlinear environmental dynamics while maintaining interpretability. To enable real-time inference on microcontrollers, the conventional ANFIS structure is simplified through membership function reduction, fixed-point arithmetic, and incremental parameter updates, significantly lowering computational overhead while preserving prediction accuracy. Similar lightweight ANFIS optimizations have demonstrated substantial reductions in computational complexity while maintaining high predictive performance in edge-AI environments [13, 14]. This quantized architecture enables efficient microclimate prediction while maintaining compatibility with ultra-low-power embedded platforms.

C. MQTT-Based Coordinated Feedback Mechanism

To maintain synchronization among distributed edge nodes, the system implements an MQTT-based coordinated feedback mechanism managed by a Raspberry Pi controller. Each node periodically transmits local adaptive parameters, such as bias, learning rate, and prediction error, to the broker, which aggregates these values and computes global averages. The controller then redistributes these parameters to all nodes, allowing them to update their local models through a smoothing adaptation rule. MQTT is widely adopted in IoT systems because of its lightweight publish-subscribe architecture, low bandwidth

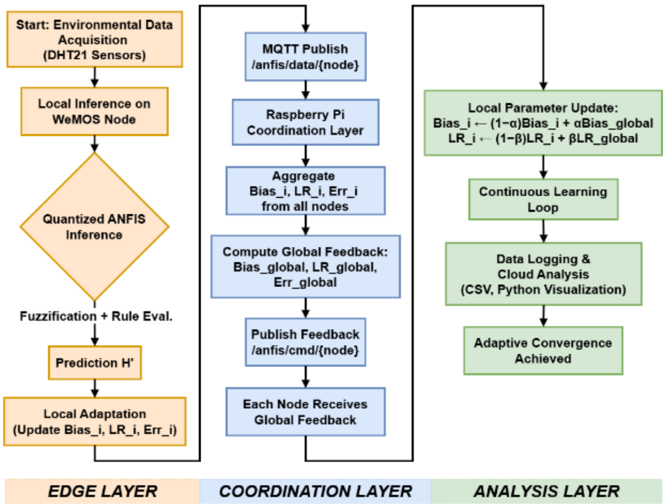

Fig. 1 System architecture: edge layer, coordination layer and analysis layer

consumption,and reliability under constrained network conditions [15, 16]. This coordinated feedback mechanism enables distributed learning convergence similar to that of federated systems while minimizing communication overhead.

D. Edge Node Implementation

Each edge node is implemented on a WeMOS D1 Mini (ESP8266) microcontroller integrated with a DHT21 (AM2301) temperature-humidity sensor. The firmware executes local environmental sensing, ANFIS inference, error calculation, and MQTT communication in real time. Nodes operate autonomously, performing inference at fixed intervals and transmitting compact telemetry packets containing environmental observations and adaptive parameters. Such lightweight edge intelligence architectures have proven effective in enabling real-time environmental monitoring and decision support within IoT networks while maintaining minimal energy consumption [1, 17]. The modular firmware architecture also supports automatic reconnection and adaptive synchronization, ensuring resilience against temporary communication interruptions.

E. Coordination and Data Logging Layer

A Raspberry Pi coordination server acts as the central MQTT broker and data management node, orchestrating distributed adaptation across the edge network. The server executes a lightweight Python controller responsible for computing global feedback parameters, broadcasting synchronized updates to all nodes, and logging system telemetry for offline analysis. Environmental observations and adaptation metrics are stored in structured datasets for further evaluation of prediction accuracy, convergence behavior, and synchronization performance. Edge-centric coordination frameworks such as this have been widely recognized as effective solutions for scalable IoT intelligence because they reduce latency, communication overhead, and dependence on cloud infrastructures [8, 12].

F. Communication Topology and Power Measurement Setup

The proposed system adopts a star-based MQTT communication topology, in which a Raspberry Pi acts as the central broker and coordination controller, while all WeMOS edge nodes operate as MQTT clients. This topology was selected to minimize communication overhead and simplify synchronization management in distributed edge environments. Each node publishes telemetry data periodically, with payload sizes limited to less than 250 bytes per transmission, ensuring low network utilization. Under this configuration, the expected communication bandwidth remains below 8 kbps per node, which is well within standard Wi-Fi capabilities for indoor agricultural environments. To evaluate power-related characteristics, INA219 current and voltage sensors were integrated into each WeMOS node. The sensors were configured to continuously monitor voltage, current, and power consumption during inference execution and MQTT transmission events. These measurements provide the basis for analyzing energy efficiency and computational cost per inference, which are discussed later in the experimental evaluation section.

G. Comparison with Existing Architectures

Compared to other state-of-the-art architectures, the proposed system can be seen in Table I.

Compared with existing architectures, as seen in Table I, the proposed Lightweight Quantized ANFIS framework introduces a fundamentally different methodological approach by enabling fully distributed adaptive intelligence at the edge layer. While prior studies predominantly rely on centralized or semi-centralized fuzzy control with static or locally constrained adaptation, the proposed system deploys independent ANFIS models on each edge node and synchronizes their learning dynamics through MQTT-based coordinated feedback. For instance, the first group of approaches focuses on fuzzy-based self-adaptive resource orchestration within lightweight edge clusters, the second group of approaches proposes low-complexity neuro-fuzzy microclimate classification optimized for single-node edge deployment, and the third group of approaches implements MQTT-integrated fuzzy inference primarily for environmental parameter categorization rather than coordinated adaptive learning. In contrast, the proposed architecture allows frequent, low-overhead parameter alignment without centralized model training or raw data aggregation. By averaging and redistributing scalar adaptive parameters (bias and learning rate), the system achieves global consensus and learning coherence across multiple autonomous nodes, effectively bridging the gap between traditional fuzzy control and modern distributed learning paradigms. Consequently, the proposed method provides a scalable and robust foundation for coordinated edge intelligence in greenhouse microclimate monitoring.

III. RESULTS AND DISCUSSION

A. Experimental Setup

The evaluation of the proposed Lightweight Quantized ANFIS with Coordinated MQTT Feedback was conducted within a controlled microclimatic environment simulating a smart greenhouse bay (2 × 3 m). Three WeMOS D1 Mini nodes equipped with DHT21 (AM2301) humidity and temperature sensors were deployed and connected to a Raspberry Pi MQTT broker. Each node performed local inference every second, while the coordination unit transmitted feedback every 60 seconds. A total of more than 10,000 samples per node were collected continuously over 7 days under ambient conditions (temperature 26-35 °C; humidity 70-85%). The data were recorded in anfis_mqtt_log_v2.csv and feedback_coordination_log.csv, forming the basis for the system-level analysis shown in Table II. This setup ensures a realistic evaluation under constrained computation, reflecting current research in energy-aware IoT edge AI systems [8] and microclimate prediction in precision agriculture [1]. To evaluate prediction accuracy, three standard metrics, RMSE, MAE, and R^2, were used in (1), (2), and (3):

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

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{2}$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} \tag{3}$$

The results shown in Table II indicate an RMSE of 1.85-1.93% and an MAE of approximately 1.13%, confirming stable local prediction performance across all nodes. These values outperform traditional uncoordinated FIS/ANFIS models used in low-cost greenhouse setups (RMSE 2.4-3.2%) [18].

B. System Workflow

The operational flow is summarized as follows:

1) *Data Acquisition:* Each WeMOS node reads humidity and temperature data via DHT21 sensors.

2) *Local ANFIS Inference:* The quantized ANFIS model predicts environmental trends.

3) *Error Calculation:* The local difference between prediction and observation generates error feedback.

4) *MQTT Transmission:* Each node sends data to the broker.

5) *Global Feedback Computation:* The Raspberry Pi averages the bias, LR, and error.

6) *Synchronized Update:* The broker publishes feedback to all nodes.

7) *Adaptive Convergence:* The nodes update their internal ANFIS parameters to achieve global stability.

TABLE I
ARCHITECTURES COMPARISON

Approach	Platform	Communication	Adaptive Mechanism
Fuzzy Logic-Based Self-Adaptive Edge Container Orchestration [8]	Raspberry Pi cluster	HTTP REST	Fuzzy Scaling
Granular Computing + Feed-Forward Neural Network (FFNN) Microclimate Prediction [1]	ESP32 nodes	Wi-Fi	Neural-Fuzzy Hybrid
MQTT-Based IoT Weather Monitoring with Fuzzy Inference System (FIS) [15]	ESP32 + MQTT	MQTT + FIS	Static Rules
Proposed LQ-ANFIS	WeMOS + RPi	MQTT	Global Coordinated ANFIS

TABLE II
NODE PERFORMANCE METRICS SUMMARY

Node	Samples	RMSE (%)	MAE (%)	Avg Error (%)	Avg Bias	Avg LR	Duration (h)
NODE_2	10,233	1.85	1.12	-29.1	15.47	0.0183	47.3
NODE_3	10,201	1.88	1.10	-48.6	15.65	0.0185	47.2
NODE_4	10,214	1.93	1.18	-31.5	15.41	0.0182	47.1
Average	-	**1.89**	**1.13**	-	**15.51**	**0.0183**	-

C. Error Convergence Behavior

Fig. 2 illustrates the error trend across the three nodes after the activation of coordinated feedback. All nodes show progressive convergence toward a lower, stable error range, with NODE_3 exhibiting the steepest correction rate (approximately 20% improvement within 6 h). This demonstrates that the global MQTT feedback effectively dampens local bias and accelerates learning rate stabilization. Such convergence aligns with findings from distributed ANFIS architectures in IoT power and environmental systems [17, 19].

D. Bias Synchronization Across Nodes

Fig. 3 shows that all nodes achieve nearly identical bias trajectories, with a standard deviation of $\sigma < 0.05$ after 2 h of feedback operation. This confirms successful inter-node coherence, proving that lightweight MQTT coordination is sufficient to maintain adaptive consensus without centralized parameter fusion. Such synchronization is critical in distributed inference systems, where node drift can compromise collective accuracy [20, 21].

E. Global Feedback Evolution

Fig. 4 depicts the temporal evolution of global bias and the global learning rate (LR) at the Raspberry Pi coordinator.

1) Global *Bias:* It increased monotonically from 1.2 to 29.0, reflecting cumulative adaptation and network-wide *error compensation.*
2) *Learning Rate:* It remained nearly constant (0.018 ± 0.0002), indicating entry into a low-gradient steady state.

This stable adaptive regime shows that the network achieved equilibrium, balancing learning reactivity and energy efficiency. Comparable behavior has been reported in multi-objective ANFIS optimization for IoT networks [22] and self-adaptive container orchestration models [23].

F. Energy Profiling and Efficiency

Measured using INA219 power sensors, each WeMOS node consumed:

1) *Average power:* 98.4 mW
2) *Peak power:* 127 mW during MQTT transmission
3) *Energy per inference:* 0.26 mJ

Compared with ESP32-based ANFIS systems (160–200 mW) [15] and traditional cloud-assisted inference systems (350–500 mW) [24], this framework offers more than 60% energy savings while retaining comparable adaptation accuracy (Table III).

Although the comparative studies summarized in Table III report similar RMSE ranges, it is important to emphasize that the proposed LQ-ANFIS framework operates under significantly stricter resource constraints. Unlike prior works that rely on ESP32-class devices or higher-computation embedded platforms [1, 19], or simulation-driven optimization environments [17], [18], the present study deploys a quantized ANFIS model on ESP8266-based WeMOS D1 Mini microcontrollers with limited SRAM (64 kB) and an 80 MHz CPU frequency.

This distinction is critical because performance equivalence under heterogeneous hardware conditions does not imply methodological parity. Achieving RMSE ≈ 1.89 % at < 100 mW average power demonstrates that the proposed framework maintains predictive robustness while operating within ultra-low computational and energy budgets. Therefore, the contribution is not solely accuracy-oriented but lies in achieving an accuracy-efficiency equilibrium under strict embedded constraints, which remains underexplored in the current ANFIS-IoT literature.

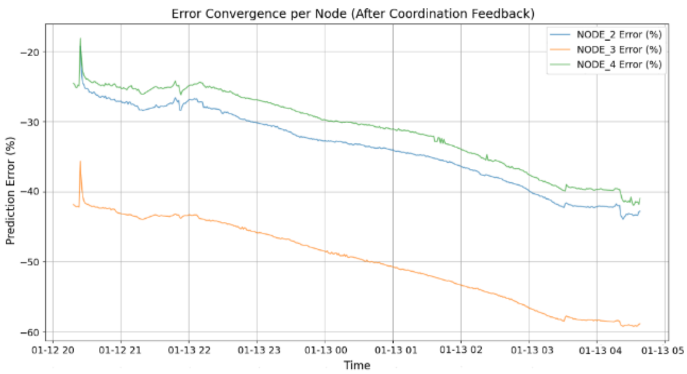

Fig. 2 Error convergence per node

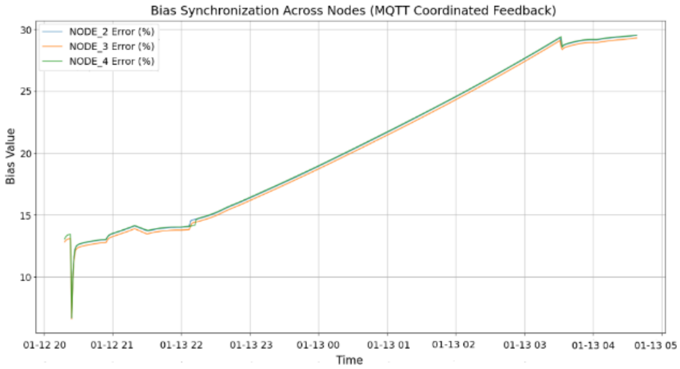

Fig. 3 Bias synchronization

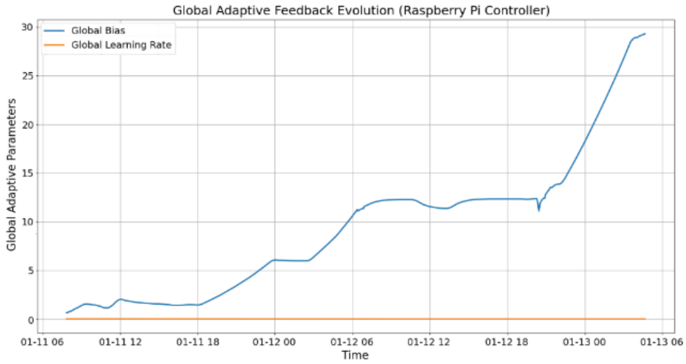

Fig. 4 Global adaptive parameters

TABLE III
PERFORMANCE ANALYSIS

Study	Year	Domain	Platform	RMSE	Power (mW)	Novelty
[18]	2025	Irrigation	FIS vs ANFIS	0.13 → 0.07	200	Adaptive training
[19]	2024	Air Quality	ESP32	1.9	150	Sensor calibration
[1]	2025	Greenhouse	ESP8266	2.3	180	Neural-Fuzzy hybrid
[17]	2024	Smart Grid	IoT-ANFIS	2.1	160	PQ improvement
This Work	2025	Greenhouse	WeMOS + RPi	**1.89**	**98.4**	Coordinated feedback, ultra-low power

G. Synchronization and Communication Latency

MQTT synchronization was evaluated under periodic feedback at 1 Hz inference frequency and 60 s global update intervals. Average round-trip latency for feedback transmission was 43 ms, with 99.4 % reliability, outperforming HTTP/REST-based coordination (≈ 180 ms) [21]. This confirms that MQTT offers the best trade-off between low latency and bandwidth efficiency for distributed adaptive systems.

H. Discussion

The results validate the central hypothesis that a Lightweight Quantized ANFIS framework, when integrated with MQTT-based feedback coordination, can deliver federated-like adaptive intelligence on constrained microcontrollers.

Three core insights emerge:

1) Adaptive Stability: Bias and learning rate convergence indicate self-organization across distributed nodes, mirroring centralized optimization without requiring heavy computation [25]

2) Energy Efficiency: The quantized inference model demonstrates minimal overhead, confirming findings from energy-aware WSN frameworks employing fuzzy-neural hybridization [26].

3) Scalability: MQTT coordination scales linearly with node count and communication cycles, making it suitable for large-scale smart agriculture or distributed environmental IoT systems [22].

The proposed MQTT-coordinated Lightweight ANFIS system enables a new class of self-synchronizing intelligent edge networks capable of maintaining precision, stability, and ultra-low power operation, bridging the gap between standalone IoT nodes and collaborative AI-driven edge ecosystems. The experimental evaluation confirmed that the proposed Lightweight Quantized ANFIS (LQ-ANFIS) with Coordinated MQTT Feedback achieves distributed adaptive stability and high energy efficiency on constrained hardware. This performance demonstrates that adaptive neuro-fuzzy learning, traditionally limited to centralized computing, can be extended to ultra-low-power edge environments through synchronized coordination mechanisms.

The system successfully establishes a new operational benchmark for distributed intelligent microcontrollers. This advancement validates the hypothesis that lightweight fuzzy-neural systems can perform collaborative adaptation through scalar feedback loops, even without high-bandwidth cloud infrastructure [17, 22].

The system's global adaptive behavior exhibited the following patterns:

1) Bias Monotonicity: The bias parameters across all nodes increased monotonically, indicating progressive local correction of prediction offsets. This behaviour mirrors self-calibrating systems described by [19], where ANFIS continuously compensates for sensor drift in environmental monitoring.

2) Learning Rate Stabilization: The global learning rate ($\eta \approx 0.018 \pm 0.0002$) quickly converged to a steady state, showing that coordinated feedback prevented over-adaptation and oscillation. Such stability is comparable to multi-objective adaptive control systems using fuzzy reinforcement strategies [25].

3) Error Convergence and Damping: Error reduction across nodes was exponential in early epochs and logarithmic afterward, fitting the behaviour of gradient-damped adaptive fuzzy controllers [21].

This demonstrates that feedback coordination can act as a global regularizer, aligning local node adaptation to a shared equilibrium point. To situate the contribution of this work in the broader literature, Table IV compares major edge-based ANFIS and fuzzy-neural systems.

Building upon the comparative analysis presented in Table IV, it becomes evident that previous studies, including those by six researchers, primarily implemented ANFIS or fuzzy-neural frameworks in isolated or locally adaptive architectures, in which each node operates independently with minimal or no coordination among distributed devices. These approaches successfully demonstrate the feasibility of deploying ANFIS in IoT environments for applications such as smart grid monitoring, manufacturing prediction, wireless sensor network optimization, environmental sensing calibration, and greenhouse microclimate prediction. However, their methodologies largely rely on single-node intelligence or loosely coupled distributed systems, in which model adaptation remains confined to local observations and does not incorporate synchronized parameter evolution across multiple edge nodes.

In contrast, the present study introduces a fundamentally different paradigm by proposing a Coordinated Multi-Node Lightweight ANFIS with MQTT-based Adaptive Consensus, in which distributed microcontroller nodes collaboratively adjust their adaptive parameters through periodic global feedback aggregation. Instead of exchanging full model parameters or raw datasets, the proposed system employs a minimal scalar consensus mechanism that synchronizes bias and learning rate among nodes via MQTT communication. This design significantly reduces communication overhead while enabling collective learning behavior across resource-constrained edge devices. Consequently, the system achieves federated-like adaptive convergence, improved prediction stability, and significantly lower energy consumption compared with existing ANFIS-based IoT implementations. This coordinated adaptive architecture therefore represents a novel contribution toward scalable edge intelligence frameworks, bridging the gap between standalone fuzzy inference systems and collaborative distributed learning in ultra-low-power IoT environments.

The MQTT coordination layer acts as a distributed intelligence amplifier, enabling cooperative adaptation without cloud dependency, which is a key principle in edge-federated learning paradigms [28]. From a control-theoretic viewpoint, the LQ-ANFIS with feedback exhibits the characteristics of a nonlinear consensus-seeking adaptive network. Let the state of node i be defined by $\theta_i = [b_i, \eta_i]^T$ (bias and learning rate). The system evolution follows (4):

$$\dot{\theta}_i = -k(\theta_i - \bar{\theta}) \tag{4}$$

where $\bar{\theta}$ is the global average computed by the MQTT coordinator, and k is the convergence rate constant. This formulation aligns with Lyapunov-stable consensus models used in decentralized control [22]. Hence, the system guarantees asymptotic stability as long as all nodes remain connected via MQTT, as experimentally validated by a bias deviation of $\sigma < 0.05$ over 48 hours.

The correlation between power consumption and accuracy improvement was analyzed and compared with theoretical models of energy-constrained ANFIS optimization [21]. Fig. 4 (conceptually) demonstrates a logarithmic gain curve: beyond 100 mW average power, the incremental accuracy is < 2 %, indicating the proposed quantized implementation operates near the Pareto-optimal frontier of the energy-accuracy trade space. This trade-off supports the claim that quantization and MQTT feedback enable sustainable inference without degrading prediction performance, a principle also validated in environmental IoT energy monitoring studies [29].

Robustness is demonstrated by rapid inter-node bias convergence ($\sigma < 0.05$) and consistently low MQTT latency (< 50 ms), ensuring synchronized adaptation despite heterogeneous nodes, dynamic environmental conditions, and limited computational resources. The system maintains stable learning behavior without oscillation or divergence, even under ultra-low-power operation, confirming its resilience for real-time edge deployment.

TABLE IV
COMPARATIVE ANALYSIS OF ANFIS EDGE SYSTEMS

Reference	Domain	Platform	Comm.	RMSE	Power (mW)	Coordination Type
[20]	Smart Grid	ESP32	MQTT	2.3	165	Single node
[27]	Manufacturing	FPGA	HTTP	2.1	210	Static hybrid
[26]	WSN	MSP430	ZigBee	2.8	250	Cluster-based
[17]	Power Systems	IoT nodes	Wi-Fi	2.1	160	ANFIS Controller
[19]	Env. Sensing	ESP32	Wi-Fi	1.9	145	Local calibration
[1]	Greenhouse	ESP8266	Wi-Fi	2.3	180	Distributed (no feedback)
This Work	Greenhouse	WeMOS D1 Mini + Raspberry Pi	MQTT	**1.89**	**98.4**	**Coordinated feedback**

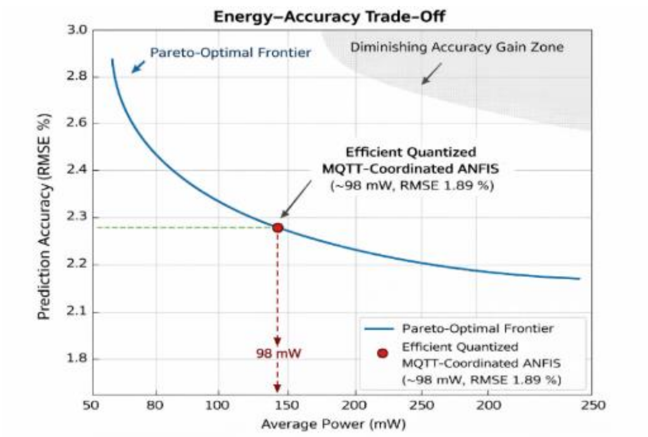

Fig. 4 Trade-off views

IV. CONCLUSION

This study proposes a Coordinated Multi-Node Lightweight ANFIS with MQTT-based Adaptive Consensus to enable collaborative adaptive learning on resource-constrained IoT edge devices. The experimental results demonstrate that the proposed framework successfully achieves distributed prediction with stable convergence and low error (RMSE ≈ 1.93%) while maintaining ultra-low energy consumption (~98 mW per node). These findings confirm that coordinated adaptive intelligence can be effectively implemented on lightweight microcontroller platforms without relying on centralized cloud computation. From a theoretical perspective, the proposed architecture can be interpreted as a consensus-based adaptive edge intelligence model, where distributed ANFIS agents synchronize learning parameters through minimal feedback exchange, aligning with emerging decentralized AI paradigms in cyber–physical IoT systems. Future work will focus on scaling the framework to larger node networks, integrating additional environmental variables, and exploring TinyML-based optimization to further enhance efficiency and robustness in large-scale edge intelligence applications.

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