

A Context-Aware Fuzzy Inference System for Energy-Efficient Data Aggregation in Industrial IoT Ecosystems

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Abstract.

Restrictive energy limitations and electromagnetic interference (EMI) present problems for Industrial Internet of Things (IIoT) ecosystems in Industry 4.0. Traditional data aggregation procedures run the danger of losing crucial information throughout power-saving cycles because they rely on deterministic logic, which is unable to differentiate mission-critical telemetry from routine data. The Multi-Input Single-Output (MISO) Mamdani engine is used in the hierarchical structure of the Context-Aware Fuzzy Inference System (CA-FIS) proposed in this study. The system assesses three context vectors using Gaussian Membership Functions: a Data Criticality (DC) index, Link Quality (LQ) obtained from Signal-to-Interference-plus-Noise Ratio (SINR), and Residual Energy (RE). In times of industrial emergency, DC suppresses aggregation by acting as a "veto" variable. The findings demonstrate that CA-FIS maintains a Packet Delivery Ratio (PDR) over 98% during anomalies while extending network lifetime by 15% over typical fuzzy models and 35% over LEACH.

Keywords. Fuzzy Inference System, Data Aggregation, Industrial IoT, Context-Awareness, Data Criticality, Energy Efficiency, Industry 4.0.

1. INTRODUCTION

The IIoT networks are essential to the expansion of Industry 4.0 because they oversee high-stakes manufacturing and processing settings [1]. The limited battery life of heterogeneous sensor nodes combined with expensive wireless transmission is a significant obstacle [2]. Standard deterministic protocols handle every packet equally, however data aggregation reduces duplicate transmissions, saving energy. As a result, during rigorous power-conservation cycles, temporary, event-driven warnings are lost. A mathematical framework for handling linguistic uncertainty and multi-criteria inputs, like channel state and remaining battery life, is provided by fuzzy logic systems (FLS) [3]. Nevertheless, situational knowledge of process dynamics is absent from current FLS models. A CA-FIS designed for IIoT is presented in this research. In order to dynamically modify data compression ratios without sacrificing industrial safety, CA-FIS integrates a MISO Mamdani controller and assesses energy availability, connection dependability, and real-time data urgency.

2. LITERATURE REVIEW

Adaptive computational intelligence has replaced strict, threshold-based strategies for energy optimization in IIoT contexts. Dynamic clustering and static duty-cycling were the

main strategies employed in initial protocol layouts, though these methods suffer from extreme EMI and dynamic process fluctuations [2]. Fuzzy logic controllers have been included into Cluster Head (CH) selection and routing systems to mitigate environmental stochasticity [3]. For instance, compared to conventional Type-1 systems, higher-order and interval-valued fuzzy models show better resilience towards signal fading. Sensor nodes may now modify their operational status in response to changes in physical processes thanks to context-aware computing [4]. Dynamic multi-criteria fuzzy clustering enhances load allocation and postpones energy depletion in multi-sensor configurations [5]. Localized inference systems currently carry out fuzzy decision-making at edge gateways due to the growth of edge computing, greatly lowering cloud offloading latency [6]. Predictive feedback loops are used in recent edge-cloud orchestration designs to make real-time adjustments to edge operating parameters [7]. Despite these developments, a significant drawback still exists: fuzzy aggregation techniques that are now in use preserve static compression criteria regardless of whether the observed data represents a crucial system abnormality or ordinary ambient noise [8]. Additionally, SINR-based fuzzy assessment is required since traditional link quality estimate techniques that just depend on physical layer RSSI frequently fail under high industrial EMI [9][10]. By implementing a Data Criticality index that supersedes power-saving regulations during crucial events, CA-FIS closes this gap.

3. PROPOSED SYSTEM ARCHITECTURE AND METHODOLOGY

The suggested CA-FIS structure Figure 1 resolves the conflict between aggressive data compression and mission-critical dependability by operating on a three-layer hierarchy [7]:

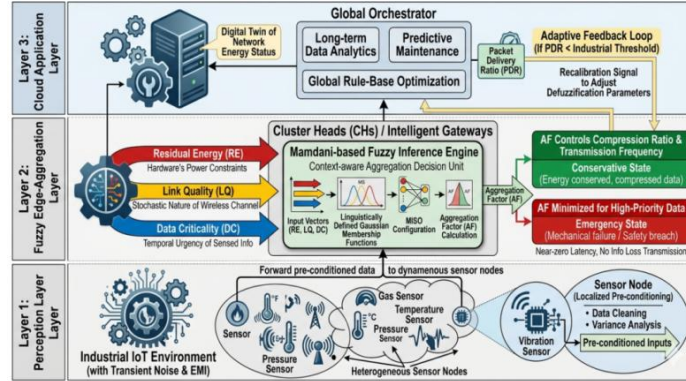


Figure 1: Proposed Architecture

Perception Layer: Suppresses EMI-induced outliers by deploying heterogeneous sensor nodes (pressure, temperature, vibration) that carry out variance analysis and local noise filtering.

Fuzzy Edge-Aggregation Layer: In order to calculate an ongoing Aggregation Factor (AF), Cluster Heads (CHs) host a MISO Mamdani Fuzzy Engine that assesses three context vectors: Residual Energy (RE), Link Quality (LQ), and Data Criticality (DC) [8].

A digital twin of the network's current condition is maintained by the cloud application layer. The Packet Delivery Ratio (PDR) is monitored by an adaptive feedback loop; recalibration signals update the edge defuzzification settings if PDR drops below predetermined industrial reliability criteria.

The CA-FIS is intended to address the inherent conflict in industrial IoT networks between aggressive data compression and critical dependability. In order to guarantee smooth,

distinct transitions among network states, the procedure starts with the fuzzification of three heterogeneous context vectors: Residual Energy (RE), Link Quality (LQ), and Data Criticality (DC) using Gaussian Membership Functions. A Mamdani-type Inference Engine, controlled by a heuristic rule-base of 27 rules, processes these inputs and establishes Data Criticality as a dominating antecedent using Lexicographic Preference Logic.

3.1. Mathematical Modelling of Membership Functions

For each input variable x , the Gaussian membership degree $\mu(x)$ is calculated as:

$$\mu(x) = \exp\left(-\frac{(x - c)^2}{2\sigma^2}\right)$$

Where c represents the center of the fuzzy set and σ determines the width of the curve. The system evaluates three primary input vectors:

Residual Energy (RE): Defined over [0, 100] % with linguistic sets {Low, Medium, High} [5].

Link Quality (LQ): Evaluated using Signal-to-Interference-plus-Noise Ratio (SINR) to filter out noise floor variations [9]:

Data Criticality (DC): A context-aware variable ranging from [0, 1] that categorizes data as {Routine, Significant, Emergency}.

3.2. The Fuzzy Rule-Base and Inference Engine

This system uses Mamdani Min-Max composition to process 33 = 27 heuristic norms. DC is designated as a dominating antecedent by lexicographic preferred reasoning. The inference engine sets AF to its lowest level when DC = Emergency, guaranteeing that raw telemetry is sent with almost no delay.

Rule 15: *IF (RE is High) AND (LQ is Good) AND (DC is Routine) THEN (Aggregation Factor is High).*

3.3. Defuzzification and Aggregation Factor

The crisp Aggregation Factor (z^*) is derived via the Centroid Method:

$$z^* = \frac{\int \mu_C(z) \cdot z \, dz}{\int \mu_C(z) \, dz}$$

4. PERFORMANCE EVALUATION AND RESULTS

4.1. Simulation Parameters and Environment Setup

Simulations were conducted in a 100x100 area with 100 heterogeneous sensor nodes (initial energy 0.5J - 2.0J). Energy dissipation uses the First-Order Radio Model ($E_{elec}=50\text{nJ/bit}$, $\epsilon_{fs}=10\text{pJ/bit/m}^2$ and $\epsilon_{mp} = 0.0013\text{pJ/bit/m}^4$). Figure 2 shows the Cumulative Network Residual Energy Comparison.

$$E_{Tx}(k, d) = E_{elec} \cdot k + \epsilon_{amp} \cdot k \cdot d^n$$

The table 1 shows the technical comparisons with existing techniques along with their foundations and drawbacks as compared with proposed work.

Table 1: Technical Comparison with Existing Techniques

Technique	Metric Foundation	Adaptability	Drawbacks in Industrial EMI
Hardware-based (RSSI/LQI)	PHY Layer signal strength	High Agility	Sensitive to noise floors; fails to distinguish between interference and actual signal quality.
Software-based (PRR/ETX)	Statistics (Packet Reception Ratio)	Medium	High latency; requires significant packet exchange to converge, wasting energy.
Hybrid	Window-based	Low	"Memory effect" leads to delayed response in

(WMEWMA)		averaging		rapidly changing electromagnetic environments.
Proposed (PbSA)	CA-FIS	Fuzzy Logic + SINR	Ultra-High	None; seamlessly handles stochastic noise and provides context-aware adaptive routing.

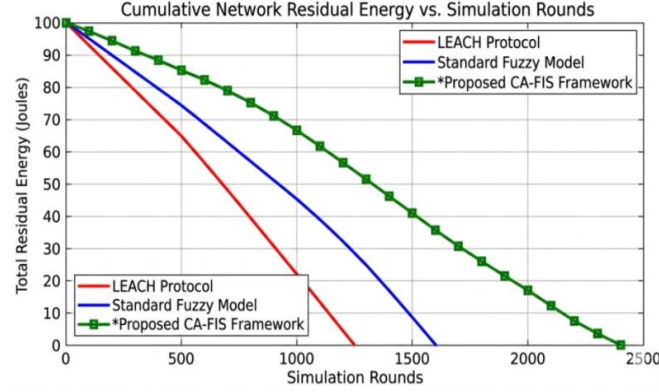


Figure 2: Cumulative Network Residual Energy vs. Simulation Rounds comparison.

5. CONCLUSION

The proposed Context-Aware Fuzzy Inference System (CA-FIS) provides an energy-efficient data aggregation solution for Industrial IoT networks. By incorporating Data Criticality (DC), Residual Energy (RE), and SINR-based Link Quality (LQ), CA-FIS balances energy conservation with data accuracy. Results show a 35% extension in network lifespan over LEACH while maintaining a 98% PDR during critical events. Future work will explore Interval-Valued Type-2 Fuzzy Logic for extreme EMI conditions.

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