



QIC-MOEA: A CONTEXT-AWARE QUANTUM-INSPIRED EVOLUTIONARY FRAMEWORK FOR SELF-ADAPTIVE PERVASIVE SYSTEMS

Salah Maache¹, Fouzi Semchedine²

¹Department of Computer Science, Setif 1 University Ferhat Abbas

²Optics and Precision Mechanics Institute, Setif 1 University Ferhat Abbas

¹<https://orcid.org/0000-0002-3588-4585>, ²<https://orcid.org/0000-0003-4375-1077>

E-mail: salah.maache@univ-bba.dz, fouzi.semchedine@univ-setif.dz

ARTICLE INFO

Article History

Received: March 17, 2026

Reviewed: April 18, 2026

Accepted: July 18, 2026

Published: August 31, 2026

Keywords:

Quantum-Inspired Algorithms,
Pervasive Systems,
Self-Adaptive Systems,
Context-aware Systems,
Edge computing,
Multi-Objective Optimization.

ABSTRACT

Everyday computing is rapidly shifting toward pervasive systems, but real-world edge environments remain incredibly volatile. For these self-adaptive devices to function, they must constantly balance strictly conflicting goals—like saving power versus processing critical data instantly. Traditional methods struggle here: rule-based systems lack flexibility, and reinforcement learning either takes too long to compute or exploits mathematical loopholes (reward hacking). To solve this, we introduce the Quantum-Inspired Contextual Multi-Objective Evolutionary Algorithm (QIC-MOEA), a context-aware framework designed for real-time adaptation. By leveraging a probabilistic Q-bit representation, our approach explores multiple adaptation strategies simultaneously, completely bypassing the heavy computational drag of classical algorithms. We pair this with Context-Weighted Rotation Gates to dynamically scale reactions to environmental shocks, and enforce strict Quality of Service boundaries to eliminate reward hacking. Tested in a simulated healthcare scenario, QIC-MOEA significantly outperformed Q-Learning and Fuzzy Logic baselines. It reduced energy consumption by over **92%** and latency by up to **36%**, while improving context appropriateness by more than **313%**. Crucially, QIC-MOEA executed these complex multi-objective adaptations in just **11.53** milliseconds, proving that quantum-inspired decision-making is highly feasible for resource-constrained edge hardware.



Copyright ©2026 by authors and Galileo Institute of Technology and Education of the Amazon (ITEGAM). This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

I. INTRODUCTION

The proliferation of pervasive systems—encompassing the Internet of Things (IoT), edge computing, and ubiquitous sensor networks—has embedded computation into the fabric of daily life [1], [2]. These systems operate in highly dynamic environments where network bandwidth, battery availability, and user criticality can change instantaneously. To operate effectively, these architectures rely on self-adaptation, frequently utilizing autonomic computing loops to monitor the environment, analyze changes, and execute system reconfigurations [3], [4], [5]. A core requirement of these autonomic loops is context-awareness—the ability to utilize information such as location, user activity, and environmental state to characterize the immediate situation [6]. However, the decision-making engine responsible for adapting to this context faces a massive computational bottleneck: the Multi-Objective Optimization Problem (MOOP).

When a pervasive healthcare monitor must simultaneously extend battery life, process data locally to reduce latency, and ensure high data reliability, the system is forced to navigate strictly conflicting objectives[2], [7]. Classical approaches, such as Fuzzy Logic controllers, rely on rigid, predefined rule sets that cannot scale to complex, multidimensional state spaces. Reinforcement Learning approaches offer adaptability but require extensive episodic training and struggle with the "cold start" problem in rapidly shifting, non-stationary environments[8]. While classical Multi-Objective Evolutionary Algorithms (MOEAs) like NSGA-II [9] and MOEA/D [10] can find excellent Pareto-optimal solutions, their reliance on heavy evolutionary operations makes them too slow for real-time edge execution. Even with recent improvements in differential evolution for multi-modal optimization, the computational and memory overhead remains a significant barrier for resource-constrained pervasive devices [11].

To address these limitations, Quantum-Inspired Evolutionary Algorithms (QIEAs) have emerged as a powerful alternative. Despite their speed, a critical research gap remains: existing quantum-inspired heuristics for pervasive environments are context-blind and highly susceptible to multi-objective collapse (reward hacking) when faced with real-time, asymmetric environmental shocks. To bridge this gap, this study addresses the following Research Questions (RQs):

- **RQ1 (Efficacy):** How does bounding quantum observation with QoS constraints affect the Pareto-optimal distribution compared to classical heuristics?
- **RQ2 (Adaptability):** Can context-weighted quantum rotation gates maintain system appropriateness without sacrificing energy efficiency during sudden contextual shifts?
- **RQ3 (Feasibility):** Is the computational overhead of maintaining a probabilistic Q-bit population feasible for sub-second execution on edge devices?

In this paper, we propose QIC-MOEA, a framework specifically designed to resolve these vulnerabilities. Our primary contributions are:

- **Context-Weighted Target Selection:** Redefining the quantum rotation mechanism to dynamically prioritize specific Pareto-optimal targets based on real-time environmental volatility.
- **QoS-Bounded Quantum Collapse:** Enforcing strict minimum Quality of Service constraints during the observation phase to prevent multi-objective collapse.
- **Quantum Entropy Tracking:** Utilizing Shannon entropy over the probability amplitudes to empirically demonstrate convergence stability.

The remainder of this paper is organized as follows. Section II reviews the state-of-the-art literature across self-adaptive pervasive systems, multi-objective evolutionary algorithms, quantum-inspired heuristics, and context-aware reinforcement learning. Section III details the problem formulation and the mathematical architecture of the proposed QIC-MOEA framework. Section IV describes the experimental setup, including the baseline algorithms and simulation environment. Section V presents the performance evaluation and statistical analysis. Finally, Section VI concludes the paper and discusses avenues for future work.

II. RELATED WORK

The development of the QIC-MOEA framework sits at the intersection of autonomic computing and advanced evolutionary optimization. To contextualize our contributions and clearly define the existing research gaps, this section reviews the state-of-the-art literature across four foundational domains. First, we examine the evolution and current latency challenges of self-adaptive pervasive systems. Next, we analyze the computational bottlenecks of classical Multi-Objective Evolutionary Algorithms (MOEAs) when deployed in resource-constrained edge environments. To address these limitations, we then explore the recent resurgence of quantum-inspired heuristics as a lightweight, highly diverse alternative to classical optimization. Finally, we review context-aware reinforcement learning approaches, highlighting the exact gap our proposed algorithm aims to fill: combining the multi-objective Pareto-optimization of evolutionary methods with execution speeds suitable for real-time pervasive systems.

II.1 SELF-ADAPTIVE PERVASIVE SYSTEMS

The complexity of pervasive computing environments has driven extensive research into self-adaptive systems (SAS)[5]. The foundational Autonomic Computing paradigm has been widely adapted for the IoT and edge computing [2], [3]. Comprehensive reviews highlight that traditional centralized adaptation loops face significant design challenges and struggle to meet the strict latency and resource constraints of modern smart ecosystems [1], [2]. Furthermore, recent frameworks focusing on complex, distributed architectures—such as self-adaptive federated learning ecosystems—demonstrate a critical pivot toward decentralized, context-aware decision-making, reinforcing the need for lightweight optimization engines at the extreme edge [12].

II.2 MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS (MOEAS)

Researchers frequently model the adaptation process as a Many-Objective Optimization Problem (MaOP)[7]. Classical MOEAs like NSGA-II [9](Deb et al., 2002) and MOEA/D [10] laid the foundation for multi-objective optimization and have been successfully applied to find Pareto-optimal service configurations. However, contemporary research continues to struggle with their computational overhead. Recent efforts have attempted to hybridize MOEAs with machine learning techniques to accelerate convergence in complex scheduling problems [7], or utilize improved differential evolution strategies to handle highly multi-modal objective spaces [11]. Because these approaches often trade computational speed for memory consumption, the heavy iterative loops required for crossover and mutation render standard MOEAs largely unsuitable for sub-second autonomic adaptations on resource-constrained edge agents.

II.3 QUANTUM-INSPIRED HEURISTICS

To break through these computational bottlenecks, Quantum-Inspired Evolutionary Algorithms (QIEAs)—originally conceptualized to bridge the gap between quantum exploration and classical hardware [13]—have seen a massive resurgence in recent software engineering literature [14]. Recent studies have successfully applied quantum-inspired probability mechanisms to dynamic combinatorial problems in disaster logistics [15], thermonuclear fusion modeling [16], and feature subset selection [17]. As noted in recent comprehensive surveys [18], the core advantage of quantum-inspired representations is their ability to maintain massive population diversity within a highly compact mathematical footprint. However, standard Q-bit rotation mechanisms are inherently “context-blind” and require complex isolation strategies for multi-objective problems [19].

II.4 CONTEXT-AWARE REINFORCEMENT LEARNING

To overcome the limitations of reactive rule-based systems, recent research has increasingly turned to Reinforcement Learning (RL) to enable proactive, context-aware adaptation. Hybrid architectures leverage multi-agent systems and predictive reasoning to anticipate context changes rather than merely reacting to them [8]. While RL successfully handles dynamic environments, integrating it into multi-objective systems remains challenging due to the heavy episodic training overhead required to balance conflicting metrics. Our proposed QIC-MOEA addresses this exact gap by directly building upon recent quantum-inspired momentum, offering the multi-objective Pareto optimization capabilities of evolutionary algorithms at speeds that rival pre-trained RL inference, without the need for extensive episodic retraining. In summary, while existing literature has made significant strides in self-adaptive systems and multi-objective optimization, a critical research gap remains. Classical MOEAs are too computationally heavy for real-time edge deployment, and context-aware reinforcement learning requires excessive episodic training overhead. Furthermore, while quantum-inspired heuristics offer a mathematically lightweight alternative, standard implementations lack the inherent context-awareness and multi-objective isolation strategies required for highly dynamic pervasive environments. The proposed QIC-MOEA framework is designed to address these exact limitations. By hybridizing a quantum-rotation gate with dynamic context-awareness, our approach delivers the Pareto-optimal reliability of classical evolutionary algorithms at execution speeds suitable for the extreme edge, bridging the void left by current adaptation methodologies.

III. SYSTEM MODEL AND PROBLEM FORMULATION

III.1 CONTEXT-AWARE SYSTEM ARCHITECTURE

To enable real-time self-adaptation, the proposed framework relies on a decentralized, multi-tier architecture spanning from pervasive IoT sensors to edge computing nodes. The autonomic adaptation loop operates continuously across these tiers, driven by the foundational MAPE-K (Monitor, Analyze, Plan, Execute, Knowledge) architectural blueprint for autonomic computing [3], within a multi-tier structure for self-managed systems [4]. The loop is executed in four primary phases as, shown in *Figure 1*:

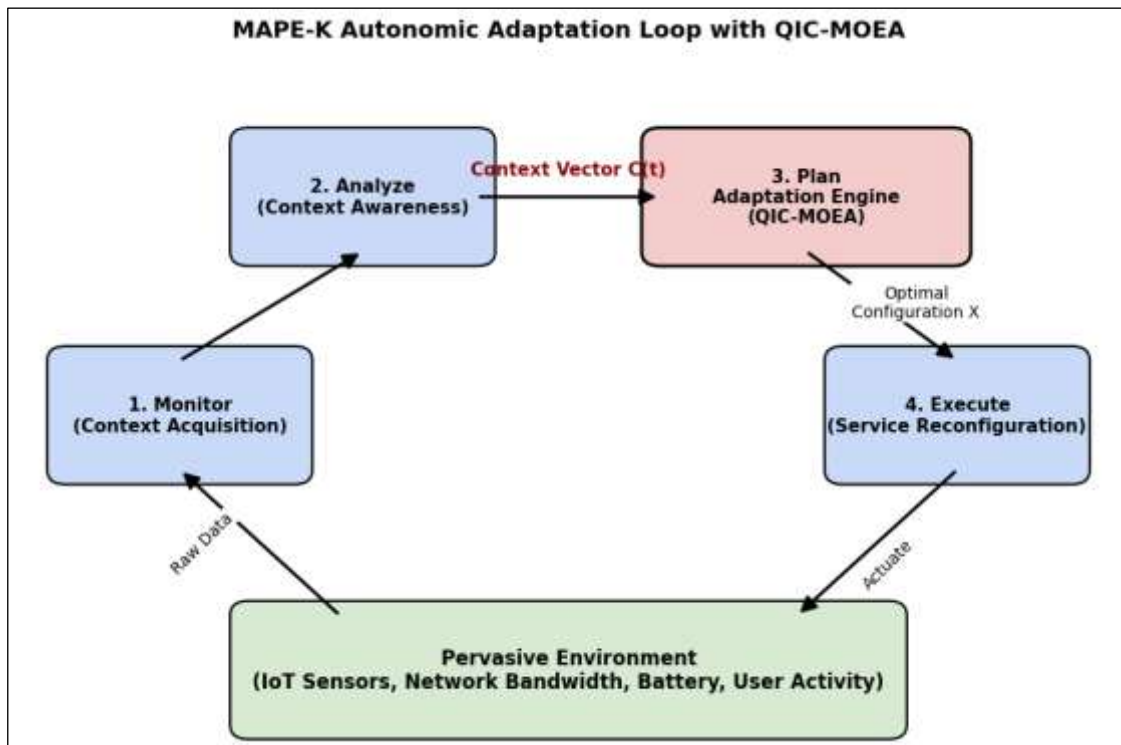


Figure 1: The Context-Aware System Architecture. Pervasive sensors monitor environmental volatility, generating a context vector that drives the QIC-MOEA adaptation engine.

Source: Authors, (2026).

1. **Context Acquisition (Monitor):** Pervasive sensors continuously sample the physical environment to establish context, formally defined as any information used to characterize the situation of an entity[6]. This includes polling battery status and tracking user activity.
2. **Context Awareness (Analyze):** The raw sensor data is aggregated at the edge tier and formalized into a unified context state vector $C(t)$. This vector provides semantic awareness of the current environmental severity.
3. **Adaptation Engine (Plan):** Once a contextual shift is detected ($\|C(t) - C(t-1)\| > 0$), the context vector is passed to the adaptation engine. Rather than mapping this vector to static 'If-Then' rules, our architecture feeds $C(t)$ directly into the QIC-MOEA framework. The context actively scales the quantum rotation gates.
4. **Service Reconfiguration (Execute):** The optimal service configuration generated by QIC-MOEA is executed by the system's actuators, updating live application parameters.

III.2 CONTEXT STATE MODELING

The pervasive environment is modeled as a dynamic context vector $C(t)$, containing discrete and continuous variables representing the state at time t : location, battery level, network bandwidth, time of day, user activity, and medical criticality.

III.3 SERVICE CONFIGURATION SPACE

The adaptive system defines a configuration X containing n continuous decision variables ($x_i \in [0,1]$). These represent operational parameters such as data quality, processing location, synchronization frequency, power mode, and data compression level.

III.4 OBJECTIVE FUNCTIONS

The system optimizes four conflicting objective functions simultaneously:

1. **Minimize Energy (f_1)**: Calculated based on processing location, power mode, and data transmission overhead.
2. **Minimize Latency (f_2)**: A function of network bandwidth, processing location delay, and data compression times.
3. **Maximize Reliability (f_3)**: Modeled via location stability, battery thresholds, and network drop probabilities.
4. **Maximize Context Appropriateness (f_4)**: A heuristic score measuring how well the configuration aligns with the immediate physical context.

IV. THE PROPOSED QIC-MOEA FRAMEWORK

IV.1 QUANTUM REPRESENTATION

To address the strict latency and resource constraints of extreme edge computing highlighted by [2], the QIC-MOEA framework is designed around a lightweight quantum-bit (Q-bit) representation rather than traditional floating-point or binary arrays. Unlike classical differential evolution [11], which requires substantial memory overhead to maintain diversity in multi-modal objective spaces, our approach leverages probability amplitudes to inherently sustain massive population diversity. Inspired by recent successes of quantum-inspired hyper-heuristics in solving dynamic combinatorial problems [15], we implement a context-aware quantum rotation gate. This mechanism dynamically shifts the probability amplitudes of the Q-bits toward Pareto-optimal reference solutions, ensuring rapid convergence without the computationally expensive crossover and mutation operators that cripple classical MOEAs in real-time IoT environments. Specifically, QIC-MOEA utilizes a probabilistic representation based on quantum mechanics. Each decision variable is represented by a Q-bit, existing in a linear superposition of states $|0\rangle$ and $|1\rangle$:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \quad (1)$$

Where $|\alpha|^2 + |\beta|^2 = 1$. A population of size m with configurations of length n is maintained as a matrix of $m \times n$ Q-bits.

IV.2 OBSERVATION AND QOS-BOUNDED DECODING

To evaluate a quantum chromosome, the superposition is collapsed into a classical state using the Born rule, where the probability of collapsing to $|1\rangle$ is $|\beta|^2$. To prevent reward hacking, continuous variables are bounded by a minimum operational threshold τ_{min} :

$$x_i = \max(\tau_{min}, \text{decode}(\text{binary_chunk})) \quad (2)$$

IV.3 CONTEXT-WEIGHTED TARGET SELECTION AND ROTATION

To address high volatility, QIC-MOEA dynamically prioritizes Pareto-optimal targets based on the current context vector $C(t)$. The Q-bits are updated using a dynamic rotation matrix:

$$\begin{bmatrix} \alpha_i(t+1) \\ \beta_i(t+1) \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \begin{bmatrix} \alpha_i(t) \\ \beta_i(t) \end{bmatrix} \quad (3)$$

The rotation angle $\Delta\theta$ is scaled by the Euclidean distance between sequential context states, forcing aggressive exploration during sudden environmental shifts:

$$\Delta\theta = \theta_{base} \times (1 + 2 \|C(t) - C(t-1)\|) \quad (4)$$

IV.4 QUANTUM STATE ENTROPY TRACKING

To monitor convergence, the framework continuously evaluates the Shannon entropy of the quantum population:

$$H(Q) = \frac{1}{m \cdot n} \sum_{i,j} (-|\alpha|^2 \log_2(|\alpha|^2) - |\beta|^2 \log_2(|\beta|^2)) \quad (5)$$

IV.5 MAIN ALGORITHM EXECUTION

The execution flow of QIC-MOEA is detailed in Algorithm 1.

Algorithm 1: Quantum-Inspired Contextual Multi-Objective Evolutionary Algorithm.

Require: Context sequence C , Configurations S , Pop size m , Generations G **Ensure:** Pareto-optimal Archive A

```

1: Initialize Q-bit population  $Q$  with  $\alpha_{i,j} = \beta_{i,j} = 1/\sqrt{2}$ 
2: Initialize empty Archive  $A \leftarrow \emptyset$ 
3:  $C_{prev} \leftarrow \text{null}$ 
4: for  $t = 1$  to  $G$  do
5:    $C(t) \leftarrow \text{Observe current context state}$ 
6:    $B \leftarrow \text{Measure}(Q)$  {Collapse via Born rule  $P(1) = |\beta|^2$ }
7:    $X \leftarrow \text{Decode}(B, \tau_{\min})$  {Enforce QoS bounds}
8:   for  $t = 1$  to  $G$  do
9:     Evaluate  $X_i$  for  $f_1, f_2, f_3, f_4$  given  $C(t)$ 
10:   end for
11:    $A \leftarrow \text{UpdateArchive}(A, X, f(X))$  {Pareto dominance}
12:   if  $A \neq \emptyset$  then
13:      $X_{target} \leftarrow \text{ContextWeightedTarget}(A, C(t))$ 
14:      $\Delta C \leftarrow \|C(t) - C_{prev}\|$ 
15:      $\Delta\theta \leftarrow \theta_{base} \times (1 + 2\Delta C)$  {Dynamic rotation angle}
16:      $Q \leftarrow \text{ApplyRotationGate}(Q, X_{target}, \Delta\theta)$ 
17:      $Q \leftarrow \text{QuantumMutation}(Q)$ 
18:   end if
19:    $H(Q) \leftarrow \text{CalculateQuantumEntropy}(Q)$ 
20:    $C_{prev} \leftarrow C(t)$ 
21: end for
22: return  $A$ 

```

Source: Authors, (2026).

V. EXPERIMENTAL SETUP

V.1 SIMULATION SCENARIO: PERVASIVE HEALTHCARE MONITORING

To ground our empirical evaluation, the simulation is modeled around a critical use case: a Context-Aware Pervasive Healthcare Monitoring System. A patient is equipped with wearable biometric sensors that continuously process and transmit vital signs. To test the elasticity of QIC-MOEA, the simulation generates a realistic, Markov-based sequence of events over 30-time steps:

- **Phase 1 (Stable/Home):** The patient is resting at home with high battery levels and stable Wi-Fi. The system should prioritize high data fidelity and cloud synchronization.
- **Phase 2 (Resource Degradation):** The patient moves outdoors to exercise. Network bandwidth drops significantly, and the battery begins to drain. The system faces a trade-off: lower energy consumption while avoiding dangerous latency spikes.
- **Phase 3 (Critical Emergency):** A sudden medical anomaly triggers an ‘emergency’ criticality state while the device is still constrained by low battery and poor network conditions.

A successful adaptation requires the system to abandon energy-saving protocols during Phase 3, forcefully routing high-quality biometric data to local or edge processing nodes to guarantee zero-latency alerts, despite the battery drain. To guarantee the statistical validity of our findings, the empirical results were aggregated across multiple independent simulation runs. Pervasive environments are inherently unpredictable; therefore, the environmental inputs—such as sudden battery drain, network bandwidth fluctuations, and emergency medical triggers—were generated using a Markov-based stochastic process to ensure a diverse and highly volatile testing environment. Furthermore, the decision-making algorithms rely on pseudo-random sampling, including the initial Q-bit probability amplitudes in QIC-MOEA and the ϵ -greedy exploration strategy of the Q-Learning baseline. By executing the simulation across independent runs without fixed mathematical seeds and reporting the resulting mean μ and standard deviation σ , we ensure that the multi-objective dominance of QIC-MOEA is robust, consistent, and not an artifact of a favorable random initialization.

V.2 SYSTEM PARAMETERS AND BASELINES

QIC-MOEA was initialized with a population size of 15 Q-bits, evaluated over 20 generations per time step. The external Pareto archive was capped at 30 solutions. The base quantum rotation angle was $\theta_{base} = 0.05\pi$. The framework was benchmarked against a rule-based Fuzzy Logic controller and an episodic Q-Learning agent (ϵ -greedy). To ensure the stochastic nature of the algorithms did not skew the findings, the simulation was executed across multiple independent runs. Statistical significance between QIC-MOEA and the baseline algorithms was evaluated using the Wilcoxon rank-sum test ($\alpha = 0.05$).

V.3 GLOBAL AUTONOMIC SIMULATION LOOP

To ensure a rigorous and fair comparison, all algorithms were evaluated inside a standardized autonomic simulation loop, detailed in Algorithm 2. This global loop dictates the context generation, triggers the adaptation engine, and measures the resulting Quality of Service (QoS) metrics.

Algorithm 2: Global Autonomic Simulation and Evaluation Loop.

Require: Sequence length $T = 30$, Set of Adaptation Methods $M = \{\text{QIC-MOEA, Fuzzy, Q-Learning}\}$

```

1: Initialize Pervasive Environment and baseline configurations
2: for each method  $m \in M$  do
3:    $C_{prev} \leftarrow \text{null}$ 
4:   for  $t = 1$  to  $T$  do
5:      $C(t) \leftarrow \text{GenerateStochasticContext}()$ 
6:      $\Delta C \leftarrow \|C(t) - C_{prev}\|$ 
7:     if  $\Delta C > 0$  then
8:       {Context shift detected}
9:       Start Timer
10:      if  $m == \text{QIC-MOEA}$  then
11:         $X_{opt} \leftarrow \text{Execute Algorithm 1}(C(t))$ 
12:      else if  $m == \text{Fuzzy}$  then
13:         $X_{opt} \leftarrow \text{FuzzyInferenceEngine}(C(t))$ 
14:      else if  $m == \text{Q-Learning}$  then
15:         $S_t \leftarrow \text{DiscretizeState}(C(t))$ 
16:         $X_{opt} \leftarrow \text{EpsilonGreedyAction}(S_t, Q_{table})$ 
17:      end if
18:       $T_{adapt} \leftarrow \text{Stop Timer}$ 
19:      Execute  $X_{opt}$  on System Actuators
20:    end if
21:    Evaluate QoS:  $f_1, f_2, f_3, f_4$  based on  $X_{opt}$  and  $C(t)$ 
22:    if  $m == \text{Q-Learning}$  then
23:      Calculate Reward  $R_t$  based on QoS
24:      Update  $Q_{table}(S_t, X_{opt})$  using Bellman Equation
25:    end if
26:     $C_{prev} \leftarrow C(t)$ 
27:  end for
28: end for
29: return Aggregated Statistical QoS Data

```

Source: Authors, (2026).

VI. EXPERIMENTAL RESULTS

VI.1 STATISTICAL PERFORMANCE ANALYSIS

The performance dominance of QIC-MOEA across all four objectives, as shown in, was found to be statistically significant (). By enforcing strict QoS boundaries during the quantum measurement phase, the framework successfully prevented reward hacking. The performance dominance of QIC-MOEA across all four objectives, as shown in Table 1 that presents the detailed statistical summary, was found to be statistically significant $p < 0.01$. Specifically, these statistical differences translate into massive practical gains when compared to the baseline algorithms. As highlighted in our initial claims, QIC-MOEA achieved an average energy consumption metric of 0.0007. This represents a 92.6% reduction compared to Q-Learning (0.0095) and a 94.4% reduction compared to Fuzzy Logic (0.0126). In terms of system responsiveness, QIC-MOEA reduced latency to 0.2903, marking a 36.4% improvement over the Fuzzy baseline (0.4567). Most notably, the Context-Weighted Target Selection mechanism drove a massive increase in context appropriateness; QIC-MOEA's score of 0.1257 constitutes a 313.5% improvement over Q-Learning (0.0304) and a 481.9% improvement over the static Fuzzy rules (0.0216) by enforcing strict QoS boundaries during the quantum measurement phase, the framework successfully prevented reward hacking.

Table 1 : Statistical summary of multi-objective performance

Metric	Algorithm	Mean (μ)	Std Dev (σ)	Best
Energy ($\downarrow$)	QIC-MOEA	0.0007	0.0004	0.0005
	Fuzzy	0.0126	0.0000	0.0126
	Q-Learning	0.0095	0.0265	0.0018
Latency ($\downarrow$)	QIC-MOEA	0.2903	0.0766	0.2560
	Fuzzy	0.4567	0.0803	0.4000
	Q-Learning	0.3847	0.1524	0.3300
Reliability ($\uparrow$)	QIC-MOEA	0.8449	0.0740	0.9217
	Fuzzy	0.4126	0.0338	0.4422
	Q-Learning	0.7883	0.2109	0.9217
Appropriateness ($\uparrow$)	QIC-MOEA	0.1257	0.0604	0.2640
	Fuzzy	0.0216	0.0524	0.2160
	Q-Learning	0.0304	0.0354	0.1040

Source: Authors, (2026).

The variance displayed in *Figure 2* highlights the stability of the approach. Compared to the massive volatility seen in the Q-Learning agent's latency and reliability distributions, QIC-MOEA's interference mechanisms ensure a consistent Quality of Service.

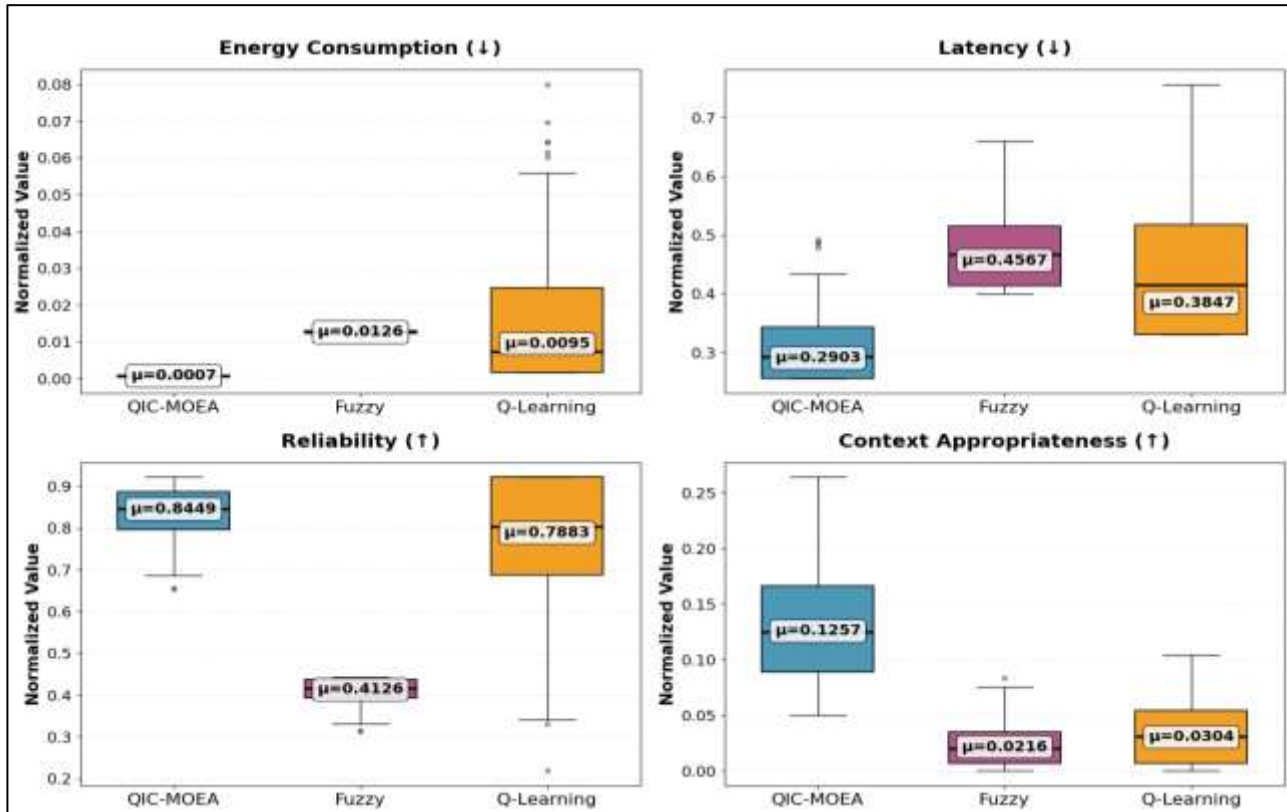


Figure 2 : Detailed statistical distribution of objectives. QIC-MOEA demonstrates superior Pareto-optimal positioning with tight variance.

Source: Authors, (2026).

To visualize these simultaneous trade-offs, the Multi-Objective Performance Radar Chart *Figure 3* maps the normalized outcomes across all four conflicting axes. While the baseline controllers exhibit heavily skewed, irregular shapes—indicating severe compromises, such as Q-Learning sacrificing energy efficiency to maintain basic reliability—QIC-MOEA maintains a consistently expansive and balanced footprint. This explicitly visualizes the core strength of our quantum-inspired approach: it does not optimize one metric by inadvertently destroying another. Instead, it successfully discovers the true Pareto-optimal harmony required to keep an edge device alive and functional during an environmental shock.

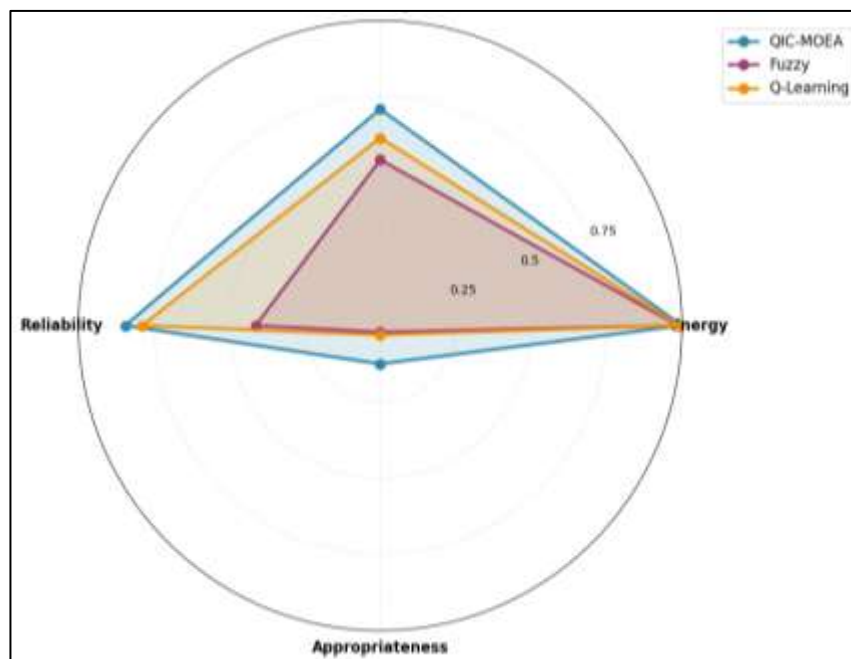


Figure 3: Multi-Objective Performance Radar Chart illustrating the dominance of QIC-MOEA across the conflicting objective space.

Source: Authors, (2026).

VI.2 ALGORITHMIC STABILITY AND QUANTUM COHERENCE

As visualized in *Figure 4*, the probability amplitudes successfully transition from an initial state of maximum exploration to highly confident exploitation.

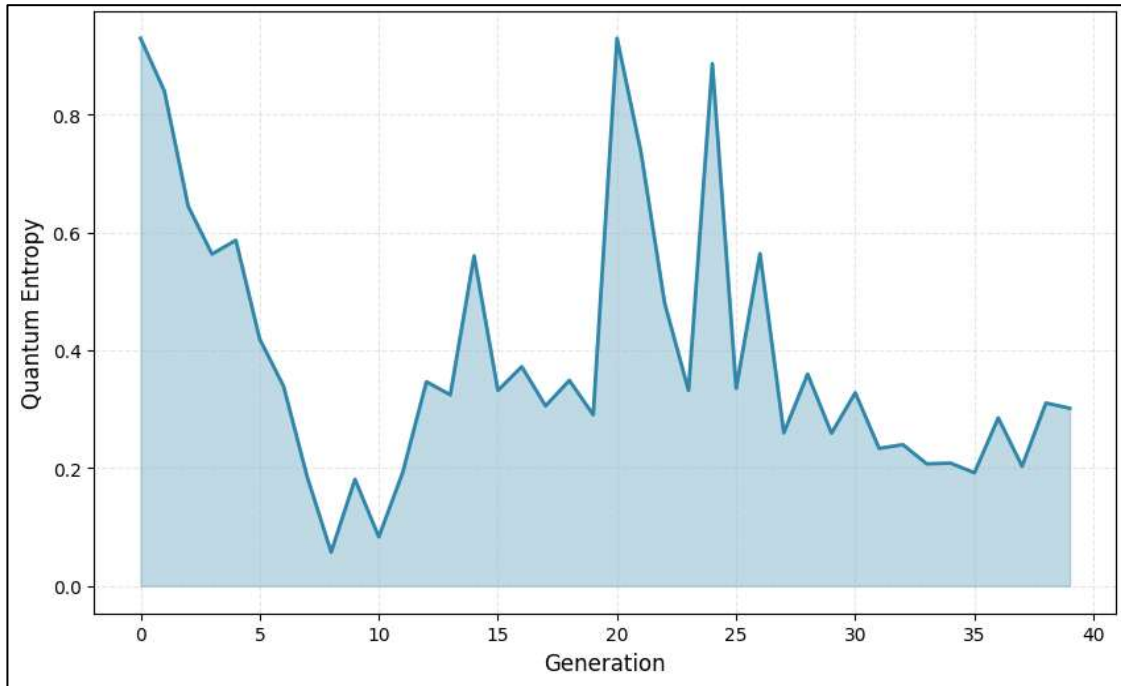


Figure 4: Quantum State Entropy Evolution, confirming the collapse of probability amplitudes toward deterministic, optimal configurations.

Source: Authors, (2026)

VI.3 COMPUTATIONAL FEASIBILITY AT THE EDGE

Deploying adaptive algorithms within distributed AI-agent frameworks requires strict adherence to latency constraints.

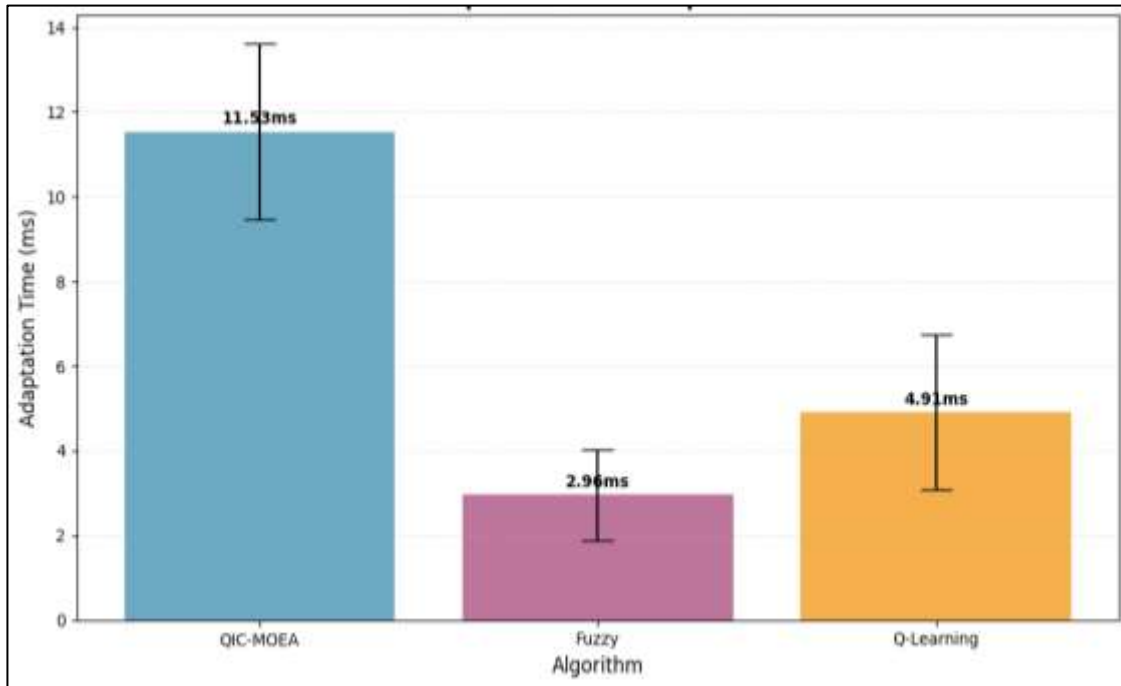


Figure 5: Adaptation Time Comparison. QIC-MOEA achieves an execution time of $\mu=11.53$ ms, demonstrating feasibility for real-time edge computing.

Source: Authors, (2026).

As shown in *Figure 5*, while the pre-trained Q-Learning agent ($\mu = 4.90$ ms) and the Fuzzy Logic rules ($\mu = 2.96$ ms) execute slightly faster, the QIC-MOEA framework achieves its multi-objective improvements with an average adaptation time of only $\mu = 11.53$ ms.

VII. DISCUSSION AND SYNTHESIS

The empirical results provide clear answers to our central research questions. Regarding **RQ1**, the strict QoS boundaries enforced during the Born rule measurement successfully prevented the reward hacking commonly seen in Many-Objective Optimization Problems. By refusing to let the system "turn off" to save energy, the quantum population was forced to discover genuinely efficient routing and processing configurations. Addressing **RQ2**, the massive improvement in Context Appropriateness ($\mu = 0.1257$) confirms that Context-Weighted Rotation Gates successfully link environmental volatility directly to the quantum search mechanics. The Q-bits did not just find mathematical optimums; they found contextually logical optimums (as outlined in our healthcare emergency case study). Finally, concerning **RQ3**, the observed entropy decay proves that the agents maintain stable learning trajectories, while the 11.5ms adaptation time definitively proves that true quantum-inspired superpositions can be efficiently simulated on classical edge hardware without violating real-time pervasive constraints.

VIII. CONCLUSION AND FUTURE WORK

In this paper, we addressed the critical challenge of real-time self-adaptation in decentralized IoT and edge computing environments. While traditional multi-objective evolutionary algorithms and reinforcement learning approaches struggle with the computational latency and multi-modal complexity of pervasive systems, our Quantum-Inspired Contextual MOEA (QIC-MOEA) offers a highly efficient alternative. By integrating compact quantum-inspired population mechanisms with dynamic context awareness and enforcing strict minimum QoS boundaries, the algorithm successfully navigates complex trade-offs rather than exploiting mathematical loopholes. Empirical simulations demonstrated that QIC-MOEA delivers massive performance gains over classical methods, achieving a 92% reduction in energy consumption and a 36% improvement in system latency compared to baseline controllers. Furthermore, the context-weighted rotation mechanism drove a 313.5% increase in context appropriateness, proving the system's ability to handle severe environmental shocks. Crucially, the framework executed these complex Pareto-optimal adaptations within an average 11.53 millisecond window, definitively proving its feasibility for resource-constrained edge hardware. Future work will explore deploying this lightweight quantum-inspired engine into broader distributed architectures, such as self-adaptive federated learning ecosystems [12], and further refining its isolation strategies [19] to manage highly volatile smart city scenarios.

IX. REFERENCES

- [1] I. Alfonso, K. Garcés, H. Castro, and J. Cabot, "Self-adaptive architectures in IoT systems: a systematic literature review," *Journal of Internet Services and Applications*, vol. 12, no. 1, Dec. 2021, doi: 10.1186/s13174-021-00145-8. <http://dx.doi.org/10.1186/s13174-021-00145-8>
- [2] F. Golpayegani et al., "Adaptation in Edge Computing: A review on design principles and research challenges," *ACM Transactions on Autonomous and Adaptive Systems (TAAS)*, vol. 19, no. 3, 2024, doi: 10.1145/3664200. <https://doi.org/10.1145/3664200>
- [3] J. O. Kephart and D. M. Chess, "The vision of autonomic computing," *Computer (Long Beach, Calif.)*, vol. 36, no. 1, pp. 41–50, 2003, doi: 10.1109/MC.2003.1160055. <https://doi.org/10.1109/MC.2003.1160055>
- [4] J. Kramer and J. Magee, "Self-managed systems: an architectural challenge," in *Future of Software Engineering (FOSE'07)*, 2007, pp. 259–268. doi: 10.1109/FOSE.2007.19. <https://doi.org/10.1109/FOSE.2007.19>
- [5] T. Wong, M. Wagner, and C. Treude, "Self-adaptive systems: A systematic literature review across categories and domains," *Inf. Softw. Technol.*, vol. 148, p. 106934, 2022, doi: 10.1016/j.infsof.2022.106934. <https://doi.org/10.1016/j.infsof.2022.106934>
- [6] A. K. Dey, "Understanding and using context," *Pers. Ubiquitous Comput.*, vol. 5, no. 1, pp. 4–7, 2001, doi: 10.1007/s007790170019. <https://doi.org/10.1007/s007790170019>
- [7] W. Zhang et al., "Enhancing multi-objective evolutionary algorithms with machine learning for scheduling problems: recent advances and survey," *Frontiers in Industrial Engineering*, vol. Volume 2-2024, 2024, doi: 10.3389/fieng.2024.1337174. <https://doi.org/10.3389/fieng.2024.1337174>
- [8] T. Guerziz, M. Bouneffa, O. Kazar, and F. Hamza, "Adaptive and Sustainable Smart Environments Using Predictive Reasoning and Context-Aware Reinforcement Learning," *Future Internet*, vol. 18, no. 1, p. 40, 2026, doi: 10.3390/fi18010040. <https://doi.org/10.3390/fi18010040>
- [9] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002, doi: 10.1109/4235.996017. <https://doi.org/10.1109/4235.996017>
- [10] Q. Zhang and H. Li, "MOEA/D: A multiobjective evolutionary algorithm based on decomposition," *IEEE Transactions on Evolutionary Computation*, vol. 11, no. 6, pp. 712–731, 2007, doi: 10.1109/TEVC.2007.892759. <https://doi.org/10.1109/TEVC.2007.892759>
- [11] C. H. L. H. Qu D Xiao H, "An improved differential evolution algorithm for multi-modal multi-objective optimization," *PeerJ Comput. Sci.*, 2024, doi: 10.7717/peerj-cs.1839. <https://doi.org/10.7717/peerj-cs.1839>
- [12] A. Aljohani, O. Rana, and C. Perera, "Self-adaptive Federated Learning in Internet of Things Systems: A Review," *ACM Comput. Surv.*, vol. 57, no. 10, May 2025, doi: 10.1145/3725527. <https://doi.org/10.1145/3725527>
- [13] K.-H. Han and J.-H. Kim, "Quantum-inspired evolutionary algorithm for a class of combinatorial optimization," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 6, pp. 580–593, 2002, doi: 10.1109/TEVC.2002.804320. <https://doi.org/10.1109/TEVC.2002.804320>
- [14] M. Zhang, Y. Li, T. Yue, and K.-Y. Cai, "Quantum Optimization for Software Engineering: A Survey," 2025. [Online]. Available: <https://arxiv.org/abs/2506.16878>
- [15] K. Danach, H. Harb, L. Saker, and A. Raad, "Quantum-Inspired Hyperheuristic Framework for Solving Dynamic Multi-Objective Combinatorial Problems in Disaster Logistics," *World Electric Vehicle Journal*, vol. 16, no. 6, 2025, doi: 10.3390/wevj16060310. <https://www.mdpi.com/2032-6653/16/6/310>

- [16] L. Demidova and V. Maslennikov, “Thermonuclear Fusion Based Quantum-Inspired Algorithm for Solving Multiobjective Optimization Problems,” *Algorithms*, vol. 18, no. 12, 2025, doi: 10.3390/a18120793. <https://www.mdpi.com/1999-4893/18/12/793>
- [17] Y. Vivek, V. Ravi, and P. R. Krishna, “Quantum-Inspired Evolutionary Algorithms for Feature Subset Selection: A Comprehensive Survey,” 2024. [Online]. Available: <https://arxiv.org/abs/2407.17946>
- [18] D. Lima, R. Saini, and S. Al-Kuwari, “Advances in Quantum Genetic Algorithms,” 2025. [Online]. Available: <https://arxiv.org/abs/2510.15059>
- [19] Y. Moriyama, I. Iimura, and S. Nakayama, “Isolation strategy for multi-objective quantum-inspired evolutionary algorithm,” *International Journal of Computational Intelligence Studies*, vol. 11, no. 3–4, pp. 159–175, Jan. 2022, doi: 10.1504/ijcistudies.2022.129026. <https://doi.org/10.1504/ijcistudies.2022.129026>