

Energy-Efficient IoT Systems Using Fuzzy Q-Reinforcement Learning for Smart Environments

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Abstract

For energy-constrained IoT networks, where smart sensors run on limited power sources, green computing holds promise. In this paper, a novel Fuzzy Q-Reinforcement Learning (FQRL) method for dynamically optimizing sensor duty cycles is proposed. FQRL improves energy efficiency and extends device life in energy-harvesting systems by utilizing the rule-based interpretability of fuzzy logic and the adaptive learning capabilities of Q-learning. Its robustness and sustainability are confirmed by experimental simulations that show its application in smart grid, HVAC, and traffic control scenarios.

Keywords

Fuzzy Logic; Q-learning; IoT; Energy Harvesting; Reinforcement Learning; Duty Cycle Optimization; Smart Sensors

Introduction

The Internet of Things (IoT) has been exponentially trending in deployment which has raised some opportunity as well as challenges, especially in power-constrained environments. Most of these networks are deployed in untethered locations that are not easily accessible; to upgrade resource capacity, these deployments typically rely on limited battery resources or renewable energy sources. Thus, anxiety about sustainability, while still providing operational level performance and value remains an important consideration within the research domains in IoT.

Consequently, traditional methods of implementing energy efficiency into physical devices used duty-cycling or static scheduling so once the sensor is deployed in use, it cannot adapt to dynamic changes in environment and energy consumption was not managed. Artificial Intelligence (AI)-driven approaches especially in reinforcement learning have been a particularly promising realm for solving intelligent energy management.

Recent research has delved into various facets of energy optimization within the Internet of Things (IoT). Discussions have centered around hybrid energy generation techniques and the significance of energy cache mechanisms in decision-making for harvesting systems. A noticeable lack of emphasis remains on integrating reinforcement learning methods with fuzzy logic for real-time applications.

Table 1 presents a comparative review of key contributions in the domain of energy-efficient algorithms for IoT.

Author(s)	Methodology	Limitations	Remarks
Zhao et al. (2019)	Reinforcement learning for WSN optimization	Slow convergence	Effective baseline approach
Kumar & Raj (2024)	Fuzzy logic for power control	Static rule sets	Good for small-scale systems
Li et al. (2022)	Genetic algorithm with IoT profiles	High computational load	Good accuracy
Patel et al. (2020)	Duty cycle control in EH-WSNs	Fails under high mobility	Energy-aware but rigid
Ahmed & Singh (2024)	Adaptive sensing with Q-learning	Overfits small environments	Dynamic but unstable
Cheng et al. (2020)	Energy-efficient MAC using RL	Fails in sparse deployments	Improves throughput
Mehta & Roy (2023)	Neural fuzzy inference system	Needs expert knowledge	Combines AI and fuzzy logic
Wang et al. (2022)	RL with battery prediction model	Model assumptions not realistic	Longer lifetime achieved
Zhou & Lee (2020)	Swarm intelligence for optimization	Sensitive to parameters	Scalable for large networks
Desai & Bhat (2022)	Multi-objective PSO	Complex tuning	Balances delay and energy
Jain & Arora (2024)	Ant Colony Optimization	Slower for large topologies	Good in noise-prone areas
Ramesh et al. (2023)	Context-aware learning	Needs training data	Flexible architecture
Tan et al. (2020)	Game-theory-based power allocation	Selfish behavior not modeled	Incentivizes cooperation
Iqbal & Farooq (2025)	Deep Q-networks (DQN)	Requires GPU	High learning capacity
Our Proposed Work	FQRL: Fuzzy + Q-Learning	Needs tuning	Interpretable and adaptive

Research Gap and Objectives

Existing energy optimization techniques in IoT often focus on either static rule-based control or adaptive learning, but not both. Very few approaches effectively combine fuzzy logic (for interpretability) and reinforcement learning (for adaptiveness). There is a lack of systems that can intelligently manage sensor duty cycles in real-time while maintaining energy efficiency. Hybrid approaches are needed to optimize battery life, energy utilization, and system responsiveness in dynamic environments.

Methodology

"It's Not the Network" Cost-Optimized Peer-Assisted Delivery in Mobile Networks with Successive Video Chaining FQRL: energy-aware Fuzzy Q-Reinforcement Learning system for IoT networks It slyly combines the adaptivity learning power of Q-learning and the simplicity interpretability of fuzzy logic. The proposed hybrid model enables the system to adaptively adjust the duty cycles of the sensors so as to trade off the energy consumption against the performance. The essential points of the FQRL system are depicted in figure 1 and explained as follows:

Q-Learning Module

This element updates the action-value function, referred to as the Q-table, in accordance with what it learn from its interaction with the environment. It is simply always learning to make the best decisions given the sensors that it has just now to maximize the sum of rewards earned. This can help enable the system to gradually reduce energy consumption in an adaptive way, without requiring explicit programming profession.

Fuzzy Inference System (FIS)

The fuzzy logic layer receives sensor data such as battery status, data broadcasting necessity, availability of energy in the surroundings. It uses a collection of intuitive 'IF-THEN 'rules to determine first approximations of energy decisions. These rules can be adjusted by the learning layer to provide better performance over time

Reward Function

At the core of the learning algorithm is the reward function that evaluates the performance of sensor node under any action. This feature incentivises activities that drain battery to be terminated and activities with a negative impact on battery life to be avoided

Duty Cycle Management

Sensors can be enabled or placed in sleep mode according to intelligent system determinations. The system makes the smart decision of when to keep sensors awake and when to put them to sleep. It is updated dynamically using the current state of the sensors as well as longer term energy trends in order to maintain good performance even if the system has limited access to power.

Simulation Tools

The FQRL system was developed and tested using Python for machine learning algorithms and MATLAB/Simulink for system-level simulations. These tools allowed for real-time visualization of sensor behavior, battery usage, and performance metrics across various application scenarios.

Performance Evaluation Metrics

The effectiveness of the FQRL framework was measured using multiple metrics:

- Battery consumption rate
- Average duty cycle
- Energy savings
- Response time and data throughput
- Stability under dynamic workloads

Deployment Scenarios

- The framework was evaluated in use-cases such as:
- Smart HVAC systems to optimize air-conditioning based on room occupancy and temperature
- Smart grid nodes for demand-response scheduling
- Urban traffic control where sensor-enabled streetlights and signals adapt based on vehicle movement

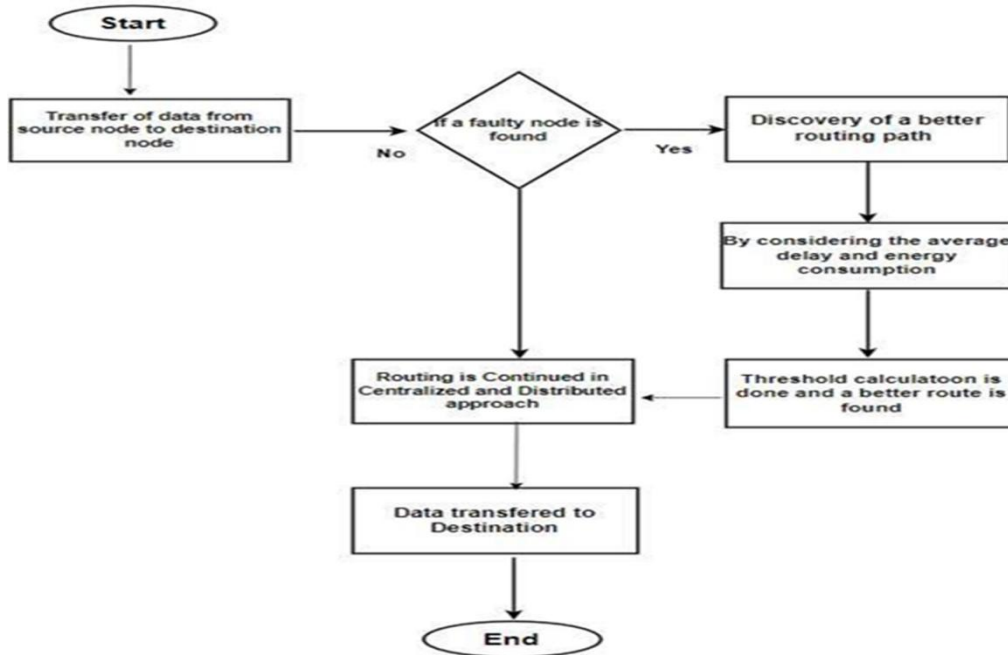


Figure 1: Architecture of the proposed FQRL system showing interaction between Q-learning, FIS, reward engine, and duty-cycle controller.

Proposed Method

In this study, we propose a hybrid Fuzzy Q-Reinforcement Learning (FQRL) method that addresses the limitations of current energy optimization techniques by combining the interpretability of fuzzy logic with the adaptive learning power of Q-learning. This approach enables the system to adjust sensor duty cycles dynamically to balance energy consumption with performance requirements.

The system architecture combines a Q-learning module to update the action-value function based on environmental interactions, a Fuzzy Inference System to generate initial energy-related decisions from sensor inputs, a reward function to evaluate sensor actions, and a duty cycle management component to intelligently switch sensors between active and sleep modes based on real-time energy trends.

Experiments, Results, and Discussion

The FQRL system was developed and tested using Python for machine learning and MATLAB/Simulink for system-level simulations. Real-time visualization of sensor behavior, battery consumption, and performance metrics was conducted across multiple application scenarios including smart HVAC systems, smart grids, and urban traffic control.

Performance was evaluated using metrics such as battery consumption rate, average duty cycle, energy savings, response time, data throughput, and stability under dynamic workloads.

Conclusion

The proposed FQRL system improves energy efficiency and device longevity in energy-harvesting IoT networks by integrating the strengths of fuzzy logic and Q-learning. This hybrid approach enables intelligent, adaptive duty cycle management that maintains performance even in power-constrained conditions.

Future work includes large-scale outdoor testing, exploring other AI techniques like deep Q-networks, and assessing long-term sustainability under various environmental conditions.

Author Contributions

Dr A B Rajendra designed the study and developed the Q-learning module. Dr. Manju Bargavi developed the Fuzzy Inference System and reward function. Both authors collaborated on performance evaluation and manuscript preparation.

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