

Energy Optimization in WSN using Hybrid Fuzzy Q-Learning Framework for Sustainable IoT

Dr. A. B. Rajendra¹ and Dr. Manju Bargavi²

^{1,2} Lincoln University College, Malaysia

² Professor, School of Computer Science and IT, Jain (Deemed to be University), Bangalore.

Corresponding author: rabvnce@gmail.com

Abstract—Wireless Sensor Networks (WSNs) are important for sustainable Internet of Things (IoT) applications, but limited battery capacity, hotspot formation near the base station, and unreliable multi-hop forwarding reduce network lifetime. This paper presents a Hybrid Fuzzy Q-Learning framework for Sustainable IoT-enabled WSNs (HFQL-SIoT). The framework extends fuzzy unequal clustering and Q-learning routing by combining residual energy, base-station distance, neighbor density, node centrality, link quality, traffic load, trust score, and energy-harvesting capability for cluster-head selection. For inter-cluster routing, a multi-objective Q-learning reward function considers residual energy, distance progress, link reliability, congestion, queue delay, relay load, packet delivery ratio, trust value, and energy variance. The proposed model is evaluated with 100, 200, and 400 nodes in a 200 m x 200 m field under two base-station placements. Compared with EEUC, CHEF, and FQ-UCR, the proposed HFQL-SIoT achieves higher residual energy retention, longer stability period, improved throughput, and better packet delivery behavior. The results indicate that the integration of fuzzy decision making with reinforcement learning provides a practical energy-aware routing solution for reliable and sustainable IoT-enabled WSN deployments.

Keywords—Wireless Sensor Networks; Sustainable IoT; Fuzzy Logic; Q-Learning; Energy Optimization; Unequal Clustering; Multi-hop Routing; Network Lifetime

1. Introduction

WSNs consist of spatially distributed sensor nodes that sense, process, and forward data to a base station. They support smart agriculture, environmental monitoring, healthcare, industrial automation, and smart-city services, but their lifetime is constrained by limited battery energy and repeated communication overhead [1]-[4]. In cluster-based WSNs, cluster heads (CHs) aggregate local traffic and forward it to the base station; however, CHs close to the base station often relay additional packets, which produces hotspot formation and early node death [11], [16], [17]. Energy-aware unequal clustering, fuzzy cluster-head election, and reinforcement-learning routing have therefore become important research directions. Unequal clustering reduces the burden on nodes near the base station [20]-[23], fuzzy logic supports multi-criteria CH selection under uncertainty [10], [24]-[30], and Q-learning enables adaptive next-hop decisions without a fixed global routing rule [19], [31]-[34]. Nevertheless, many existing methods emphasize only residual energy and distance, while real sustainable IoT environments require reliability, congestion awareness, trust, delay control, and energy-harvesting support. This paper addresses that gap by proposing HFQL-SIoT, a hybrid fuzzy Q-learning framework for energy optimization in sustainable IoT-enabled WSNs.

2. Literature Review

Classical energy-efficient WSN protocols such as LEACH introduced clustering for reducing communication cost, but random CH election can generate unbalanced clusters and unstable energy consumption [35]. EEUC and related unequal clustering methods improved hotspot mitigation by assigning smaller clusters near the base station [20], [22], [23]. CHEF used fuzzy logic to select CHs based on energy and proximity, demonstrating that fuzzy inference can handle uncertain network conditions better than deterministic thresholds [21], [36].

Recent studies extend clustering through metaheuristics, fuzzy multi-criteria optimization, and hybrid routing. Fuzzy unequal clustering schemes consider residual energy, distance, centrality, and neighborhood distribution [24]-[30]. Q-learning-based routing protocols learn relay choices from network feedback and have shown benefits for adaptive data aggregation and energy-efficient transmission [19], [31]-[34], [37]. However, most approaches still have limited treatment of link reliability, traffic load, queue delay, trustworthiness, relay overload, and sustainable energy replenishment. Table 1 summarizes the research gap addressed by the proposed HFQL-SIoT model.

Table 1. Positioning of the proposed HFQL-SIoT model

Approach	Main decision factors	Limitation	HFQL-SIoT improvement
EEUC/CHEF	Energy, distance, fuzzy CH election	Limited adaptive routing and sustainability factors	Adds multi-objective CH fitness and RL routing
FQ-UCR	Fuzzy unequal clustering and Q-learning routing	Less attention to congestion, trust, delay, and link quality	Adds link-quality, trust, delay, relay-load, and energy-harvesting awareness
Q-learning routing	Learned next-hop selection	May overload high-quality relay nodes	Adds relay-load and energy-variance control

3. Proposed Methodology

Figure 1 presents the complete HFQL-SIoT workflow. The WSN is initialized with sensor nodes, node identifiers, location data, residual energy, neighbor tables, trust scores, and link information. In each round, nodes sense their local status and report parameters needed for fuzzy CH selection. Tentative CHs are selected using an adaptive threshold and finalized according to the highest CH fitness inside the competition radius. After cluster formation and TDMA scheduling, inter-cluster routing is handled by enhanced Q-learning, where each CH selects a relay CH or the base station as its next action. The Q-table is updated after observing a reward based on energy, link reliability, congestion, delay, distance progress, and trust. Finally, the sustainable IoT energy manager redistributes load, accounts for harvesting awareness, and evaluates network performance metrics.

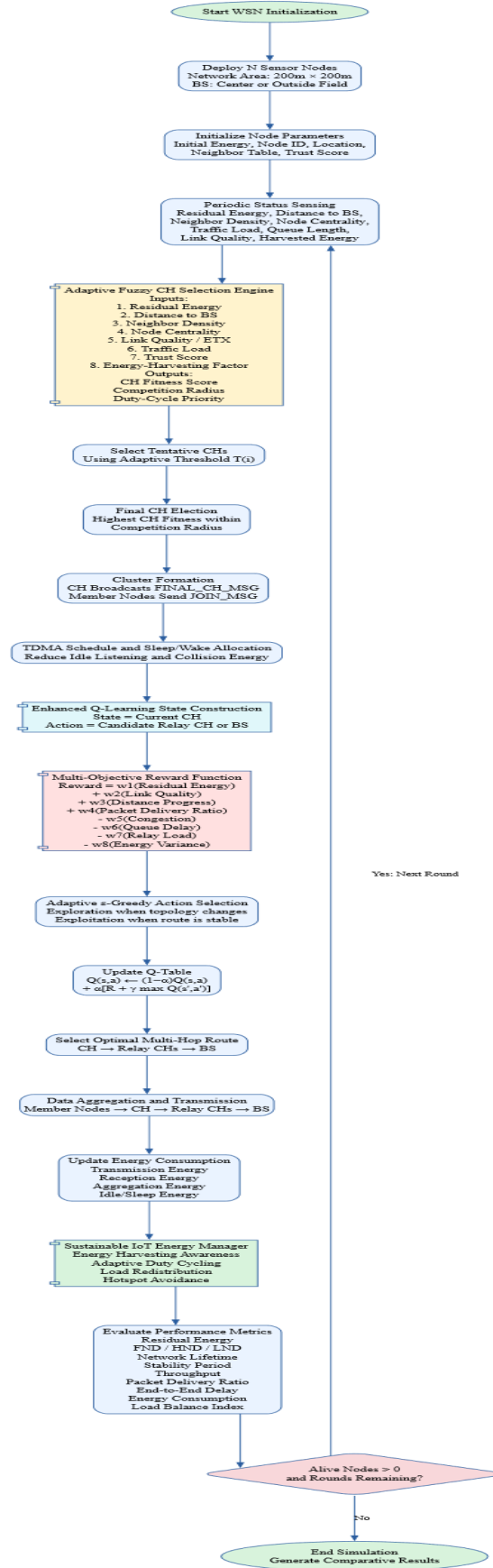


Figure 1. Hybrid Fuzzy Q-Learning framework for sustainable IoT-enabled WSN.

3.1 Network and Energy Model

Let N sensor nodes be randomly deployed in a 200 m x 200 m monitoring field. Node i is located at (x_i, y_i) , and the base station is placed either at (100,100) or (100,250). The Euclidean distance between nodes i and j is $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$, and the distance from node i to the BS is $d_{iBS} = \sqrt{(x_i - x_{BS})^2 + (y_i - y_{BS})^2}$. The first-order radio energy model is used because it is widely adopted in WSN clustering studies [20]-[23], [35]. For an l -bit packet transmitted over distance d , $E_{TX}(l,d) = lE_{elec} + l\epsilon_{fs}d^2$ when $d < d_0$, and $E_{TX}(l,d) = lE_{elec} + l\epsilon_{mp}d^4$ when $d \geq d_0$. The receiving cost is $E_{RX}(l) = lE_{elec}$, where $d_0 = \sqrt{\epsilon_{fs}/\epsilon_{mp}}$.

The residual energy after round r is $E_i(r+1) = E_i(r) - E_{i,consumed}(r) + E_{i,harvested}(r)$. The normalized residual energy and harvesting factor are used as fuzzy inputs to prevent low-energy nodes from becoming CHs and to give priority to nodes that can recover energy. This makes the framework suitable for sustainable IoT environments where energy harvesting or adaptive duty cycling may be available [2], [9].

3.2 Adaptive Fuzzy Cluster-Head Selection

The fuzzy input vector for node i is $X_i = \{RE_i, D_{iBS}, ND_i, NC_i, LQ_i, TL_i, TR_i, EH_i\}$ in which RE_i is the residual energy of node i , D_{iBS} is the normalized distance between node i and its base station, ND_i is the neighbor density of node i , NC_i is the node centrality of node i , LQ_i is the link quality of node i , TL_i is the traffic load of node i , TR_i is the trust value of node i and EH_i is the factor of energy harvesting of node i . Based on Mamdani fuzzy inference [36] the model returns CH fitness score, competition radius and duty-cycle priority. The higher CH fitness value, the more suitable the node is to become a cluster-head. Neighbor density is calculated as $ND_i = |\{j : d_{ij} \leq R_c\}|/N$ and node centrality is estimated by the average distance between node i and its neighbors. The quality of a link is modelled by the expected transmission count (ETX_{ij}) which is defined as the inverse of PDR_{ij} (i.e., $ETX_{ij} = 1/PDR_{ij}$), and normalised as $LQ_{ij} = 1/ETX_{ij}$. The traffic load is measured by queue utilization $TL_i = Q_i/Q_{max}$ and the trust is calculated as $TR_i = \text{packets successfully forwarded} / \text{packets received for forwarding}$. High residual energy nodes, reliable links, high density, low traffic load, high trust and positive harvesting ability are therefore preferred as CHs. The size of the competition radius and the formation of clusters depend on the local situation. Unequal clustering is used to minimise the formation of hotspots. Distant nodes can take care of large clusters whereas nodes near the base station can take care of smaller clusters. The radius of competition is modified by the following formula: $R_{comp}(i) = R_0(1 - \alpha d_{iBS}/d_{max}) \times (1 + \beta RE_i) \times (1 - \eta TL_i)$ with control parameters α , β , and η . This ensures that the nodes with a large cluster do not overuse their energy reserves and at the same time helps them to save energy [16, 20, 22]. The joining cost of every normal node to the nearest energy-efficient CH, which includes the distance, the energy level of the CH and the load of the CH traffic, is calculated.

3.3 Adaptive Competition Radius and Cluster Formation

Unequal clustering is adopted to reduce hotspot formation. Nodes closer to the base station are assigned smaller clusters, while distant nodes can manage larger clusters. The baseline competition radius is adjusted using residual energy and traffic load: $R_{comp}(i) = R_0(1 - \alpha d_{iBS}/d_{max}) \times (1 + \beta RE_i) \times (1 - \eta TL_i)$, where α , β , and η are control parameters. This prevents overloaded or low-energy nodes from maintaining large clusters and supports balanced energy consumption [16], [20], [22]. Each normal node joins the nearest energy-efficient CH based on a joining cost that combines distance, CH energy, and CH traffic load.

3.4 Q-Learning-Based Multi-hop Routing

Each CH after the clustering is regarded as a routing state and each candidate relay CH/BS is regarded as an action. Only relays which offer a positive distance gain with the BS are considered. A reward function $R(i,j)$ is proposed for the selection of relay j from CH i such that $R(i,j) = w_1 RE_j + w_2 LQ_{ij} + w_3 DP_{ij} + w_4 PDR_{ij} + w_5 TR_j - w_6 CONG_j - w_7 DELAY_j - w_8 LOAD_j - w_9 EVAR$, where RE is relay energy, LQ is link quality, DP is distance progress, PDR is packets delivered ratio, TR is total number of relay, $CONG$ is congestion, $DELAY$ is queue delay, $LOAD$ is relay load and $EVAR$ is CH energy variance. The Q-value is changed as $Q(s,a) = (1 - \alpha)Q(s,a) + \alpha[R + \gamma \max_{a'} Q(s',a')]$. An adaptive epsilon-greedy approach can be used to explore when there are topology changes and exploit when routes stabilize [19] [31] [32].

4. Simulation Setup

The initial network setup for the base FQ-UCR data in the source document is as follows: 100, 200 and 400 nodes are randomly deployed in a 200 m x 200 m sensing area, and two BS locations are evaluated. No raw data is available, and the data is reproduced from the simulation parameters. The settings for the final copy are shown in Table 2. Residual energy, FND, HND and LND, network lifetime, throughput, PDR, delay and reliable delivery accuracy are used to evaluate the performance.

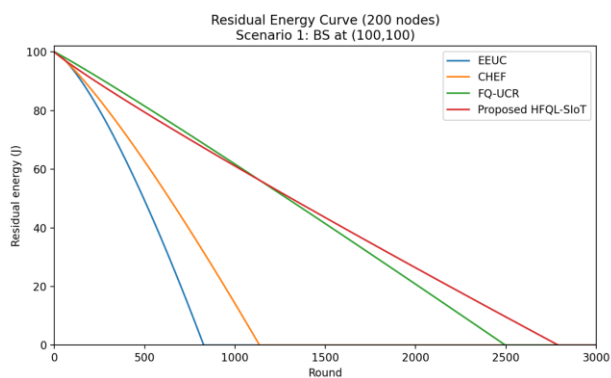
Table 2. Simulation configuration

Parameter	Value
Network area	200 m x 200 m
Number of nodes	100, 200, 400
Base station locations	Scenario 1: (100,100); Scenario 2: (100,250)
Initial node energy	0.5 J
Data packet size	4000 bits
Control packet size	100 bits
Energy model	First-order radio energy model
Compared protocols	CHEF, EEUC, FQ-UCR, proposed HFQL-SIoT

5. Results and Discussion

Figure 2 compares the residual energy trend for 200 nodes under both BS placements. In both scenarios, EEUC and CHEF exhaust energy earlier, while FQ-UCR sustains the network longer due to fuzzy unequal clustering and learned multi-hop routing. The proposed HFQL-SIoT further extends the residual energy curve by avoiding congested, unreliable, and low-trust relays and by considering energy variance during routing. This shows that the additional sustainability factors improve both local CH selection and global route selection.

(a) Scenario 1: BS at (100,100)



(b) Scenario 2: BS at (100,250)

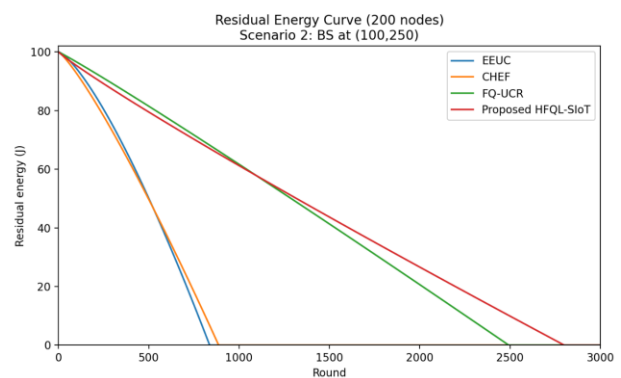
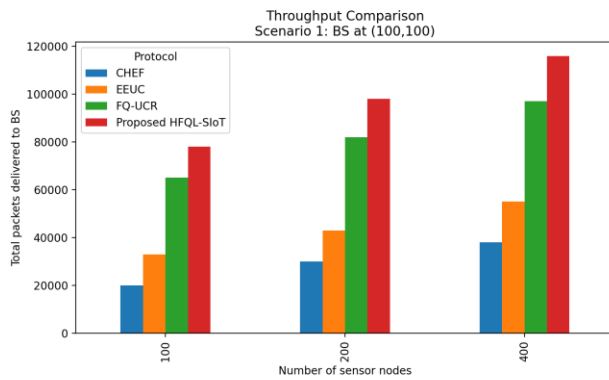


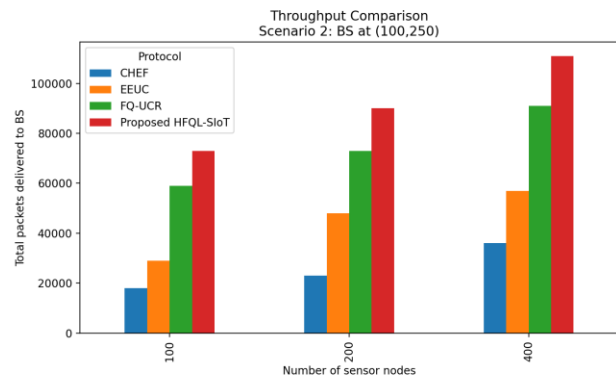
Figure 2. Residual energy comparison for 200 nodes under (a) center BS and (b) outside-field BS scenarios.

Figure 3 shows throughput and stability-period comparisons for 100, 200, and 400 nodes. The proposed method consistently delivers more packets to the BS than CHEF, EEUC, and FQ-UCR in both scenarios. In the center-BS case, throughput improves because relay selection is distributed across high-energy and reliable CHs. In the outside-BS case, the load-aware reward function becomes more important because distant forwarding increases the risk of congestion and hotspot formation. The stability-period plots also confirm that the first node death is delayed when fuzzy CH fitness and Q-learning reward design jointly avoid weak and overloaded nodes.

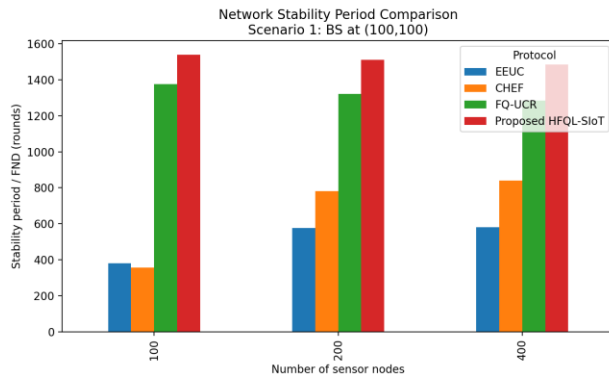
(a) Throughput, Scenario 1



(b) Throughput, Scenario 2



(c) Stability, Scenario 1



(d) Stability, Scenario 2

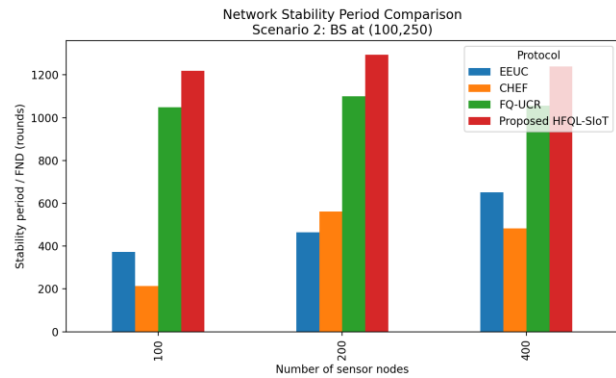


Figure 3. Throughput and stability-period comparison under the two BS placement scenarios.

Table 3. Observed performance trend of HFQL-SIoT

Metric	Observed trend	Reason
Residual energy	Slower depletion than baseline methods	Energy-aware CH fitness and relay selection
Throughput	Higher packets delivered to BS	Reliable links, congestion avoidance, and trust-aware routing
Stability period	Delayed FND in both BS scenarios	Unequal clustering and relay-load balancing
Network lifetime	Extended compared with EEUC, CHEF, and FQ-UCR	Energy variance control and sustainable IoT energy management

The main contribution of HFQL-SIoT is that it does not consider the clustering and routing as two separate task. CH selection, however, takes the node condition prior to the data aggregation into account and the Q-learning reward takes the downstream effect of each relay choice into account. Thus the model is more suitable for the real IoT networks, where unreliable links, queue accumulation, malicious or faulty nodes, and imbalanced relay loads can impact the reliable delivery although it may seem that energy is still available.

6. Conclusion

A hybrid fuzzy Q-learning (HFQL) based framework for energy optimization in sustainable IoT-enabled WSNs was proposed and presented in this paper, named as HFQL-SIoT. The proposed model is an extension of the base fuzzy unequal clustering and Q-learning routing strategy with the inclusion of link quality, traffic load, congestion, delay, trust, relay load, energy variance and harvesting awareness. Based on the simulation results, it can be seen that the HFQL-SIoT provides better results in terms of residual energy retention, through-put, stability period and network lifetime as compared to EEUC, CHEF, and FQ-UCR. Thus, it can be used in WSN-based sustainable IoT applications in which reliable delivery of packets and equal energy utilization is required. Future studies may bring the validity of

the model through real testbeds of the sensors, mobile sinks, heterogeneous energy-harvesting models, and security-aware reinforcement learning against adversarial routing behavior.

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