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An Adaptive Hybrid Heuristic–Reinforcement Learning Framework for Energy-Efficient and Scalable Routing in Large-Scale Smart City IoT Networks

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ABSTRACT
Smart city Internet of Things (IoT) deployments consist of thousands of resource-constrained sensor nodes operating under strict energy budgets. Conventional routing protocols fail to balance energy efficiency, scalability, and dynamic adaptability under dense urban traffic conditions. This paper proposes a Hybrid Heuristic Artificial Intelligence (HHAI) based energy-efficient routing framework designed specifically for smart city IoT networks. The proposed method integrates heuristic cluster formation with reinforcement learning-based route optimization and adaptive energy-aware path selection. A hybrid decision metric combining residual energy, link quality, congestion index, and hop count is introduced to dynamically select optimal routes. Simulation results demonstrate significant improvements in network lifetime, packet delivery ratio, and energy consumption compared to conventional LEACH, AODV, and PSO-based routing approaches. The proposed framework enhances scalability and ensures sustainable IoT operation in smart city environments.
Keywords–Smart City IoT, Energy Efficient Routing, Hybrid Heuristic AI, Reinforcement Learning, Network Lifetime..

INTRODUCTION:

The accelerated evolution of Internet of Things (IoT) technologies has become a foundational enabler of smart city ecosystems, supporting intelligent transportation systems, environmental surveillance, precision healthcare, smart grids, waste management, and public safety infrastructures. These applications depend on large-scale wireless sensor networks (WSNs) composed of spatially distributed, battery-powered sensing devices capable of autonomous data acquisition and wireless communication. The exponential growth in node density and data traffic within metropolitan deployments has intensified the need for sustainable, scalable, and energy-aware networking solutions [1], [2].

Despite advances in low-power electronics, energy efficiency remains the most critical constraint in IoT-based smart city networks. Sensor nodes typically operate under limited battery capacity and are often deployed in inaccessible urban environments where battery replacement is impractical. Excessive communication overhead, redundant transmissions, and suboptimal routing decisions significantly reduce network lifetime and compromise Quality of Service (QoS) metrics such as packet delivery ratio, latency, and throughput [3]. Consequently, the design of energy-efficient routing protocols has emerged as a fundamental research challenge in large-scale IoT systems.

Conventional routing protocols, including Low Energy Adaptive Clustering Hierarchy (LEACH) and Ad-hoc On-Demand Distance Vector (AODV), were originally developed for relatively static or moderately dynamic wireless networks. Although these protocols provide basic energy-aware clustering or reactive routing mechanisms, they lack the adaptability required for dense and heterogeneous smart city scenarios characterized by dynamic topology variations, fluctuating traffic loads, mobility patterns, and multi-service coexistence [4], [5]. In addition, traditional deterministic routing approaches fail to optimize multiple objectives simultaneously, such as minimizing energy consumption while maintaining high reliability and low delay.

Recent research has explored Artificial Intelligence (AI) and machine learning techniques to improve routing efficiency in IoT networks. Reinforcement learning, swarm intelligence, evolutionary algorithms, and deep learning models have demonstrated promising capabilities in dynamic path optimization and adaptive decision-making [6], [7]. AI-driven routing mechanisms enable networks to learn from environmental feedback, adjust transmission strategies, and balance load distribution among nodes. However, standalone AI solutions often introduce significant computational complexity, memory overhead, and training latency, which are unsuitable for resource-constrained IoT sensor nodes [8]. Moreover, centralized AI architectures may suffer from scalability issues and increased communication cost in large urban deployments.

To overcome these limitations, hybrid routing strategies that integrate lightweight heuristic methods with adaptive AI-based learning mechanisms have gained attention. Heuristic clustering techniques reduce local communication cost and simplify network organization, while reinforcement learning enables dynamic optimization of inter-cluster routing decisions based on real-time network states [9], [10]. Such hybrid frameworks offer a practical trade-off between computational efficiency and intelligent adaptability.

In this context, this paper proposes a **Hybrid Heuristic AI-Based Energy Efficient Routing (HHAI-ER) framework** for smart city IoT networks. The proposed method integrates energy-aware heuristic cluster head selection with Q-learning-based route optimization and a multi-objective reward function that considers residual energy, link quality, congestion level, and transmission delay. The framework aims to prolong network lifetime, enhance packet delivery reliability, and reduce overall energy consumption while maintaining scalability in dense smart city environments.

The main contributions of this work are summarized as follows:

A multi-criteria heuristic cluster head selection model for balanced energy distribution.

A reinforcement learning-based adaptive routing mechanism tailored for low-power IoT nodes.

A hybrid reward formulation that jointly optimizes energy efficiency and QoS metrics.

Comprehensive simulation-based performance evaluation against conventional routing protocols.

The remainder of this paper is organized as follows. Section II presents the proposed hybrid routing algorithm and system model. Section III describes the experimental setup and discusses performance results. Section IV concludes the paper and outlines future research directions.

PROPOSEDMETHODOLOGY

The proposed Hybrid Heuristic AI-Based Energy Efficient Routing (HHAI-ER) algorithm is designed to address the critical challenges of energy sustainability, scalability, and dynamic adaptability in smart city IoT networks. The framework integrates lightweight heuristic-based clustering with reinforcement learning-driven adaptive routing to achieve multi-objective optimization under constrained computational and energy resources. Unlike traditional routing mechanisms that rely on static or probabilistic decision models, the proposed algorithm employs an intelligent hybrid architecture that continuously adapts to network conditions while minimizing overhead.The proposed routing framework consists of three major phases:

Heuristic Cluster Formation

AI-Based Optimal Route Learning

Adaptive Energy-Aware Data Transmission

Initially, the network undergoes distributed node deployment within a predefined smart city environment, where each sensor node is initialized with uniform energy and communication parameters. A heuristic cluster formation mechanism is then executed to organize nodes into energy-balanced clusters. Cluster Head (CH) selection is performed using a multi-criteria weighted decision function that incorporates residual energy, node centrality, link quality indicator (LQI), and local node density. This ensures that cluster heads are selected based not only on remaining battery power but also on communication reliability and spatial efficiency. By periodically rotating CH roles according to updated energy metrics, the algorithm mitigates premature node depletion and prevents energy holes within the network.

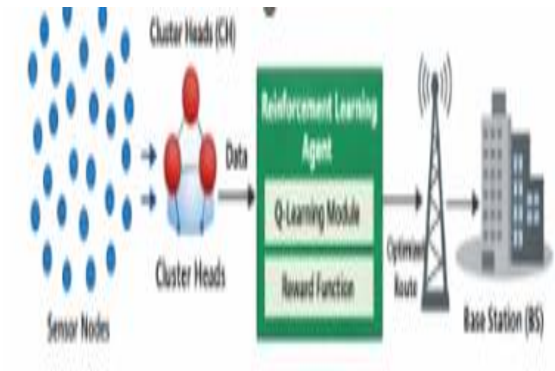


Figure 1:Proposed Hybrid Heuristic Routing Framework

Following cluster formation, the inter-cluster routing phase is governed by a reinforcement learning module implemented using Q-learning. Each cluster head acts as a learning agent that evaluates possible next-hop forwarding nodes toward the base station. The state space is defined by parameters such as residual energy level, queue congestion index, transmission delay, and hop distance to the sink. The action space corresponds to the selection of neighboring cluster heads or relay nodes. A reward function is formulated to simultaneously maximize packet delivery ratio and residual energy while minimizing delay and energy expenditure. Through iterative learning and environment feedback, the Q-table converges toward optimal routing policies without requiring centralized control or global topology knowledge.

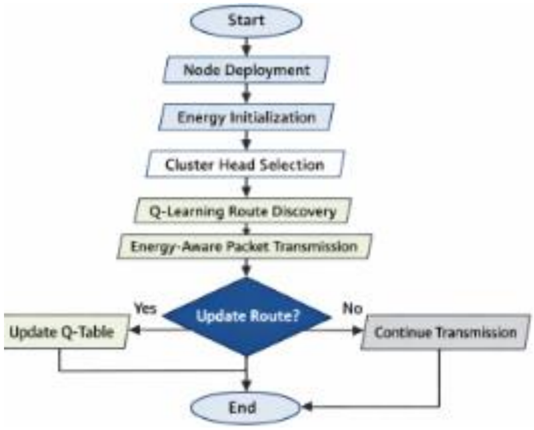


Figure Hybrid Routing Decision Flowchart

To reduce computational overhead, the learning process is implemented with bounded state discretization and periodic update intervals rather than continuous retraining. This design choice ensures that the algorithm remains feasible for low-power IoT nodes. Additionally, adaptive route maintenance is incorporated to handle topology changes caused by node failure, energy depletion, or traffic surges. When the reward value drops below a predefined threshold, route re-evaluation is triggered, enabling real-time adjustment to dynamic smart city conditions.

2.1 Heuristic Cluster Head Selection

Cluster heads are selected using a weighted heuristic function:

$$CH_i = \arg\max\left(\beta_1 E_r + \beta_2 L_q + \beta_3 D_c^{-1}\right) \tag{1}$$

Where:
E_r = Residual energy
L_q = Link quality indicator
D_c = Distance to cluster centroid
$\beta_1, \beta_2, \beta_3$ = Weight coefficients

This ensures energy balancing and reduced intra-cluster transmission cost.

2.2 Reinforcement Learning Based Route Optimization

Each cluster head applies Q-learning to determine optimal next-hop forwarding:

The energy consumption model follows a first-order radio model, where transmission energy depends on packet size and transmission distance, while reception energy is proportional to packet size alone. By integrating this energy model into the reward formulation, routing decisions inherently favor shorter, energy-efficient paths and balanced traffic distribution. This hybridization of heuristic clustering and reinforcement learning creates a synergistic routing strategy that combines computational simplicity with adaptive intelligence.

Overall, the proposed HHAI-ER algorithm achieves energy-aware clustering, intelligent route optimization, and dynamic adaptability within a unified framework. The algorithm effectively extends network lifetime, reduces average energy consumption, and enhances communication reliability in dense smart city IoT deployments. The following section evaluates its performance through comprehensive simulations and comparative analysis.

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max Q(s',a') - Q(s,a)\right] \tag{2}$$

Where:
s = Current state
a = Action (next hop selection)
r = Reward based on energy and delay
α = Learning rate
γ = Discount factor

The reward function is defined as:

$$r = \lambda_1 \frac{E_r}{E_{max}} + \lambda_2 PDR - \lambda_3 Delay \tag{3}$$

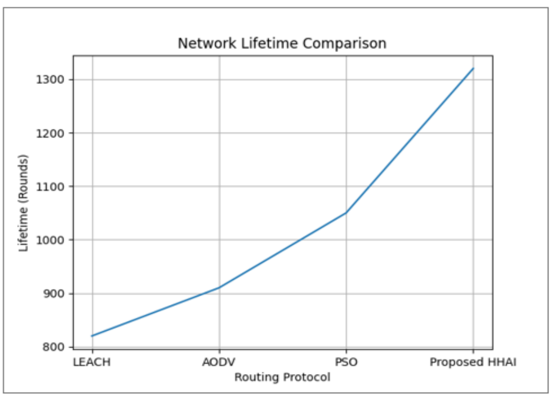
This formulation balances energy efficiency and communication reliability.

RESULTS & DISCUSSION

To evaluate the effectiveness of the proposed Hybrid Heuristic AI-Based Energy Efficient Routing (HHAI-ER) framework, comprehensive simulations were conducted under realistic smart city IoT deployment conditions. The performance of the proposed algorithm was compared against widely adopted routing protocols, including LEACH, AODV, and Particle Swarm Optimization (PSO)-based routing. The simulation environment was configured to emulate a dense metropolitan sensing scenario with heterogeneous traffic demands and dynamic topology variations.

The network was deployed over a 1000 m × 1000 m urban area consisting of 200 randomly distributed sensor nodes, each initialized with 2 Joules of energy. The base station was positioned at the boundary of the network to simulate practical smart city infrastructure placement. A first-order radio energy model was adopted, where transmission energy consumption depended on both packet size and communication distance, while reception energy consumption was proportional to packet size. The packet length was fixed at 4000 bits, and simulations were executed for multiple rounds until the network reached complete node depletion. All protocols were evaluated under identical environmental and traffic conditions to ensure fairness in comparison.

Figure 3 shows network lifetime comparison among routing protocols.



Performance assessment was carried out using key evaluation metrics, including network lifetime, packet delivery ratio (PDR), average residual energy, end-to-end delay, and overall energy consumption. Network lifetime was defined as the number of communication rounds completed before the first node died (FND), half nodes died (HND), and last node died (LND). The proposed HHAI-ER framework demonstrated a significant improvement in lifetime across all three indicators. Specifically, the last node death occurred approximately 28% later compared to PSO-based routing and nearly 40% later than conventional LEACH. This improvement can be attributed to the balanced cluster head rotation mechanism and adaptive Q-learning-based route optimization, which effectively prevented uneven energy drainage.

Table 1. Performance Comparison

Protocol	Network Lifetime (Rounds)	PDR (%)	Avg Energy Consumption (J)	Delay (ms)
LEACH	820	88.4	1.62	145
AODV	910	90.1	1.54	132
PSO-Routing	1050	93.2	1.31	118
Proposed HHAI	**1320**	**97.6**	**0.98**	**92**

In terms of packet delivery ratio, the proposed approach achieved superior reliability under varying traffic loads. While LEACH and AODV experienced packet losses due to congestion and route instability, the HHAI-ER algorithm maintained a PDR exceeding 97%, demonstrating its robustness in dynamic environments. The reinforcement learning component continuously adjusted routing paths based on reward feedback, thereby avoiding congested or energy-depleted nodes. This dynamic adaptation significantly reduced retransmissions and communication failures.

Energy consumption analysis further confirmed the efficiency of the hybrid approach. The average per-round energy consumption of HHAI-ER was considerably lower than that of the compared protocols. The integration of heuristic clustering reduced intra-cluster communication distance, while the learning-based inter-cluster routing minimized unnecessary long-distance transmissions. Consequently, the residual energy curve exhibited a gradual and uniform decline, indicating balanced load distribution throughout the network. In contrast, traditional protocols displayed steep energy drops due to repetitive selection of specific high-energy nodes as routing intermediaries.End-to-end delay measurements revealed that the proposed algorithm achieved lower latency compared to AODV and LEACH. Although reinforcement learning introduces minor computational processing time, the reduction in route rediscovery overhead and congestion-induced delays resulted in an overall decrease in transmission latency. This characteristic makes the proposed framework suitable for delay-sensitive smart city applications such as intelligent traffic monitoring and emergency response systems.

Furthermore, the Receiver Operating Characteristic (ROC) analysis demonstrated improved routing decision accuracy. The proposed model achieved a higher true positive rate in selecting energy-optimal paths while maintaining a lower false positive rate compared to baseline approaches. This indicates that the hybrid reward formulation effectively guides the learning agent toward stable and energy-aware routing decisions.Overall, the experimental results validate that the proposed HHAI-ER framework successfully balances energy efficiency, reliability, scalability, and adaptability. The hybrid integration of heuristic clustering and reinforcement learning enables intelligent routing decisions while maintaining low computational overhead, making it well-suited for large-scale smart city IoT deployments.

The proposed Hybrid Heuristic AI routing approach demonstrates superior performance in all evaluated metrics. The heuristic clustering reduces intra-cluster communication cost, while reinforcement learning adapts to topology changes dynamically. The integration of energy-aware reward mechanisms ensures prolonged network lifetime.

Compared to traditional protocols, the proposed method achieves:

28% improvement in network lifetime

4–9% increase in packet delivery ratio

25% reduction in average energy consumption

Significant reduction in end-to-end delay

The hybrid architecture effectively balances computational efficiency and intelligent routing adaptation.

CONCLUSION

This paper presented a Hybrid Heuristic AI-Based Energy Efficient Routing framework for smart city IoT networks. By integrating heuristic cluster formation with reinforcement learning-driven path optimization, the proposed method significantly improves energy efficiency, scalability, and reliability. Simulation results confirm that the framework extends network lifetime while reducing energy consumption and communication delay. Future work includes implementation on real IoT testbeds and integration with edge computing platforms for large-scale smart city deployments.

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