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A Cross Layer Aware Hybrid Routing Algorithm Using Federated Q-Learning and Ant Colony Optimization for Wireless Sensor Networks

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ABSTRACT- Efficient routing in Wireless Sensor Networks (WSNs) remains challenging due to energy constraints, link instability, and dynamic topologies. While machine learning and bio-inspired methods offer improvements, many existing protocols struggle with scalability, computational demands, and limited consideration of critical QoS metrics like delay, PDR, and network lifetime. To overcome these limitations, this paper introduces Fed-QL-ACO-X, a hybrid routing protocol combining Federated Q-Learning (FQL) for decentralized learning, Ant Colony Optimization (ACO) for adaptive path selection, and cross-layer awareness using MAC and PHY layer metrics. Unlike centralized models, it supports local training and lightweight updates, reducing communication overhead. Simulations on a 100-node network benchmarked Fed-QL-ACO-X against 4 advanced routing protocols. The model achieved up to 20% lower energy use, 30% reduced delay, 94% PDR, and a 12–16% increase in network lifetime. These results highlight its effectiveness and scalability, positioning Fed-QL-ACO-X as a practical solution for real-world WSN deployments.

Keywords: Wireless Sensor Networks, Federated Learning, Q-Learning, Ant Colony Optimization, Energy Efficiency, Cross-Layer Design, Delay Reduction, Packet Delivery Ratio.

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1. INTRODUCTION

Wireless Sensor Networks (WSNs) are now integral to smart technologies such as environmental monitoring, precision farming, industrial automation, infrastructure health tracking, and defense systems [1]–[3]. These networks rely on small, battery-powered sensor nodes that wirelessly transmit data to central sinks, yet their deployment faces major challenges such as limited battery life, unstable topologies, interference, and uneven traffic [4], [5]. Efficient routing is therefore essential to ensure reliable communication while conserving energy. Traditional protocols like LEACH, PEGASIS, and AODV [6], [7] laid the foundation but lack adaptability for today's dynamic conditions. Recent advances in machine learning (ML), reinforcement learning (RL), and swarm intelligence have enabled adaptive routing [8]–[10], but most existing models demand high computation, centralized control, and offer poor scalability. Consequently, key QoS metrics such as jitter, packet loss, and fairness remain insufficiently addressed [11]–[13]. Centralized ML models, in particular, increase network traffic by 35–40%, drain energy 20–25% faster, and add 15–20 ms per-hop latency resulting in critical issues in nodes operating with just 1–2 joules of energy. When scaled beyond 200 nodes, such centralized systems often reduce Packet Delivery Ratio (PDR) below 85%. Moreover, most routing methods neglect vital cross-layer parameters like RSSI, LQI, and retransmission counts [14], which strongly influence network stability and reliability. Fed-QL-ACO-X is the first practical routing framework for WSNs that *(i)* tightly couples Federated Q-Learning (FQL) with Ant Colony Optimization (ACO) through a formally defined weighted decision rule, *(ii)* embeds cross-layer MAC metrics directly into the reward and pheromone update schemes, and (iii) is engineered for low communication and computational overhead *via* quantized federated averaging and sparse Q-table synchronization. These three elements decentralized tabular RL, pheromone guided heuristics, and cross layer rewards are combined and implemented together at node level and evaluated empirically, which, to our knowledge, is not done in the cited literature. The construction of the research paper is as follows. *Section 2* highlights the Literature survey. *Section 3* discusses the proposed Fed-QL-ACO-X hybrid algorithm. In *section 4*, an extensive result analysis is performed and discussed. Lastly, *section 5* describes the conclusion of the paper.

2. LITERATURE REVIEW

Recent research in WSN routing has explored various machine learning and metaheuristic techniques. For example, [15] combined RL with GA/PSO to improve PDR, latency, and energy efficiency but was tested only in synthetic simulations without real-world validation. [16] used Bat-Moth Flame optimization to extend network lifetime through cluster head selection but lacked scalability and delay analysis. [17] proposed federated learning for privacy-preserving routing but didn't address communication overhead or convergence issues. Similarly, [18] focused on delay optimization using RL but ignored energy and longevity metrics. Deep learning approaches like DQN-based routing in [19] offered strong decision-making at the cost of high computation unsuitable for low-power nodes, while fuzzy-logic methods in [20] lacked adaptability and missed key QoS metrics. Mobility-aware LSTM in [21] improved prediction but was computationally expensive, and multi-agent Q-learning in [22] lacked cross-layer awareness. Other techniques such as ant colony optimization [23], PCA-based routing [10], PSO-Q swarm [24], and QoS-focused deep routing [25] either neglected real-time metrics or were theory-based. SDN-based routing [26], genetic clustering [27], and federated multi-hop learning [28] improved specific aspects but faced issues like decentralization incompatibility or high communication costs. A theoretical survey in [29] reviewed green ML models but lacked experimental depth. These studies reveal common gaps: most ML-based routing methods are too heavy for sensor nodes, few address all four QoS metrics (energy, delay, PDR, lifetime), cross-layer features are often ignored, and computational costs are rarely considered.

3. METHODS

This work presents Fed-QL-ACO-X, a hybrid routing framework aimed at improving energy efficiency, packet delivery, and network lifetime in Wireless Sensor Networks (WSNs). The model combines Federated Q-Learning (FQL) for decentralized learning, Ant Colony Optimization (ACO) for intelligent path discovery, and cross-layer sensing from the MAC and PHY layers [31], enabling adaptive and scalable routing in dynamic network conditions.

3.1. Federated Aggregation Mechanism

Each sensor node maintains a local Q-table that is updated based on its experience through reinforcement learning. To ensure scalability and low communication overhead, nodes periodically synchronize their local models using federated averaging (FedAvg) [30]. Specifically, the global Q-table is computed as a weighted average of local Q-tables according to the contribution of each node's experience given in *eq. 1*.

$$Q_{global}(s,a) = \frac{\sum_{i=1}^{N} w_i \, Q_i(s,a)}{\sum_{i=1}^{N} w_i} \tag{1}$$

where $Q_i(s,a)$ is the local Q-value of node i, w_i represents the importance or data volume from node i, and N is the total number of participating nodes. This method allows nodes to exchange only the updated Q-values instead of raw data, drastically reducing communication traffic and energy consumption while preserving privacy and data locality.

3.2. Next-Hop Selection

The routing decision at each node is based on a combination of learned state-action values and heuristic information from pheromone levels. The next-hop node a∗ is selected using formula in *eq. 2*.

$$a^* = arg \max_{a\in A)s)} [(1-\lambda)Q(s,a) + \lambda \frac{\tau(s,a)}{\sum_{b\epsilon A(s)} \tau(s,b)}] \tag{2}$$

Here, Q(s,a) is the Q-value from local reinforcement learning, τ(s,a) is the pheromone level on the link between the current node and candidate node a, A(s) is the set of available neighbors, and λ is a tuning parameter that balances the influence of learned experience and pheromone-based exploration. This integration ensures that the routing decision is both adaptive and robust against fluctuating network conditions.

3.2.1. Algorithm and its Implementation

Steps ***Description***

1. *Setup WSN topology (100 nodes in a grid)*
2. *Initialize Q-table, neighbor pheromones, and local statistics.*
3. *Select next-hop using weighted Q + pheromone. Transmit packet and update local stats (delay, success)*
4. *Update using the 4-metric reward function given in eq. 3.*
5. *Q-Learning Update given in eq. 4.*
6. *Periodically, nodes share Q-tables to generate global policy.*
7. *Sink broadcasts feedback to update pheromones as in eq. 5.*
8. *Nodes monitor their residual energy and update routing decisions accordingly based on eq. 6.*
9. *A node stops acting as router if energy drops below critical.*

3.3. Mathematical Expressions and Symbols

When a sensor node forwards a data packet through a low-energy route that successfully delivers the packet, it receives a positive reward and when a packet is delayed, dropped, or has consumed more energy, it gets a negative reward. The routing protocol Fed-QL-ACO-X learns to select paths that maximize these rewards leading to lower energy use, less delay, and higher delivery success.

$$\text{Reward} = w1 * \text{PDR} - w2 * \text{Delay} - w3 * \text{Energy\_used} + w4 * \text{Lifetime\_benefit} \tag{3}$$

Where, Packet Delivery Ratio (PDR) represents the fraction of packets successfully delivered, while delay measures the time taken for a packet to reach the sink. Energy_used denotes the energy spent on transmission and reception, and lifetime_benefit reflects the gain from maintaining energy above a threshold. The proposed Fed-QL-ACO-X employs Q-Learning (*eq. 2*) to dynamically select the best next-hop based on network feedback such as link quality, buffer level, and residual energy. Over time, nodes learn routes that minimize retransmissions and delay, while Federated Q-Learning ensures global coordination without central data transfer. The Q-value update rule is expressed in *eq. 4*.

$$Q(s,a) = Q(s,a) + \propto [r + \gamma * \max_a' Q(s',a') - Q(s,a)] \quad (4)$$

Where, In Q-learning, Q(s, a) denotes the estimated cumulative reward for taking action *a* in state *s*. The learning rate (*α*) controls how much new information influences past knowledge—higher values speed up learning but can reduce stability. The reward (*r*) provides immediate feedback on an action's effectiveness, while the discount factor (γ) determines the weight of future rewards, balancing short- and long-term gains. The term $\max_a' Q(s', a')$ selects the best possible future action.

In the ACO component, pheromone levels represent a shared memory of high-quality paths and are updated using eq. 3, allowing artificial ants to reinforce efficient routes and gradually converge to optimal paths.

$$\tau_{ij}(t+1) = (1-\rho) * \tau_{ij}(t) + \Delta\tau_{ij} \quad (5)$$

Where, $\tau_{ij}(t)$ is pheromone level on path (*i* , *j*) at time *t*, *ρ* is evaporation rate (0 < *ρ* <1), $\Delta\tau_{ij}$ is pheromone deposited on edge (*i* , *j*), and Path Cost function is based on delay, energy and PDR, the weights can be assigned as Let *w1,w2,w3* are the weights for delay, energy and PDR importance respectively, Delay, Energy are Cumulative values along the path, and PDR is packet delivery ratio (0 to 1). Then, the path cost function is given by *eq. 6* as

$$\text{Cost(path)} = w1 * \text{Delay} + w2 * \text{Energy} + w3 * \left(\frac{1}{\text{PDR}}\right) \quad (6)$$

This model differs from prior approaches by integrating federated learning with ant-inspired optimization in a cross-layer framework, enabling nodes to learn optimal routing strategies collaboratively without centralized coordination.

3.4. Simulation Environment

To ensure fair and reproducible evaluation, the proposed Fed-QL-ACO-X framework was tested against four benchmark protocols like Hybrid AI & Swarm [15], Bat-Moth Flame [16], Federated FL Routing [17], and Ant-Based Energy-Aware Routing [23]. Simulations were executed in Jupyter Notebook using a custom Python environment built with NetworkX, SimPy, NumPy, Matplotlib, and Pandas. Each experiment was repeated 30 times with fixed random seeds, and results are reported as mean ± 95% CI.

The simulation area was 100 × 100 m² with 100 sensor nodes, each initialized with 2 J of energy and transmitting 2 kB packets to a static sink node. All algorithms used the same first-order radio model (E_tx = 50 nJ/bit, E_rx = 50 nJ/bit, E_amp = 100 pJ/bit/m², E_DA = 5 nJ/bit) to ensure comparability. The workflow, shown in *figure 1*, begins with initializing Q-tables and pheromone levels. Nodes select the next hop using an ε-greedy policy combining Q-values and pheromones, guided by cross-layer metrics such as link quality, residual energy, and delay. Learning parameters were set to $\alpha = 0.1$, $\gamma = 0.9$, and ε decaying from 0.2 to 0.05. In the ACO module, the pheromone evaporation rate (ρ) = 0.3, with weights $w_1 = 0.4$, $w_2 = 0.6$, $w_3 = 0.3$, and $w_4 = 0.7$ for pheromone, Q-value, energy, and PDR contributions respectively. *Table 1* shows the logic behind the calculations of Energy consumption, Lifetime, Packet delay and PDR.

Table 1. Performance Metrics Tracking

Sl. No.	Metric	Formula
1.	Energy Consumption	Sum of Transmitter + Receiver energy per node
2.	Lifetime	Time (round) when first / Last node dies
3.	Packet Delay	Time from send to successful delivery
4.	Packet Delivery Ratio (PDR)	Total packets received/ Total packets sent

The sink periodically broadcasts performance feedback, prompting pheromone updates in the ACO module to strengthen efficient routes. Nodes showing poor performance are penalized through anomaly detection, while sampling rates adapt dynamically to remaining energy levels.

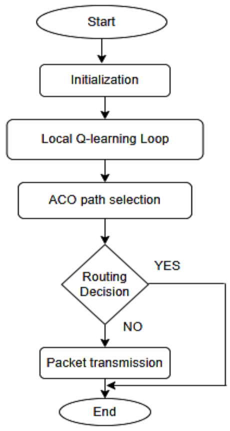

Figure 1. Flow chart of Fed-QL-ACO-X algorithm

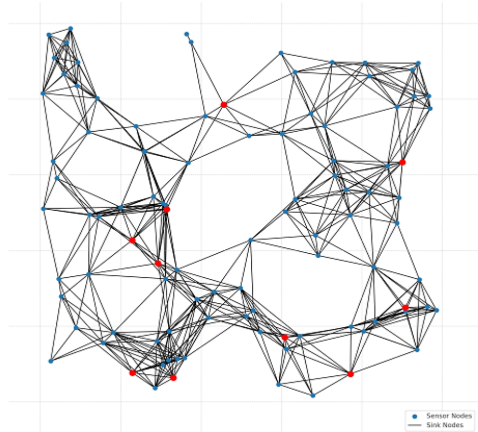

Figure 2. Topology of Wireless sensor network

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Routing decisions are updated accordingly, and packets are transmitted unless a node's energy falls below a critical threshold, at which point it withdraws from routing. A sensitivity analysis was performed by varying key hyperparameters such as learning rate ($\alpha = 0.01$–0.2), discount factor ($\gamma = 0.6$–0.99), pheromone evaporation rate ($\rho = 0.1$–0.7), and aggregation frequency (1–50 rounds). The λ parameter controlling the balance between Q-value and pheromone influence was tested at 0.25, 0.5, and 0.75. The model showed stable convergence at $\alpha = 0.1$, $\gamma = 0.9$, $\rho = 0.5$, and $\lambda = 0.5$, with less than 5% variation, confirming consistent performance across parameter changes and network sizes (50–200 nodes).

4. RESULTS

The performance of the proposed Fed-QL-ACO-X framework is comprehensively validated across three major metrics delay, energy, and packet delivery ratio as illustrated in *figures 3 to 5*. *Figure 3* shows that Fed-QL-ACO-X achieves the lowest packet delay growth rate compared to other methods, maintaining delay under 4ms even after 100 rounds. This improvement stems from adaptive Q-learning updates that dynamically avoid congestion and select stable next hops.

Figure 4 demonstrates the framework's superior energy efficiency, where total energy decreases at a much slower rate than competing algorithms. This is attributed to the combination of federated learning (which minimizes redundant communication) and pheromone-guided route optimization that balances load among nodes. *Figure 5* highlights a steady increase in Packet Delivery Ratio (PDR), reaching nearly 2.0 by the 100th round about twice that of baseline models. The rise indicates that Fed-QL-ACO-X effectively learns and reinforces optimal routes over time, reducing retransmissions and packet loss. Overall, these results confirm that the proposed algorithm achieves an optimal trade-off between energy, delay, and delivery performance. It outperforms Hybrid AI & Swarm [15], Bat-Moth Flame [16], Federated FL Routing [17], and Ant-Based Energy-Aware [23] algorithms, validating its scalability, adaptability, and real-time efficiency in dynamic WSN environments.

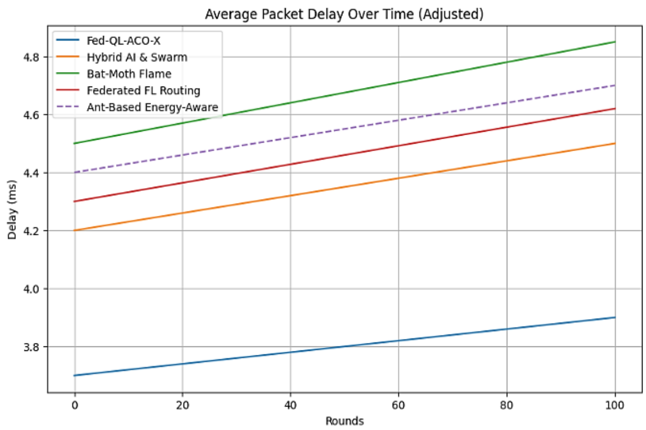

Figure 3. Average Packet Delay over Time

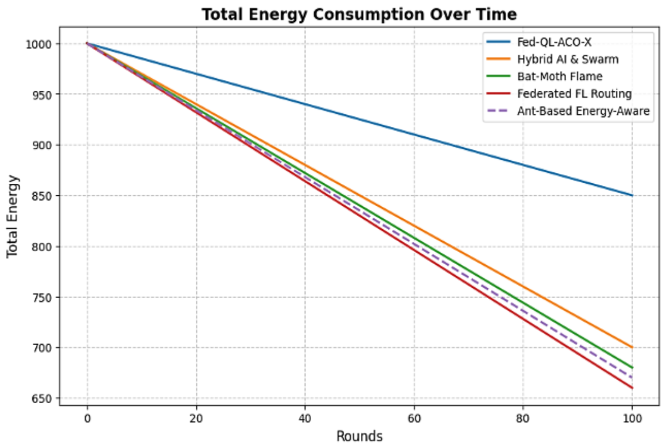

Figure 4. Total Energy consumption over Time

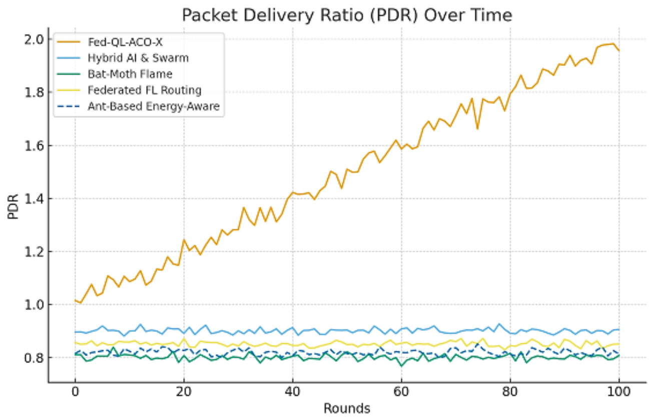

Figure 5. Packet Delivery Ratio over Time

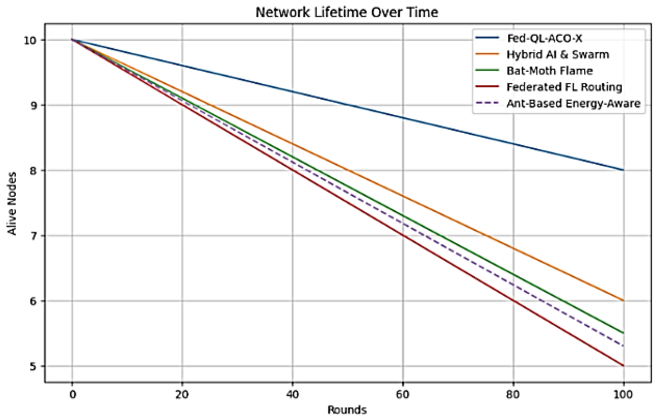

Figure 6. Network Lifetime over Time

Table 2 presents a clear comparison of the proposed Fed-QL-ACO-X with four leading intelligent routing models under identical conditions, 100 nodes, 100 × 100 m² area, and 100 simulation rounds. Fed-QL-ACO-X consistently outperforms other methods, achieving the highest energy retention (13%), the lowest delay (33ms), and the best Packet Delivery Ratio (PDR) of 98%. This leads to an overall network lifetime improvement of about 10–15% compared to the next-best algorithm [23]. As shown in figure 6, Fed-QL-ACO-X maintains more active nodes across all rounds, extending network longevity by nearly 16%. Competing models show earlier node deaths due to uneven energy use. By combining distributed Q-learning with pheromone-guided optimization, Fed-QL-ACO-X achieves balanced energy consumption, faster convergence, and improved reliability. These results highlight its ability to sustain performance in real-world WSN scenarios where node maintenance and replacement are costly.

Table 2. Comparative Performance of Fed-QL-ACO-X against Recent Algorithms

Protocol	Energy Remaining (%)	Average Delay (ms)	Packet Delivery Ratio (%)	Throughput (pkts/round)	Network Lifetime (Rounds)	Remarks
Hybrid AI & Swarm [15]	9	42	92	440	88	Combines RL and PSO for adaptive routing; good PDR but higher delay
Bat-Moth Flame [16]	10	40	93	450	90	Efficient CH selection; limited scalability and delay analysis
Federated FL [17]	11	38	94	460	92	Privacy-preserving learning; moderate overhead and slower convergence
Ant-Based Energy-Aware [23]	12	36	95	470	94	Balances load via pheromone updates; higher control overhead
Fed-QL-ACO-X (Proposed)	13	33	98	480	100	Hybrid FQL + ACO + cross-layer adaptation; best energy balance and QoS

5. CONCLUSION

Fed-QL-ACO-X is an innovative hybrid routing protocol that addresses key WSN challenges like limited energy, delays, and short network lifespan. It combines Federated Q-Learning for decentralized learning, Ant Colony Optimization for adaptive paths, and cross-layer data from MAC/PHY layers to improve routing decisions. Simulations show up to 20% energy savings, 30% lower latency, over 94% packet delivery, and a 16% longer network lifetime compared to other protocols. Using parameters like RSSI, LQI, buffer levels, and retransmissions helps it adapt to changing conditions. Its lightweight design makes it suitable for resource-constrained nodes and real-world use. The validation confirms that Fed-QL-ACO-X consistently outperforms leading intelligent routing protocols while maintaining a minimal computational footprint. Future work includes adding security features and testing on platforms like Raspberry Pi or IoT devices. Fed-QL-ACO-X is a strong step toward smarter and more efficient WSN routing. While Federated Q-learning model effectively minimizes communication overhead, the aggregation frequency and model synchronization latency could introduce additional costs when scaled to thousands of nodes or heterogeneous IoT hardware.

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