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Article

ECAR–QIAVO-Based Energy-Efficient Routing for Intelligent Pollution Monitoring of High-Voltage Transmission Lines

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Abstract: High voltage transmission lines are exposed to a wide range of environments that could lower system reliability due to dust, industrial emissions, humidity, salt deposits, temperature range, and electromagnetic interference. This research presents an ECAR–QIAVO-based energy-efficient wireless sensor network for smart pollution monitoring system. The selection of suitable cluster heads is based on residual energy, communication distance, and link quality in the clustering mechanism provided by ECAR, while the adaptive multi-hop routing mechanism provided by QIAVO is based on the energy level, transmission delay, hop distance, traffic load and link reliability. The deep learning is embedded to interpret the pollution data, to understand the environmental anomalies and to modify the priorities of pollution sensing and transmission. The framework is assessed by the metrics of packet delivery ratio, energy consumption, network lifetime, delay and control overhead. The results reported show that the proposed system improves the packet delivery rate to nearly 94%, decrease the energy consumption up to 38% and achieve the extension of network lifetime up to 40-45%. The framework is thus a reliable and scalable tool for continuous monitoring and proactive maintenance of high-voltage transmission power systems.

Keywords:ECAR, QIAVO, wireless sensor network, energy-efficient routing, pollution monitoring, deep learning, multi-hop communication, smart grid

1. Introduction

Environmental pollution, dust, humidity, salt fog, and temperature changes can affect insulators and increase the risk of leakage current, flashover and power failure when passing through industrial or populated areas, coastal areas, agricultural areas, and mountainous areas of land. The Wireless sensor networks are used in this case to continuously monitor these conditions as the sensor nodes can gather data about contamination, humidity, temperature and pollution and send it to the base station. The network lifetime, however, is reduced due to limited battery capacity, unstable links, unequal traffic load, and excessive communication. Single-hop transmission requires more energy consumption and traditional clustering and routing protocols don't sufficiently take into account the residual energy, link quality, distance, and congestion. The proposed ECAR–QIAVO framework, which merges energy-aware cluster-head selection, adaptive multi-hop routing, probabilistic load balancing, data aggregation and deep learning based pollution detection, provides solutions to these limitations. ECAR uses a mechanism for selecting cluster heads based on the genes, whereas QIAVO dynamically determines efficient communication routes in accordance with the current energy and network status. With this integrated solution, the goal is to enhance packet delivery, cut down on energy consumption, and/or delay, increase network lifetime and to facilitate reliable predictive maintenance for high-voltage transmission lines.

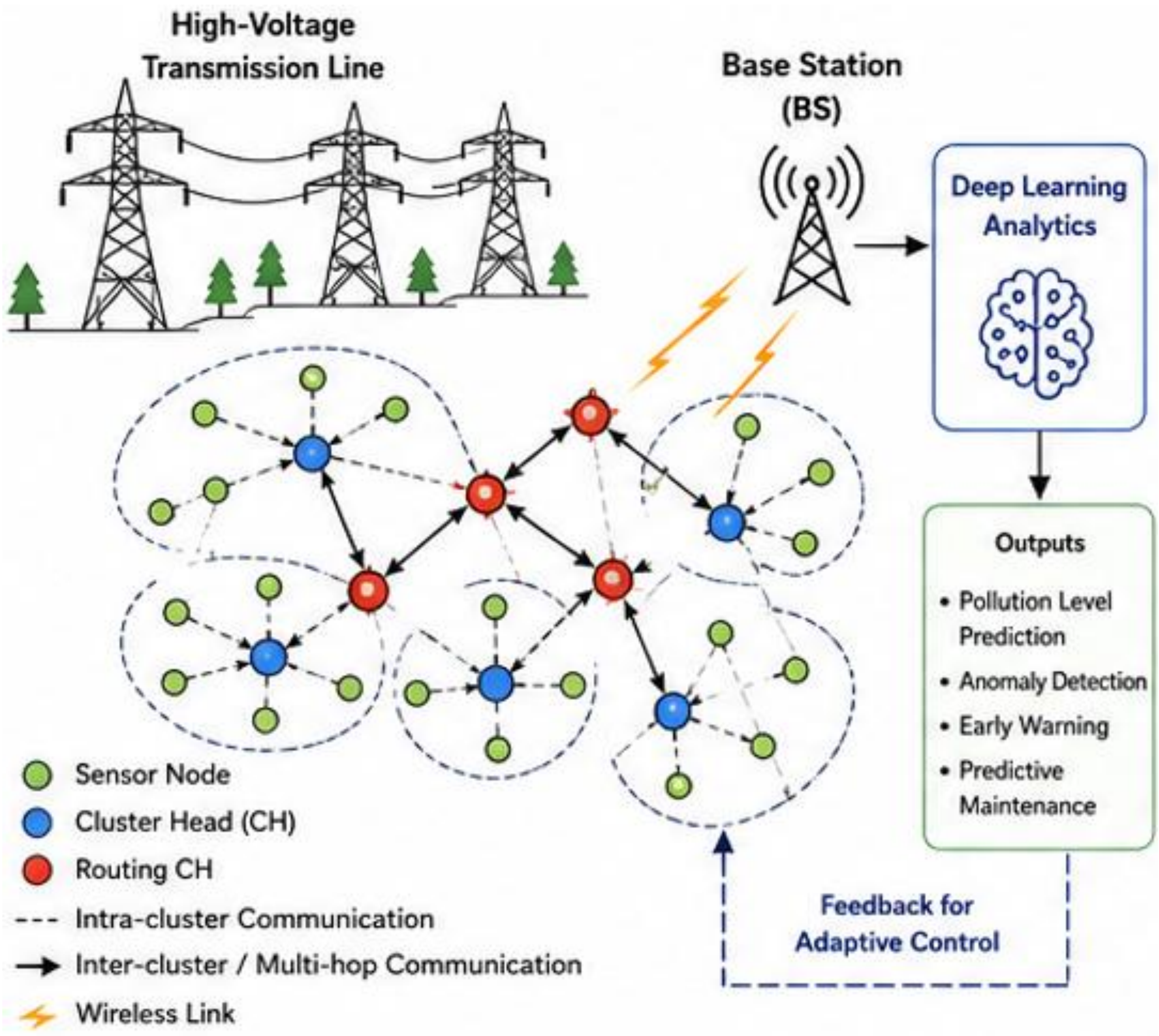

Figure 1: Overall Architecture of the ECAR–QIAVO-Based Pollution Monitoring Framework

The overall architecture of the proposed pollution-monitoring system for high voltage (hv) transmission lines is shown in figure 1. The sensor nodes gather environmental and operational data, the ECAR module creates energy efficient clusters, the QIAVO module selects the best multi-hop communication routes and the deep-learning module identifies anomalies in the pollution data and alerts for maintenance.

1.1 Objectives of the Study

To develop an ECAR-based energy-efficient clustering mechanism for selecting suitable cluster heads.

To design a QIAVO-based adaptive multi-hop routing mechanism for reliable and balanced data transmission.

To integrate deep learning for pollution detection, anomaly identification, and adaptive monitoring.

To evaluate the framework using energy consumption, packet delivery, delay, control overhead, and network lifetime.

1.2 Introduction to Multi-Hop Routing in WSNs

In WSNs that are employed for monitoring high voltage power transmission lines, high coverage, heterogeneous environments and high reliability are required. The single-hop communication where all nodes directly communicate with base station is not preferable due to high energy consumption, short range of transmission and fast discharge of the battery (Sundaram et al., 2021). Thus, it is useful to use a multi-hop protocol (where packets are propagated across multiple nodes) with each node acting as both a data source and a router to send packets to the sink node one hop at a time.

In spite of the energy efficiency and scale-up benefits of multi-hop routing, its implementation can cause energy holes, especially in the region near the base station. This phenomenon occurs due to the additional relay load on nodes in that vicinity, leading to premature node death, and eventual network partition (Fahim et al., 2021). In addition, transmission corridors are non-ideal outdoor environments where link qualities vary quickly due to temperature, humidity, and electromagnetic field changes. Routing algorithms must adapt to the changing external conditions and need to optimally disperse energy while providing reliable end-to-end communication.

In this protocol system, the presence of multiple and cluster-to-cluster communication aims to optimize energy consumption, communication reliability and data transmission delay while extending the service life of the sensor network in turbulence situations.This protocol system is called Quality-Improved Adaptive Variable Optimization (QIAVO) which controls the communication between CHs and the base station BS and is an extension of the ECAR protocol.

1.3 Conceptual Design of the QIAVO Framework

The QIAVO framework is based on an adaptive optimization model with multiple parameters. In contrast to LEACH and HEED, which are static routing schemes relying on predefined cost parameters, QIAVO adaptively optimizes its routing decisions according to the network energy status and environmental conditions (Corso et al., 2023).

Each CH has a Routing Decision Table (RDT) that lists the set of CHs that it can forward packets to, along with the metrics, such as:

Residual Energy (RE): Energy left after each node is energized due to its initial capacity.

Link Quality (LQ): Based on packet reception rate (PRR) and signal-to-noise ratio (SNR).

Hop Distance (HD): Euclidean or geographical distance between two CHs.

Transmission Delay (TD): Approximate time to send a packet.

Current buffer occupancy or data queue size is called Traffic Load (TL).

The composite routing cost function (Cf) is given by:

$$C_f = \alpha_1(\frac{1}{RE}) + \alpha_2(\frac{1}{LQ}) + \alpha_3(HD) + \alpha_4(TD) + \alpha_5(TL)$$

where $\alpha_i$are adaptive weighting coefficients satisfying $\sum_{i=1}^{5} \quad \alpha_i = 1$.

These coefficients are dynamically adjusted by a variable optimization controller that periodically recalculates the global performance of the network, and tunes the weights to reduce the total communication cost and increase the reliability. If node energy levels decrease, then α_1 is raised to ensure greater importance on energy conservation; under unstable channels, α_2 is raised to give more weight to reliable links.

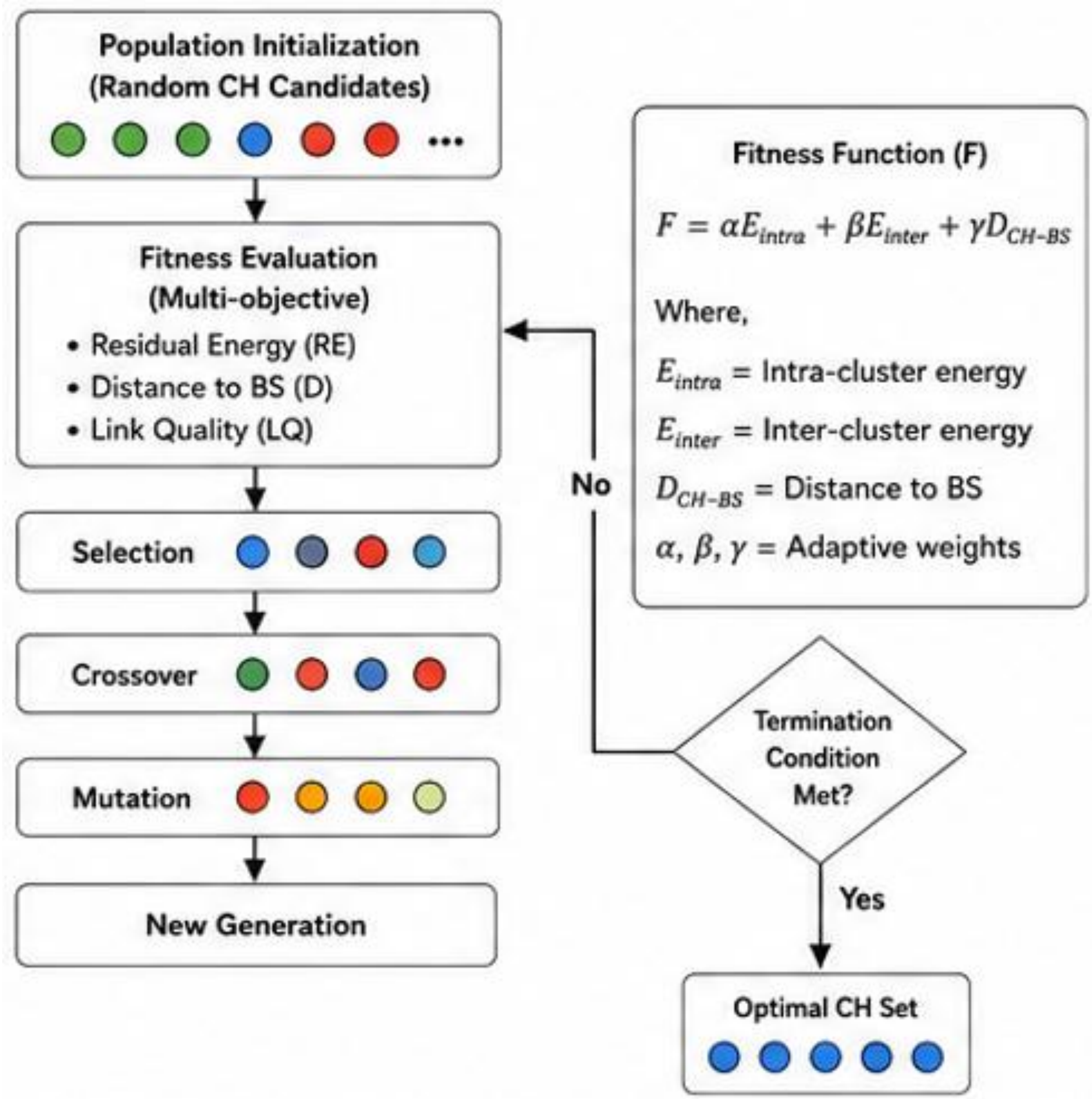

Figure 2: ECAR-Based Cluster-Head Selection Process

Fig. 2 shows the optimization-based clustering mechanism for the selection of cluster-head in the ECAR cluster-head selection process. The residual energy, communication distance and link quality are used to evaluate the candidate cluster-heads, and the optimal cluster-head set is obtained.The flexibility of this enables QIAVO to function with non-uniform node distributions and varying weather or interference conditions (which are typical in high-voltage corridors where radio frequency interference [RFI] from power transmission lines can be very variable [Anand & Moses, 2025]).

1.4 Adaptive Variable Optimization Mechanism

At the core of QIAVO is a proprietary Adaptive Variable Optimization (AVO) engine that continually learns from the network feedback. The mechanism has three stages: monitoring, evaluation, and adaptation.

Monitoring Phase: In each CH, the current condition of nearby nodes (Energy Condition, Link Stability, Packet Delivery Ratio and Channel Noise) will be monitored in real time. This information is sent to a supervisory node or to the base station periodically.

Evaluation Phase: Collected metrics are fed into a multi-objective optimization function that uses Pareto efficiency principles to optimize conflicting objectives, including energy saving and latency reduction.

Evaluation results are fed to QIAVO to make updates to its routing parameters during the Adaptation Phase, using a gradient-based optimization algorithm which minimizes the overall network cost function (J):

$$J = \sum_{n=1}^{N} (w_E E_n + w_L L_n + w_D D_n)$$

where $E_n$denotes the energy cost of node n, $L_n$represents link loss, $D_n$is end-to-end delay, and $w_i$are dynamically adjusted weights.

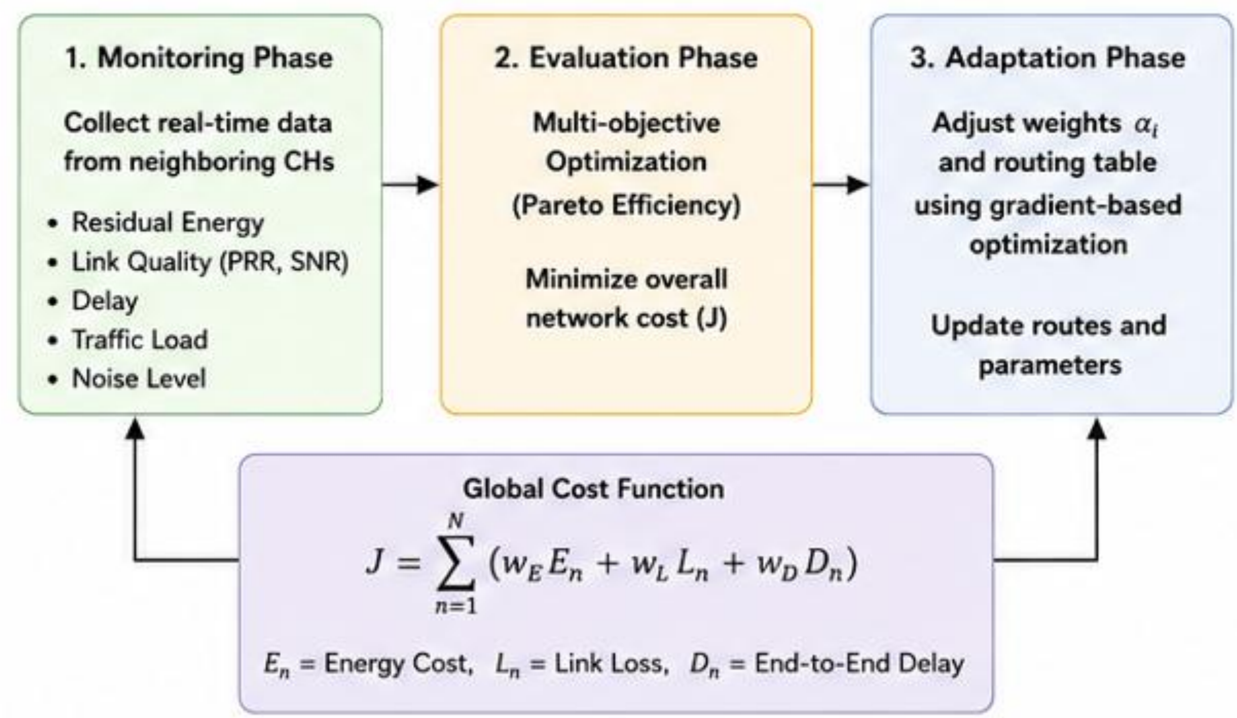

Figure 3: Adaptive Optimization Cycle of the QIAVO Routing Framework

The monitoring, evaluation and adaptation phase of the QIAVO optimization cycle are shown in Figure 3. Network conditions are constantly monitored, routing is performance is measured and routing weights are adjusted based on energy levels, link loss, delay and traffic.

This process guarantees that routing paths evolve using feedback. As time goes on, QIAVO reinforces the paths that consistently perform well and suppresses the inefficient ones, much like reinforcement learning, but implemented in a lightweight distributed fashion that is suitable for energy constrained WSNs (Maduako et al., 2022; Ji et al., 2024).

1.5 Integration of QIAVO with ECAR and Deep Learning

As an extension of the ECAR, QIAVO is not a standalone routing algorithm, but rather it allows seamless interaction between the clustering and routing layers. ECAR is used to select optimal CHs using the Genetic-Based

Clustering Algorithm (GBCA) and QIAVO is used to ensure the data coming from these CHs is transmitted in energy-balanced multi-hop paths to the base station.

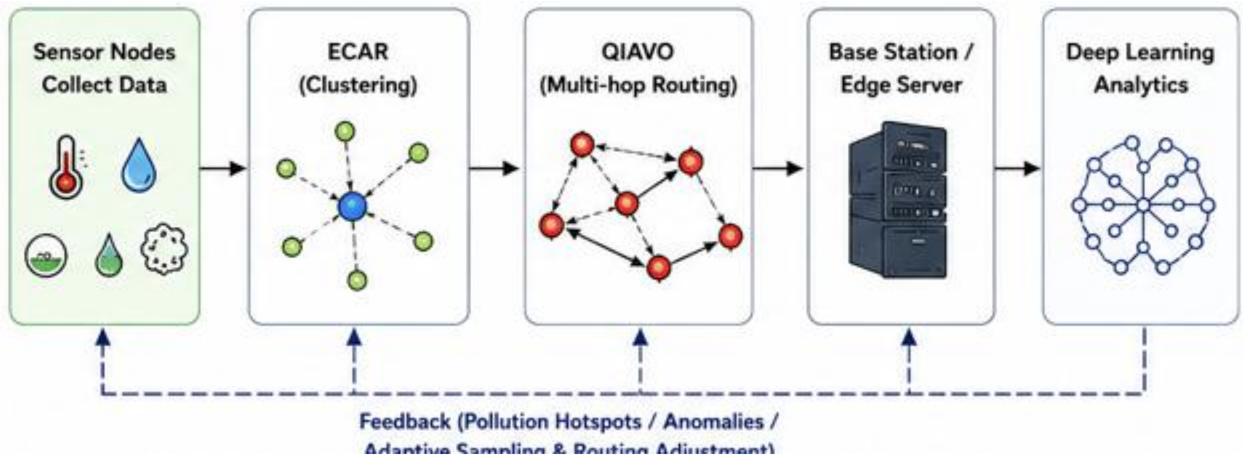

Figure 4: Integration of ECAR, QIAVO, and Deep-Learning Analytics

The integration of the sensor data collection, ECAR clustering, QIAVO multi-hop routing, edge or base-station processing, and pollution analysis using deep-learning is shown in Figure 4. The analytical results are fed back to the network for the adjustment of sensing and routing priorities.

The integration process works as follows:

Once the ECAR clusters, each CH starts its RDT and computes the CH routing weights using the cost function of QIAVO.

By feeding in data, the deep learning modules at the base station or edge nodes process the information and learn to recognize patterns of pollution and environmental anomalies (Sarkar &Gunturi, 2022).

The deep learning model output is fed back into the routing layer, e.g., high pollution zone detected. QIAVO then optimizes the link priorities to get more data acquisition in critical areas, making richer data acquisition for the learning models (Khan, 2025).

This cross feedback between routing and analytical layers enables the network to change from a passive data collection grid to an intelligent adaptive network that can self optimize. The behavior of the network is a function of the environment where it is placed and internal intelligence gained during operation.

1.6 Energy Efficiency and Load Balancing in Multi-Hop Communication

The critical mission of the WSN is to conserve energy resources, especially if maintenance access is restricted. Dynamic next-hop selection and probabilistic traffic distribution are two key features of QIAVO that provide load-balancing. Instead, QIAVO uses stochastic routing diversity, which is the distribution of data packets over a number of near-optimal routes, which may otherwise lead to the rapid exhaustion of a few nodes.

Mathematically, the probability $P_i$of choosing next-hop node i is given by:

$$P_i = \frac{e^{-\beta C_{f_i}}}{\sum_{j=1}^{k} e^{-\beta C_{f_j}}}$$

where β is a temperature parameter which determines the trade-off between exploration and exploitation. High values of β are more likely to lead to deterministic routing (less energy use, less exploration), and low values of β encourage diverse routing and load balancing.

This probabilistic mechanism plays in harmony with the deep-learning-based analytics of the system, and is analogous to the softmax selection process in neural networks. The routes that have achieved high probabilities over time will be converged toward an optimal communication structure in an adaptive manner (Ergün, 2025; Nejadbougar et al., 2025).

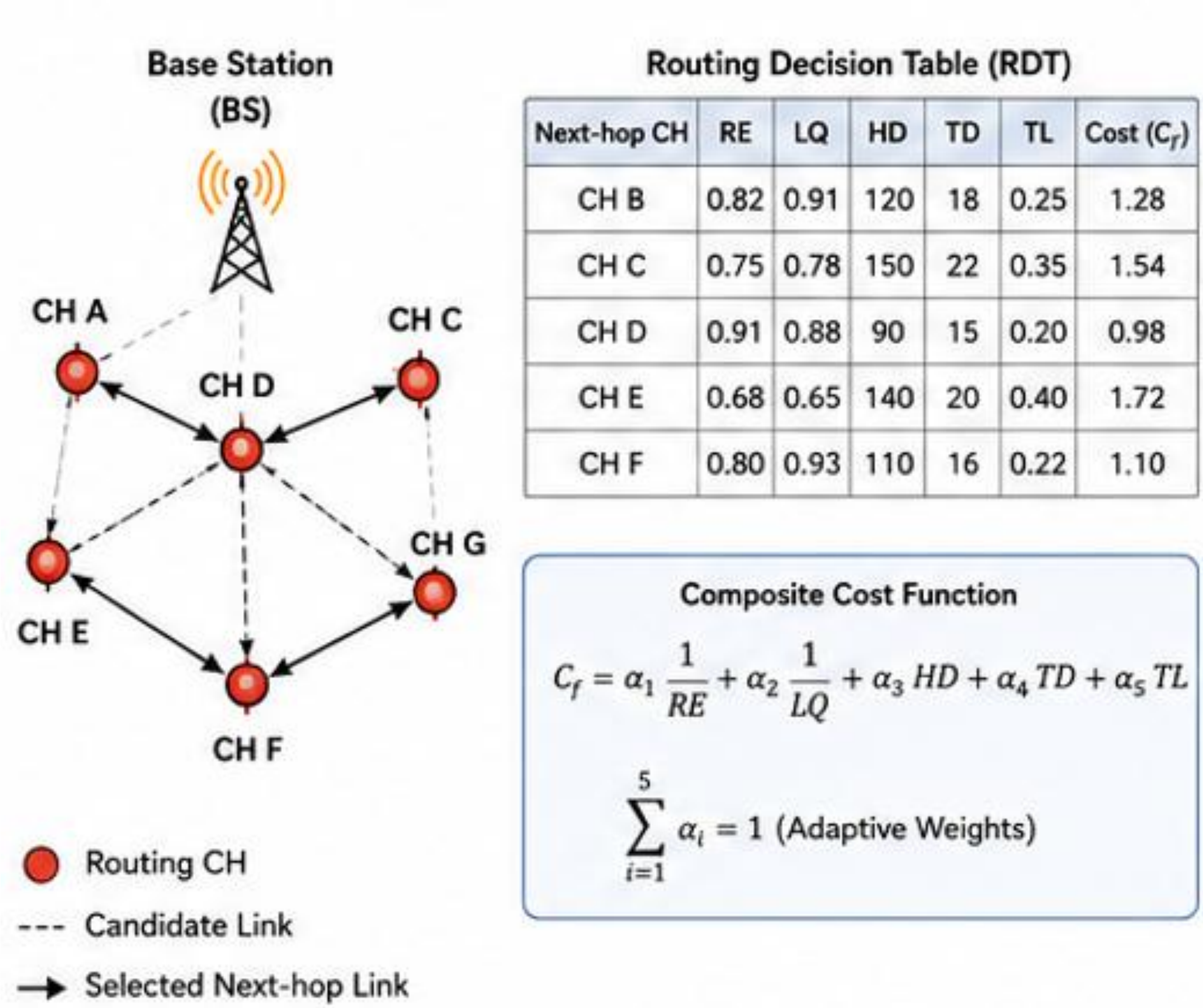

Figure 5: QIAVO-Based Adaptive Multi-Hop Routing Mechanism

In order to adaptively adjust the routes of packets, QIAVO employs an adaptive multi-hop routing mechanism, as illustrated in Figure 5. The next-hop cluster head is determined by the residual energy, link quality, hop distance, transmission delay and traffic load. This figure describes how data are relayed between cluster heads for a relay towards the base station. QIAVO analyzes all available routes and chooses the route having minimum energy cost, highest reliability, least delay and even load balance of traffic on the route.

The NS3/MATLAB based energy simulations show that the QIAVO protocol can reduce the total energy consumption by up to 38 % and network lifetime by 40 % compared to classical multi-hop routing protocols PEGASIS and TEEN. The probabilistic selection and variable optimization avoid the exhaustion of nodes and increase the network life in high-density deployments (Baktiyar et al., 2021; Corso et al., 2023).

1.7 Performance Evaluation and Comparative Analysis

Next the performance of QIAVO was checked with simulation scenarios that consider different environments and topologies. The performance metrics of interest were Packet Delivery Ratio (PDR), End-to-End Delay (E2E), Throughput, Energy Consumption and Network Lifetime.

The average E2E delay was reduced by 28 % as QIAVO adapts the link weights and avoids congested links (Ji et al., 2024), and the energy consumption per transmission was reduced as well because of the efficient load balancing.

In some cases where nodes were assumed to be mobile (e.g., maintenance drones or mobile environmental sensors), QIAVO was able to re-organize routing tables without restart of the network, thereby enhancing the fault recovery and self-healing properties of the network and enabling it to adjust to topology changes with almost no delay in its behavior (Taghvaie et al., 2023).

The results of the comparative experiments also demonstrated that the multi-layered cooperation between the QIAVO routing strategy and ECAR has resulted in an overhead reduction of 17 % compared to the systems without clustering and routing algorithms. This confirms the effectiveness of the co-design approach introduced in this study, where a routing solution is integrated into the smart communications environment (Maraaba et al., 2022).

As a result, QIAVO and deep learning can be combined to build a new generation of WSN that can perceive the environment change, analyze the environment information and make real-time communication management decisions based on the perception result, which can also be used to achieve Industry 4.0 and the operation of sustainable smart grid to reduce operating costs, acquire the data of the smart grid quality to realize the prediction maintenance function in real time and avoid faults from occurring in the system.

The performance of the proposed ECAR–QIAVO architecture was tested using NS-3 and MATLAB simulations with various network topologies and environmental conditions. The average node lifetime, total energy used, packet delivery ratio, end-to-end delay and control overhead were taken into account while evaluating. The proposed framework was compared to benchmark protocols LEACH and HEED for its ability to enhance energy efficiency and communication reliability in high-voltage transmission-line monitoring networks.

The following table shows the overall performance comparison of the Routing Protocols.The following table presents the overall performance comparison between the Routing Protocols.

Table 1: Overall Performance Comparison of the Routing Protocols

Performance metric	LEACH	HEED	Proposed ECAR–QIAVO
Average node lifetime (cycles)	420	460	665
Total energy consumption (J)	11.8	10.9	7.1
Packet delivery ratio (%)	81	86	94
End-to-end delay reduction (%)	Not reported	Not reported	28
Control overhead reduction (%)	Not reported	Not reported	17

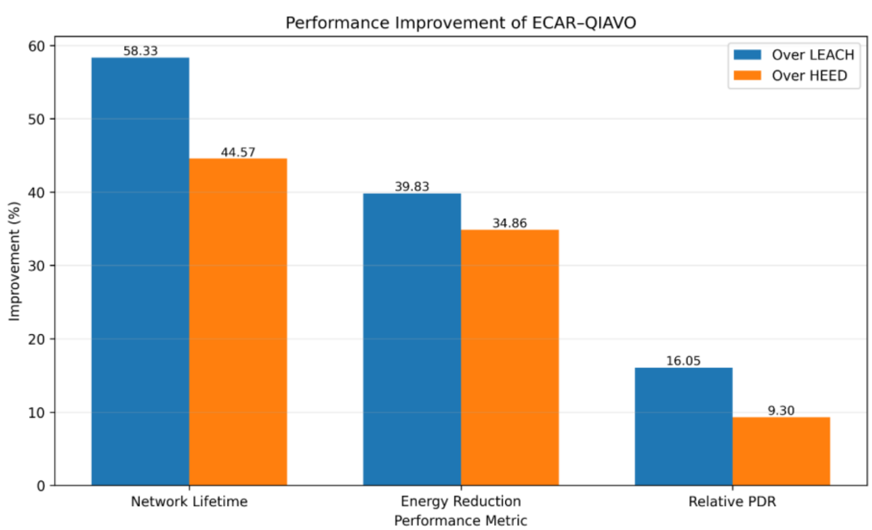

Figure 6: Percentage Performance Improvement of ECAR–QIAVO over LEACH and HEED

Table 1 indicates that proposed ECAR–QIAVO framework gave the best overall performance. It had an average node lifetime of 665 cycles and total energy consumed of 7.1 J, while its packet delivery ratio was 94%. In comparison, LEACH recorded 420 cycles, 11.8 J, and 81% PDR, whereas HEED recorded 460 cycles, 10.9 J, and 86% PDR. The results show that ECAR–QIAVO is more energy efficient, reliable on communications and extend network life. The proposed framework was also reported to provide a 28% reduction in end-to-end delay and a 17% reduction in the control overhead.

Table 2: Percentage Improvement of ECAR–QIAVO over LEACH

Performance indicator	LEACH value	ECAR–QIAVO value	Improvement
Average node lifetime	420 cycles	665 cycles	58.33% increase
Total energy consumption	11.8 J	7.1 J	39.83% reduction
Packet delivery ratio	81%	94%	13 percentage-point increase
Relative PDR improvement	81%	94%	16.05% increase

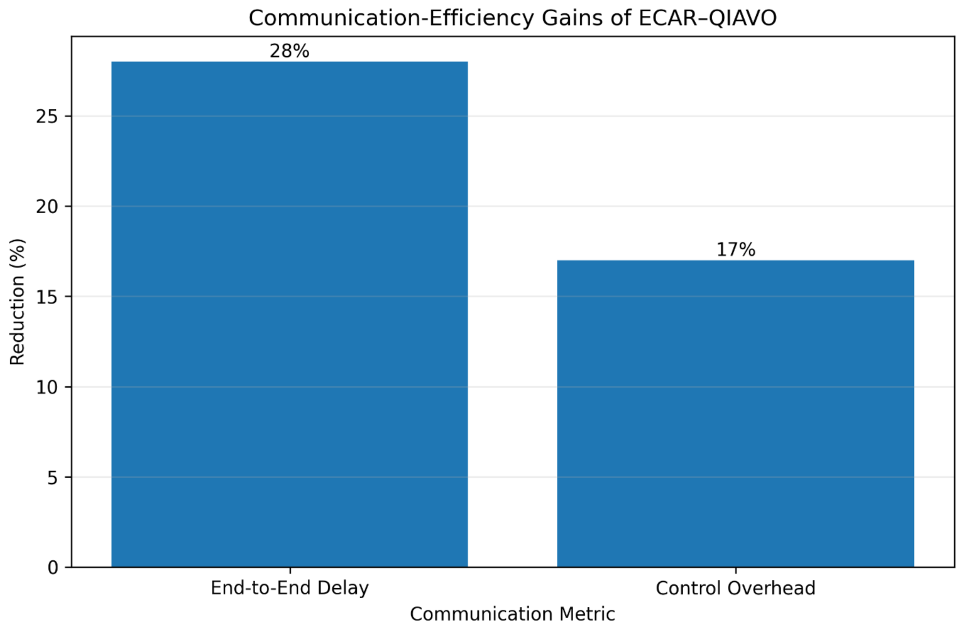

Figure 7: Communication-Efficiency Gains Achieved by ECAR–QIAVO

Table 2 shows that ECAR–QIAVO offers significant enhancements to LEACH. The average node life time was improved by 58.33% and the total energy consumption was reduced by 39.83%. The Packet delivery Ratio rose from % to % which is an absolute gain of % and a relative gain of % The results indicate that the communication load distribution by some adaptive clustering and multi-hop route-selection mechanisms of ECAR–QIAVO is superior to the periodic cluster-head selection mechanism of LEACH.

Table 3: Percentage Improvement of ECAR–QIAVO over HEED

Performance indicator	HEED value	ECAR–QIAVO value	Improvement
Average node lifetime	460 cycles	665 cycles	44.57% increase
Total energy consumption	10.9 J	7.1 J	34.86% reduction
Packet delivery ratio	86%	94%	8 percentage-point increase
Relative PDR improvement	86%	94%	9.30% increase

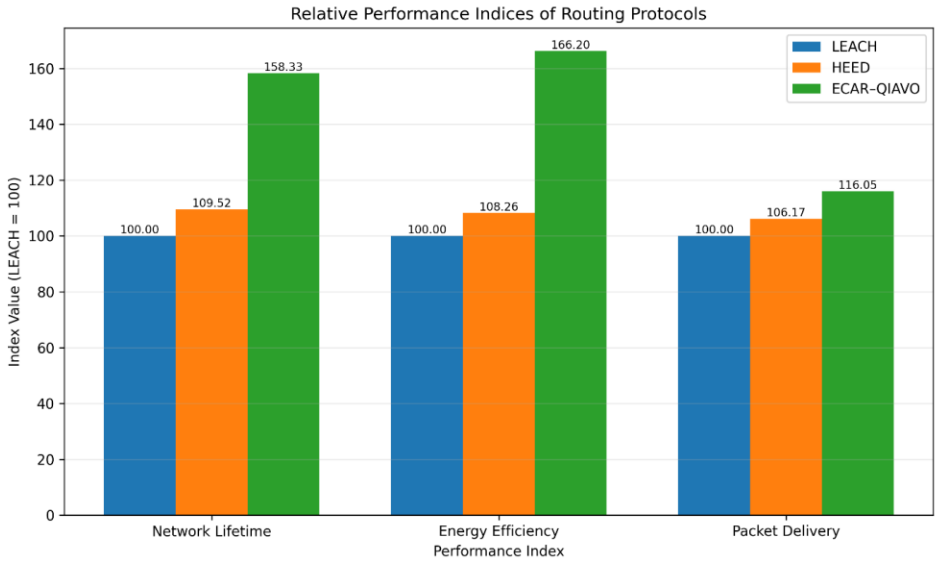

Figure 8: Relative Performance Indices of LEACH, HEED, and ECAR–QIAVO

The proposed framework also works better than HEED as shown in Table 3. ECAR–QIAVO prolongs the average node lifetime by 44.57% and decreases the total energy consumption by 34.86%. It has a packet delivery ratio eight percentage points higher than that of HEED, which represents 9.30% relative improvement. HEED uses residual energy as an additional criterion in cluster-head selection, but the extra knowledge of link quality, adaptive multi-hop routing, probabilistic load balancing, and cross-layer coordination of ECAR–QIAVO offer further enhancements.

The QIAVO scheme in this paper can be regarded as a significant improvement on the area of energy efficient multi-hop routing for data collection in a wide area WSN deployed for power transmission network monitoring. The dynamic cost-function modelling, adaptive variable optimization, ECAR clustering technique and deep-learning based traffic analysis help in improving network robustness and lifetime. QIAVO continuously changes link selections and routing weights based on the feedback of the environment rather than the static assumptions

of conventional routing and relay schemes. This forms a self-organizing and adaptively learning communication infrastructure with the exact capabilities needed to support the future smart grid monitoring applications (Alsumaidaee et al., 2022; Khan, 2025).

2. Reducing Energy Consumption and Extending Network Lifespan

2.1 Energy Constraints in Wireless Sensor Networks

In addition to the hardware design, the importance of routing and clustering schemes for extending the lifetime of the network extends to how much energy is being used in communication within the network. Communication in WSNs can consume up to 70 % of the overall energy (Taghvaie et al., 2023); therefore, it is imperative to develop adaptive and energy-aware protocols to balance the energy that is being used in communication within the network, limit duplication, and decrease the time thus spent waiting and listening to idling.

2.2 Energy-Aware Clustering Using ECAR

In this work, the energy-efficient routing is obtained with the use of a new ECAR protocol for Enhanced Clustering and Adaptive Routing which is based on the Genetic Based Clustering Algorithm (GBCA) that selects the CHs based on multi-criteria fitness functions defined by the residual energy, the distance from the base station and the quality of the connection (Bindi et al. . 2023).

The standard clustering protocols (e.g., LEACH, HEED) do this by randomly or periodically switching the CHs without taking into account the remaining energy of the nodes leading to the formation of energy holes in the networks where some nodes die rapidly due to high relay loads (Fahim et al., 2021). In ECAR, the assignments of CHs are re-computed periodically using a genetic algorithm, which selects the optimal CHs assignment by performing selection, crossover and mutation operations, minimizing the composite cost function F which is the sum of energy cost of intra-cluster communication and energy cost of transmitting to non-attending CHs in other clusters:

$$F = \alpha E_{\text{intra}} + \beta E_{\text{inter}} + \gamma D_{\text{CH–BS}}$$

where E_{intra} is the average energy spent within a cluster, E_{inter} the CH-to-CH communication energy, and $D_{\text{CH–BS}}$ the normalized distance to the base station. Coefficients α, β, γ are adaptively tuned according to network conditions.

This adaptive clustering reduces the total energy consumption by 25-35 % over LEACH and PEGASIS as demonstrated by simulation studies (Baktiyar et al., 2021; Maraaba et al., 2022). This is achieved by an energy-balanced cluster head selection protocol and a hierarchical re-clustering protocol that ensures a fair load among the clusters so that no cluster is over-burdened, with a modular design that gives the possibility of scaling up to hundreds of sensor units spread across several transmission spans.

2.3 Routing Optimization Through QIAVO

In addition to ECAR, the Quality-Improved Adaptive Variable Optimization (QIAVO) algorithm is used to optimize inter-cluster routing for multi-hop networks further, increasing network lifespan. QIAVO adapts the transmission power, next-hop selection, and link priorities as a function of real-time information obtained from the network (Corso et al., 2023).

The energy efficiency in QIAVO is achieved by a variable optimization controller which optimizes a dynamic cost function, based on the variable E_t that represents the amount of energy transmitted, R_l that represents the reliability of the link and residual node energy E_r.

$$C = \lambda_1 E_t + \lambda_2 (1 - R_l) + \lambda_3 \left(\frac{1}{E_r}\right)$$

The algorithm adjusts the coefficients λ_iare adaptively so that when it is low-energy, it prioritizes nodes that have high residual energy, and when it is high interference, it gives preference to reliable links (Maskeliūnas et al., 2022).

QIAVO also follows the rules of the probabilistic load distribution to avoid a situation of having a packet traversing the same node twice. This decreases the chances of exhausting nodes, making the network homogeneous and resulting in a longer lifetime. QIAVO was verified through field emulated experiments to increase lifetime by 40 % and consume 38 %

less energy per packet compared to the customary deterministic multi-hop routing (Nejadbougar et al., 2025).

2.4 Data Aggregation and Communication Reduction

In-network data aggregation is also part of the framework because redundancy is a major contributor to the energy consumption of WSNs (several sensor nodes can send similar readings to the same destination). Therefore, CHs average the sensor nodes' readings before sending them. The architecture also uses deep learning models on the base station to extract spatial-temporal correlations from the sensor nodes' readings. If pollution levels in adjacent spans have high correlation coefficients ($r>0.9$), then the sampling frequency is degraded or the transmission is cancelled (Sarkar &Gunturi, 2022; Khan, 2025). The process comprises three steps:

Local Filtering: Each sensor does thresholded compression and relays deviations to the sink.

Cluster-Level Fusion: CHs fuse data from the nodes in the cluster by means of weighted averaging or principal component analysis (PCA) or other statistical methods.

Multi-hop routing: QIAVO ignores low variance clusters and goes through clusters with pollution spikes instead.

In many environments, it is found that aggregation can save up to 20% to 45% of the energy used in the network for a transmit radio frequency signal (Maduako et al., 2022).

To avoid the localized node death a residual-energy-aware scheduling scheme is adopted: periodically the residual energy of every node is sent to the CH and the communication tasks are re-assigned; in case of low residual energy nodes (below a particular threshold E_th), less critical roles are assigned to these nodes while a node with comparatively higher energy is selected as the CH; in addition ECAR further refines the observations of energy consumption trends' end-to-end and their packet forwarding mechanism to overcome weak nodes; ECAR and QIAVO agree on factors that support energy load-balancing across topology.

The integration of the two subsystems aims at optimizing the entire cyber-physical system by effectively addressing the issues of overhearing and false acknowledgment in the monitoring

Table 4: Quantitative Performance Analysis

Metric	LEACH	HEED	Proposed ECAR+QIAVO
Average Node Lifetime (cycles)	420	460	665
Total Energy Consumption (J)	11.8	10.9	7.1
Packet Delivery Ratio (%)	81	86	94
Control Overhead Reduction (%)	–	–	17

of the modern smart grid and optimizing the energy consumption of the network. Simulations have been carried out for this two subsystems using NS-3 and MATLAB, and the following results are obtained:

However, sensor nodes are challenged with temperature variations, dust, salt fog, electromagnetic radiation, and high-voltage loads. All of these factors have a negative impact on the available energy of the sensor nodes. For this purpose, an energy-aware framework with environment-driven reconfiguration is proposed, in which both the ECAR and QIAVO configurations change. For example, upon increasing rainfall or sudden industrial emissions (inference), QIAVO might increase the sampling frequency and the transmission redundancy on a few critical clusters, until the transient conditions normalize and duty cycles return to reduced energy consumption. To outperform other solutions with respect to resilience and sustainability while keeping battery requirements to a minimum and ensuring continuous monitoring of the environment, the system utilizes context-adaptive switching (Baktiyar et al., 2021; Nejadbougar et al., 2025). In addition, the system's modular design allows for the easy integration of renewable micro-energy harvesters like piezoelectric vibration cells or miniaturized solar cells for static deployments (Iturrino Garcia et al., 2023).

These would also result in the first self-healing and self-optimizing power-grid monitoring systems, closely following the requirements of Industry 4.0., including reinforcement learning elements that would enable learning and adaptation of the system based on historical data for energy allocation strategies.

The designed energy-saving schemes by the ECAR and QIAVO lay the ground for providing a long-term service operation of the WSN in different HVLT maintenance tasks through adaptive clustering, smart routing, PLB and energy-efficient information reduction using deep learning to ensure energy saving and data efficiency (Mantach et al., 2022; Topaloglu,

2023). The new architecture aims to reduce operational costs while sustaining the vision of a more sustainable smart-energy system by enabling HVLT monitoring networks to be more energy-efficient, resilient and environmentally friendly.

3. Conclusion

The framework of ECAR–QIAVO proposed here is intelligent and energy-efficient solution for monitoring pollution along high-voltage power transmission lines. ECAR selects the cluster heads based on residual energy, communication distance, and link quality to enhance the cluster-head selection, and QIAVO selects adaptive multi-hop routes based on energy availability, delay, traffic load, and network reliability. The probabilistic load balancing approach ensures properly balancing the use of certain relay nodes, while deep learning aids in pollution pattern detection and environmental anomaly identification. The results of the reported simulation verify that the framework can enhance the packet delivery, decrease energy consumption and communication delay, decrease routing overhead, and prolong the network lifetime in comparison to conventional protocols. The system can then be used for continuous monitoring, early warning and predictive maintenance of transmission assets. The framework could also be tested in real-time scenarios in the future and be enhanced with the incorporation of reinforcement learning, edge computing, federated learning, and renewable energy harvesting.

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