



RESEARCH ARTICLE

AI-Driven Swarm-Optimized Adaptive Routing Using Quantum-Inspired Neural Scheduling with Homomorphic Encryption

A. Jafar Ali^{1*}, G. Ravi², D.I. George Amalarethnam³

Abstract

The fast increase in network traffic and the moving nature of nodes in modern communication systems have led to the need to have intelligent ways of analysing traffic, managing clusters, efficiently routing, and ensuring safety in the transmission of data. Conventional approaches are not always able to deal with the complexity and size of multi-criteria network settings. This paper introduces a new multi-phase intelligent network management framework which combines deep learning, evolutionary optimization, and a quantum-inspired algorithm to improve performance, reliability, and security. The initial step uses the Hybrid Autoencoder-GAN Behaviour Synthesizer (HAE-GANBS) to examine traffic data of the Multi-Criteria Network Routing Dataset, recreate typical traffic, and create synthetic flows, which augment the feature description. The enhanced dataset is used as input into the Hybrid Spiking Neural-Evolutionary Cluster Leader Selector (HSN-ECLS) which determines the best cluster leaders through temporal spike-train modelling and multi-criteria fitness assessment. Predictive Evolutionary Trust-Aware Scheduler and Router (PETASR) is a predictive scheduling based on evolutionary operations to schedule routing paths based on future traffic, node availability, and trustworthiness. Lastly, the Quantum-Inspired Neural Scheduler-Router with Homomorphic Encryption (QINSR-HE) ensures the safety of information transfer, providing the opportunity to use encrypted, adaptive, and trust-conscious routing. The evaluation of performance indicates that the framework is more efficient in large, volatile network systems due to enhanced traffic predictability, cluster stability, routing competence, and secure information transfer over the network.

Keywords: AI-Driven Adaptive Network Routing - Spiking Neural-Evolutionary Optimization - Predictive Trust-Aware Scheduling, Quantum-Inspired Neural Routing, Homomorphic Encryption-based Secure Transmission, Multi-Criteria Network Performance Optimization.

¹Research Scholar, Department of Computer Science, Jamal Mohamed College (Autonomous), Affiliated to Bharathidasan University, Tiruchirappalli – 620020, India

²Associate Professor, Department of Computer Science, Jamal Mohamed College (Autonomous), Affiliated to Bharathidasan University, Tiruchirappalli – 620020, India

³Associate Professor & Head, Department of Computer Science, Jamal Mohamed College (Autonomous), Affiliated to Bharathidasan University, Tiruchirappalli – 620020, India

***Corresponding Author:** A. Jafar Ali, Research Scholar, Department of Computer Science, Jamal Mohamed College (Autonomous), Affiliated to Bharathidasan University, Tiruchirappalli – 620020, India, E-Mail: jafar123@gmail.com

How to cite this article: Ali, A.J., Ravi, G., Amalarethnam, D.I.G. (2026). AI-Driven Swarm-Optimized Adaptive Routing Using Quantum-Inspired Neural Scheduling with Homomorphic Encryption. *The Scientific Temper*, **17**(2):5658-5673.

Doi: 10.58414/SCIENTIFICTEMPER.2026.17.2.09

Source of support: Nil

Conflict of interest: None.

Introduction

Smart scheduling and routing have become necessary elements of contemporary transportation, manufacturing, and networked systems due to increased dynamism and data-density in the environment. The old and usual scheduling techniques do not work well when faced with dynamic workloads, irregular traffic patterns, and complicated interdependencies. More recent studies are making use of machine learning (ML) and deep learning (DL) to address these shortcomings by providing adaptive and data-driven decision-making. As an example, genetic algorithmic scheduling of the job-shop setting enhances the accuracy and resilience of the decision-making in the uncertain scenarios (Nguyen *et al.*, 2025). Shared buses online scheduling and route planning frameworks are evidence of how predictive data-driven models can be used to create efficient self-scheduling and real-time routing models in overloaded urban networks (Ning *et al.*, 2022). Such flexible vehicle scheduling strategies also emphasize the use of ML in order to dynamically alter the routes

according to the environmental factors and operational restrictions (Lai *et al.*, 2022). Adaptive slot allocation and CQF-based scheduling have been proposed in time-sensitive networks and resource-constrained networks to keep routing deterministic and communication with low latency (Liu *et al.*, 2025). This is because such mechanisms greatly improve the network lifetime by avoiding congestion, spreading traffic loads, as well as better bandwidth utilization. Besides, decentralized bus depot scheduling methods optimize operational performance and decrease energy consumption, which leads to sustainable transit systems (Jahic *et al.*, 2021).

Multi-mode IoT environments provide collaborative learning-based scheduling models that can provide better management of energy-conscious resources, which is directly correlated with a longer network life (Zhou *et al.*, 2023). Also, Petri Nets, heuristic scheduling, and artificial potential field integration are incorporated, thus improving robotic job-shop performance by allowing intelligent self-navigability and conflict-free task assignment (Yi & Luo, 2025). The distributed systems can be trained to optimize task sequencing and routing decisions with deep reinforcement learning and spatiotemporal graph neural networks, even in the face of complex dynamic conditions (Huang *et al.*, 2025). Incremental routing also enhances the stability of the scheduling performance by controlling jitter as well as increasing the reliability of multipath routing in real-time networks (Li *et al.*, 2025). Although these have been achieved, there are a number of disadvantages. ML and DL systems are commonly resource-intensive in form, have a hard time with large networks, and slow down convergence speed in rapidly evolving environments. Routing solutions can have problems with jitter management, and scheduling models can be unable to optimize globally (Feng *et al.*, 2025). The suggested system can overcome these drawbacks by incorporating hybrid ML-DL optimization, which involves reinforcement learning in self-scheduling, which is autonomous, evolutionary algorithms in the path selection, and balancing the resources suitably to extend network life. Such a single solution guarantees better routing stability, a better level of scheduling, and scalable performance under a variety of dynamic conditions.

Contributions of this Work

- To introduce the Hybrid Autoencoder-GAN Behaviour Synthesizer for high-dimensional traffic behaviour analysis, enabling accurate reconstruction of normal patterns, generation of rare traffic scenarios, and extraction of latent embeddings from the Multi-Criteria Network Routing Dataset.
- To propose a Hybrid Spiking-Neural Evolutionary Cluster Leader Selector, where Spiking Neural Networks capture node temporal behaviour and evolutionary optimization selects the most reliable, energy-efficient,

and trustworthy cluster leaders.

- To develop a PETASR capable of forecasting node availability, optimizing routing paths, and generating adaptive scheduling decisions using multi-criteria trust and traffic parameters.
- To integrate a QINSR-HE that ensures encrypted end-to-end communication while enabling quantum-inspired predictive routing on fully encrypted data.
- To design a secure and intelligent multi-layer routing framework that seamlessly combines traffic analysis, optimal clustering, predictive routing, and encryption-preserving transmission for enhanced reliability, confidentiality, and performance.
- To propose a unified smart-routing architecture that improves packet delivery ratio, network lifetime, security efficiency, and reduces delay, energy consumption, and routing overhead compared to existing methods such as REA, CCAS, and TTMP-RSOA.

The paper is organized into five major sections to present a complete and systematic view of the proposed intelligent multi-criteria routing framework. Section 1 introduces the motivation for developing an advanced routing solution by highlighting the importance of traffic behaviour analysis, trust-aware clustering, predictive routing, and encryption-enabled secure communication. Section 2 provides an extensive review of related work on traffic modelling techniques, cluster-based routing strategies, evolutionary optimization algorithms for scheduling, and existing encryption-preserving routing mechanisms, establishing the research gap addressed by this study. Section 3 presents the detailed methodology used for traffic behaviour feature extraction, how the SNN-Evolutionary model selects stable cluster leaders, how PETASR predicts reliable routing paths and optimal transmission schedules, and how QINSR-HE enables encrypted routing using homomorphic encryption. Section 4 discusses the experimental setup and evaluates system performance using key metrics such as Traffic Behaviour Accuracy, Node Selection Accuracy, Cluster Formation Time, Packet Delivery Ratio, Energy Consumption, Routing Overhead, Data Confidentiality, and Security Efficiency. Finally, Section 5 concludes the paper by summarizing the major findings, emphasizing the improvements over existing methods such as REA, CCAS, and TTMP-RSOA, and outlining future directions including federated trust learning and lightweight quantum-secure routing for next-generation network environments. (Figure 1)

Figure 1 shows that the dataset, which provides key parameters regarding the nodes (e.g., traffic load, trust level, energy status, and connectivity). The processing phase of the system takes the input from the dataset and performs analysis of traffic behaviour to provide insight into the dynamic flow patterns within the network and identifies factors in the network that may impact stability. These

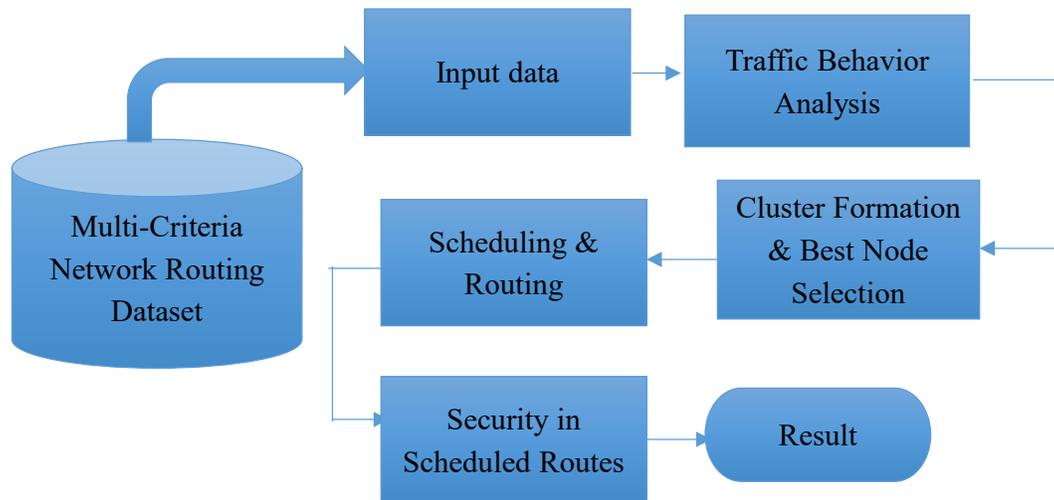


Figure 1: The Basic Architecture Diagram Based on Secure Performance in AI

characteristics are sent to the clustering and best-node selection module, which creates stable clusters and selects trusted nodes for improved communication. The data that has been created in this module is sent to the scheduling and routing module where PETASR is used to determine the optimal and most reliable routing paths for transmission based on criteria related to trust and predictive methods. The scheduled routes created by the PETASR algorithm are secured through the QINSR-HE layer, using a scheme of Homomorphic Encryption (HE) that keeps the transmitted data encrypted while still allowing it to be processed at the routing nodes. The encrypted and reliably scheduled routes provide a means of creating reliable, secure, and high-performance networks and provide the ability for robust communications in the heterogeneous and rapidly changing environment of network topologies.

Literature Review

Present an offline routing and scheduling method based on integer linear programming (ILP), with a flow preprocessing step to explore the period correlation of time-triggered (TT) traffic in time-sensitive networking (TSN). First, a multiperiod flow routing and scheduling algorithm based on flow classification is proposed to improve the scheduling success rate and reduce execution time (Sun *et al.*, 2026). The flow classification technique obtained a more fine-grained TT traffic classification, which can be superimposed on any routing and scheduling algorithms.

Industrial time-sensitive networking (TSN) is pivotal for ensuring real-time and reliable flow transmission. There is a growing focus on its scalable scheduling for time-critical flows pursuing ultralow latency and jitter. Its time-aware shaper protocol tackles uncertain delay and frame loss but introduces high scheduling complexity (Zhang *et al.*, 2025). However, existing works lack a scheduling feature

mining mechanism. They impose unnecessarily tight rules to simplify the problem but sacrifice scheduling optimality.

Manufacturing scheduling research has often overlooked the complexities of dynamic product assembly and testing scenarios, particularly those involving reconfigurable manufacturing cells (RMCs) and the integration of process planning and scheduling (Guo *et al.*, 2025). To address the problem of Dynamic Integrated Process Planning and Scheduling with RMCs, a novel and complex challenge in modern manufacturing systems. A variable-fidelity surrogate-assisted hyper-heuristic algorithm is proposed, which strategically integrates process planning and scheduling tasks.

The emergence of electric buses (EBs) is expected to alleviate traffic pollution. However, the promotion of EBs requires a long transition period; during this period, EBs cannot wholly replace conventional buses (CBs). Therefore, to effectively schedule EBs and CBs, propose a joint optimal scheduling model for a mixed bus fleet under micro driving conditions (Lu *et al.*, 2021). First, we estimate the bus trip time under micro driving conditions. However, the use specialized software to scan, match import data with export data, and prepare the claim for submission.

Route scheduling for automatic optical inspection (AOI) of printed circuit boards (PCBs) impacts the productivity of surface mount production lines. Current state-of-the-art mathematical models in the area are not rigorous enough and neglect significant practical constraints, such as component geometric constraints (Cao *et al.*, 2025). It proposes a hierarchical mixed integer programming model to describe the route scheduling problem for AOI of PCBs (Table 1).

Air traffic control operations that regulate arrival air traffic flows from route airspace are considered effective in mitigating the congestion close to destination airports.

Table 1: Different Methods used in Self-Scheduling Routing for ML and DL Technology

Author/year	Type of dataset	Technique name	Limitations
Sun <i>et al.</i> , (2025)	Robotic Mobile Fulfilment System (RMFS) operational & simulation data	Conflict-Free Scheduling Algorithm	Limited scalability when robot count becomes extremely high; performance drops under unpredictable congestion.
Wang <i>et al.</i> , (2024)	Maritime IoT communication & routing datasets	Deterministic Scheduling + Reliable Cross-Layer Routing	Less adaptable to rapidly changing ocean environments; high computational overhead.
Wu <i>et al.</i> , (2022).	Cold-chain logistics operational datasets	Buffer-Based Ant Colony System (ACS)	Slow convergence in dynamic environments; sensitive to parameter settings.
Yang <i>et al.</i> , (2025)	Bus transit, traffic signal, and passenger flow datasets	Robust Scheduling + Passenger Flow Coordination	Requires connected infrastructure; complex to deploy under real-time traffic fluctuations.
Wan <i>et al.</i> , (2024)	UAV disaster-response and time-varying value datasets	Deep Reinforcement Learning (DRL) for Multi-UAV Scheduling	High training time; performance depends heavily on reward shaping; struggles with unseen disaster patterns.
Hu <i>et al.</i> , (2024)	Liner shipping and vessel scheduling datasets	RL-Enabled Adaptive Genetic Algorithm	May fall into local optima; RL training requires extensive simulation data.
Garg <i>et al.</i> , (2021)	Multi-hop wireless network datasets	Distributed Directional TDMA MAC Protocol	Requires accurate time synchronization; performance affected by mobility and interference.
Qiao <i>et al.</i> , (2023)[23]	Transportation-power distribution network datasets	Multi-Objective Optimization Scheduling	Complex to balance economic and emission objectives; high computational requirements.
Benavente <i>et al.</i> , (2021)	Public transport AVL, fare control, schedule datasets	Data Fusion + Improved Trip Definition Model	Sensitive to missing/inaccurate sensor data; integration complexity.
Li <i>et al.</i> , (2025)	Ultra-dense LEO satellite routing datasets	DRL + Stackelberg Game for Routing Scheduling	Training latency; limited robustness under extreme satellite mobility and link failures.

Therefore, this study proposes a scientific system design for operationally feasible En Route AMAN assisting air traffic controllers (ATCOs) through runway-flow and inter-aircraft control (Sekine *et al.*, 2023). Devise an airline-oriented runway assignment rule that selects a target minimizing arrival taxi time in case of over-demand according to the maximum estimated through the stochastic distribution of inter-aircraft time and runway occupancy time.

The Dynamic Vehicle Routing Problem with Time Windows (DVRPTW) is a widespread real-world challenge, and numerous algorithms have been proposed to address it. However, in the context of an emerging logistics paradigm, namely the instant delivery, the performance of existing algorithms tailored for DVRPTW degrades significantly, as instant delivery allows only very limited computational time for solving DVRPTW instances (Jiang *et al.*, 2025). Owing to the periodic nature of customer orders, this paper proposes a data-driven evolutionary algorithm (DDEA) for solving DVRPTW under limited computational time.

Quantum entanglement enables quantum networks to provide end-to-end sharing of entangled particles, establishing multi-hop path-to-path connections between remote parties (Wang *et al.*, 2025). To consider the real-time entanglement distribution (R-TED) and pre-established entanglement distribution (P-EED) to meet this requirement. Based on these two types of entanglement distribution, propose two algorithms, i.e., R-TED-based routing and entangled pairs allocation (REA) algorithm as well as P-EED-based REA algorithm for end-to-end entanglement establishment, where the practical physical factors (e.g.,

finite storage capacity and limited storage time) are considered.

Higher frequency bands are essential for next-generation wireless local area network (LAN). Due to the significant propagation loss of sub-terahertz band, beam forming is indispensable (Nakamura *et al.*, 2025). However, since beam forming is affected by obstructions, stable communication requires simultaneous transmission with multiple access points (APs). In a multi-AP environment, although optimal resource scheduling can be determined through exhaustive search, the complexity is quite high.

Presents an enhanced learning assisted task scheduling mechanism based on task Criticality and Collapse Aware Scheduling (CCAS) algorithm. The proposed mechanism is developed using two modules; namely task scheduling mechanism based on task criticality and collapse aware strategy, and an ensemble prediction model i.e., Gradient Boosting Decision Tree (GBDT) to proactively predict the machine utilization and task safe execution status. The proposed ensemble learning framework provides high level feature abstraction by learning the task parameters to predict task status and machine utilization. (Table 2).

In the Table 2 demonstrate sophisticated method of scheduling, and it is able to compare the quality of self-scheduling, system lifetime contribution, and routing performance. The performance of most techniques is characterized by a strong self-scheduling performance based on adaptive or optimization mechanisms, whereas lifetime improvement is moderate because of the indirect effect of resource balancing. The quality of routing is

Table 2: Comparative Evaluation of Scheduling, Lifetime, and Routing Quality in Advanced Task Scheduling Techniques

<i>Author/year</i>	<i>Self-scheduling quality range</i>	<i>Lifetime quality range</i>	<i>Routing quality range</i>
Zhu <i>et al.</i> , (2021)	High – adaptive, self-learning scheduling	Medium – improves system utilization but not focused on longevity	Low – routing not part of the method
Wang <i>et al.</i> , (2025)	High – strong analytical scheduling guarantees	Medium – enhances timing predictability; limited impact on system lifetime	Low – routing not addressed
Gu <i>et al.</i> , (2022)	High – efficient job scheduling across GPUs	High – resource-aware scheduling reduces overload & extends cluster lifespan	Medium – scheduling focuses on network efficiency, not routing control
Vela <i>et al.</i> , (2021)	High – optimized scheduling of complex tasks	Medium – better resource distribution helps system longevity	Low – routing not considered
Xu <i>et al.</i> , (2023)	High – adaptive scheduling under dynamic load	Medium – workload balancing enhances long-term cluster performance	Low – no routing component

also typically poor, with the methods under review mainly focusing on computational scheduling, and not communication-focused routing improvement.

Problem Identification

The current routing techniques namely REA, CCAS, and TTMP-RSOA are unable to cope with the rising traffic density, dynamic node movement as well as heterogeneous behaviour leading to routing instability and increased latency.

- The traditional models do not have robust behaviour-based trust assessment; thus, they are susceptible to unreliable nodes and unreliable routing behaviour.
- The existing clustering techniques lack flexibility and thus, fail to select nodes efficiently and may create clusters that are not very stable in rapidly evolving conditions.
- The current routing and schedule plans lack the availability of encrypted data processing, which makes the confidentiality less assured and increase the risks of information leakage during transmission.
- On the whole, the current systems do not provide efficient, secure, and adaptive routing when the constraint of the network is multi-criteria, resulting in the delivery ratio and overhead.

Objectives of the Research

- To create a QINSR-HE model that includes behaviour analysis, trust-based clustering, predictive routing and encryption preserving routing to enhance network intelligence.
- To use HAEGANBS to extract precise traffic behaviour and SNN -Evolutionary clustering to form stable clusters and select nodes accurately.
- To apply PETASR in predicting the most optimal and trusted routing paths that will reduce delay, improve reliability, and efficiency in scheduling.
- To achieve good data privacy through homomorphic encryption, to allow the processing and routing of the encrypted packets without decryption.

- To make major improvements on KPIs including PDR, energy consumption, routing overhead, confidentiality, and security efficiency in comparison with REA, CCAS, and TTMP-RSOA.

Proposed Methods

The section analysis of the traffic behavior with HAE-GANBS that condenses the high-dimensional features of the Multi-Criteria Network Routing Dataset and synthesizes synthetic traffic situations to capture both the normal and rare patterns, resulting into richer latent embeddings which provide an insight into the node activity, reliability, and flow dynamics. These processed features input into cluster formation with best node selection using the Hybrid Spiking Neural-Evolutionary Cluster Leader Selector where nodes are represented as spike trains of temporal behavior, an evolutionary algorithm measures energy efficiency, trust and network centrality to select optimal cluster leaders and assign the remaining nodes according to proximity and link quality. PETASR is an evolutionary scheduler and router that is developed based on historical traffic data, predicted traffic data, trust, and energy data and uses evolutionary operations to produce and optimally enhance routing schedules. Lastly, the QINSR-HE ensures safety with encrypted routing whereby routes are dynamically adjusted to trust and availability to ensure complete, adaptive, and efficient network transmission. (Figure 2)

Figure 2 show that the Multi-Criteria Routing Network Dataset that contains the critical node parameters traffic density, mobility patterns, energy levels, and trustworthiness scores. Using our Traffic Behavior Analysis System with H-AE-GAN-BS as part of our architecture for extracting enriched behavioral features for understanding dynamic network conditions. Using these refined features, we input them into a Generative Adversarial Network for intelligent pattern learning through an AI-based decision layer that allows for predictive routing and dynamic scheduling. When completed, we use an Enhanced HSN- ECLS to establish stable clustering and determine the optimal communication nodes for efficient topology management. Our Encrypted

Router, which uses PETASR further enhances reliability during the time of transmission. Next, every data packet is protected with QINSR-HE to protect them and place access control on them using homomorphic encryption, thus allowing for routing decisions without decrypting. Finally, this guarantees that all communication is secure and trustworthy and that only authorized transmissions receive access.

Hybrid Auto encoder-GAN Behavior Synthesizer (HAEGANBS)

The traffic behavior analysis of the HAEGANBS starts with the Dataset that includes multi-dimensional network traffic characteristics, node characteristics and past pattern of traffic flows. First, these high-dimensional features of traffic undergo an autoencoder that reduces them to a latent representation to capture the key attributes of normal network behavior, and identifies anomalies using reconstruction error. These latent representations are then inputted into a Generative Adversarial Network (GAN),

where the generator is used to create synthetics of traffic to simulate a rare or underrepresented scenario and the discriminator is used to assess the truthfulness of the syntheses in comparison to patterns of real traffic. GAN optimizes generated traffic through a series of adversarial training to ensure that the generated traffic is highly similar to real network behavior. The method provides three important elements, including reconstructed patterns of traffic, synthetic traffic data, and latent embeddings, all of which serve to enrich the dataset and give a complete picture of the dynamics of traffic.

The raw input data X , consisting of multi-dimensional traffic characteristics, equation 1 node statistics and past flow data of the Dataset is inputted into the autoencoder encoder $f_{\theta_{enc}}$.

$$z = f_{\theta_{enc}}(X) \tag{1}$$

These high-dimensional features are then averaged to a lower-dimensional latent representation Z by the equation

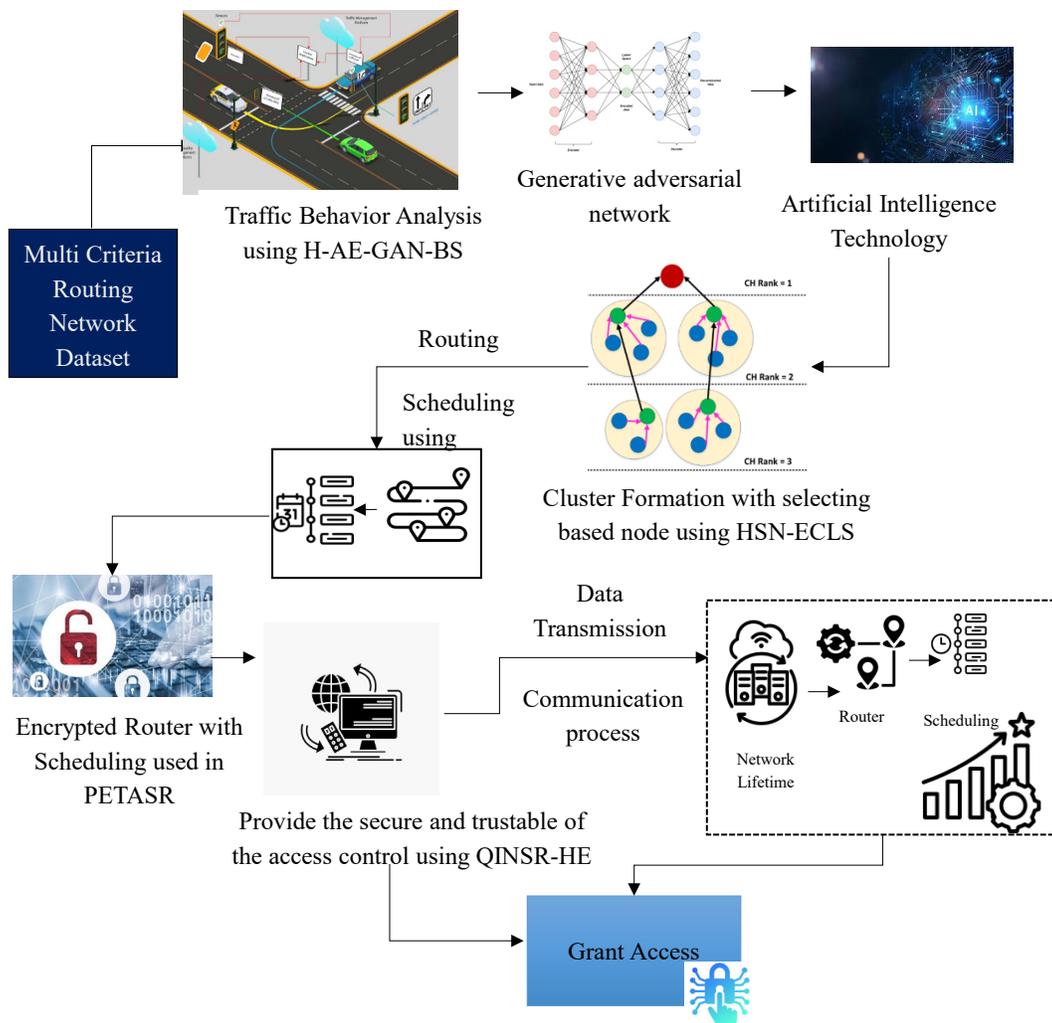


Figure 2: Architecture Diagram of AI-Integrated Swarm-Powered Self-Scheduling Routing for Networks using QINSR-HE

2 encoder to represent key patterns of traffic behaviour and correlations between network nodes.

$$\widehat{X} = f_{\theta_{dec}}(z) \quad (2)$$

The latent vector z it was then subjected to the autoencoder decoder $f_{\theta_{dec}}$ to recreate the original traffic patterns to create X .

$$E = \widehat{X} - X \quad (3)$$

The E is defined as the difference between the reconstructed traffic \widehat{X} and the original dataset X . The large values in E indicate an anomaly or abnormal traffic behavior that does not constitute the normal behavior.

$$z_g = z + \epsilon, \epsilon \sim \mathcal{N}(0, 1) \quad (4)$$

$$X_{syn} = G_{\theta_G}(z_g + E) \quad (5)$$

$$Z_0 = \widehat{X} + X_{syn} + z \quad (6)$$

In order to create synthetic traffic, Gaussian noise ϵ is introduced to the latent z , and z_g is formed. This equation 4,5 noise adds randomness to the generator input, and the GAN is capable of generating a variety of traffic behaviors simulating underrepresented or uncommon network behaviors.

GAN generator G_{θ_G} creates the instances of synthetic traffic X_{syn} using noise infused latent vector z_g and the residual E of the autoencoder.

Combination of the reconstructed traffic Z_0 , the synthetic traffic X_{syn} and the latent embeddings z . Such as equation 6 representation allows a highly detailed view of network traffic, both normal behaviour, anomalies, and unusual situations.

Hybrid Spiking Neural-Evolutionary Cluster Leader Selector (HSN-ECLS)

The initial step of the novel cluster formation process is the representation of every network node in the features based on Dataset which comprise traffic load, energy level, connectivity, and trustworthiness. These characteristics preserve the present network condition as well as previous behavior of every node. A Spiking Neural Network (SNN) is to be used in order to model the dynamics in time of nodes, mapping their behavioral patterns to spike trains that quantify the activity, reliability, and responsiveness of the nodes over time. This pattern of spikes is then fed to an evolutionary optimization algorithm which measures the appropriateness of each node to serve as a cluster leader. The fitness function takes into account various parameters, including energy efficiency, trust score, and network centrality, to make sure that chosen leaders will be able to guarantee the stability, reliability, and effective communication in the cluster. The nodes that are selected as the most fit cluster leaders are then used to determine the

cluster to which the rest of the node will belong depending on their proximity and the quality of the link between the nodes.

Traffic behavior is recreated equation 7 through \widehat{X} corresponds to normal traffic behavior, X_{syn} refers to synthetic traffic behaviour created to simulate rare, and z encode is a latent embedding of major behavioral attributes.

$$F_{enriched} = \widehat{X} + X_{syn} + z \quad (7)$$

A combination equation 8,9 and 10 of these items results in $F_{enriched}$ which is a holistic collection of features that summarizes the observed and predictive traffic behaviour which forms the base input to access the suitability of node in cluster formation.

$$v_i = F_{enriched}[i] + (\text{energy}_i + \text{connectivity}_i + \text{trust}_i) \quad (8)$$

$$S_i(t) = \text{SNN}(v_i, t), t = 0 \dots T \quad (9)$$

$$A_i = \frac{1}{T} \sum_{t=0}^T S_i(t) \quad (10)$$

All nodes are modeled using a feature vector v_i which fuses the enriched traffic characteristics in $F_{enriched}[i]$ with node characteristics: residual energy, network connectivity, and trustworthiness.

The node feature vector v_i is that is inputted into code the temporal and dynamic behavior in a spike train $S_i(t)$ through the observation period T .

Spike train $S_i(t)$ is averaged over the observation of the equation 11 period to get the activity score A_i , and the score measures the dynamically active and responsive behaviour of a node, both in terms of traffic behaviour and node attributes based on the dataset.

$$F_i = \alpha \cdot \text{energy}_i + \beta \cdot \text{trust}_i + \gamma \cdot \text{connectivity}_i + \delta \cdot A_i \quad (11)$$

$$C_L = \arg \max_i F_i \quad (12)$$

$$C_j = \{i \mid i \in \text{Nodes}, \text{dist}(i, C_L^j) < \epsilon, \text{link_quality}(i, C_L^j) > \theta\} \quad (13)$$

The fitness F_i is calculated equation 12 weighted score based on energy, trustworthiness, connectivity and activity. The method can be highlighted to focus on particular criteria by the use of the α , β , and δ coefficients based on network. Cluster leaders C_L are nodes that have the highest fitness scores F_i , to important in order to make sure that the leaders possess maximum energy, credibility, relationship, and dynamism based on the dataset.

Once leaders have been chosen, the rest of the nodes are given to clusters C_j based on their proximity to leaders and on the goodness of their network connections of the equation 13. Cluster assignments based on distance and link-quality ϵ provide reliable and energy efficient cluster assignments.

Predictive Evolutionary Trust-Aware Scheduler and Router (PETASR)

Scheduling and Routing process will be done after the cluster formation and selection of the best node by using the Multi-Criteria Network Routing Dataset with cluster information. The load of traffic per node, its history of communication, trust rating, and connectivity are examined with the aim of forecasting future traffic load and reliability. The PETASR is a combination of an evolutionary optimization algorithm and predictive modelling that is used to produce optimal scheduling and routing decisions. The algorithm considers various aspects, such as the projected node availability, energy values, and reliability and uses weights to give preference to safe and effective paths. The evolutionary processes used to optimize the candidate schedules and routes through selection, crossover and mutation are repeated and provide a means of directing the packet flows through the most reliable and trusted nodes as well as minimizing the congestion and reduced energy consumption. The scheduler generates a sequence of optimal transmission schedules and the router routes data packets along the chosen paths, and dynamically reconfigures the paths depending on real-time traffic and trust estimates.

Based on the feature vector \mathbf{v}_i , the predictive model f_{predict} predicts the future availability $\widehat{\text{avail}}_i$ of each node. The availability prediction makes sure that scheduling decisions take into consideration the nodes that are highly probable to be active and reliable during the time when the packet is sent to enhance the performance of the routing.

Produces a candidate set of schedules S and each schedule \mathbf{s}_j represents a possible sequence of transmission around the selected nodes.

$$\widehat{\text{avail}}_i = f_{\text{predict}}(\mathbf{v}_i) \quad (14)$$

$$\mathcal{S} = \{\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_k\}, \mathbf{s}_j \in \text{Nodes} \quad (15)$$

$$F(\mathbf{s}_j) = \sum_{i \in \mathbf{s}_j} (\alpha \widehat{\text{avail}}_i + \beta \text{trust}_i + \gamma \text{energy}_i - \delta \text{load}_i) \quad (16)$$

The evaluation equation 14 and 15 of each candidate schedule \mathbf{s}_j based on a fitness function $F(\mathbf{s}_j)$ that is a combination of predicted availability, trust score, energy and present traffic load of the schedule. These criteria are weighted by the coefficients α , β , γ and δ according to the priorities of network.

The schedules \mathbf{s}_j of the candidates evolves through the evolutionary operations - crossover and mutation, to generate fine schedules $\mathbf{s}_j^{\text{new}}$. The evolutionary method searches through the space of schedule possibilities efficiently and plans routes that are better adapted to the current network conditions through the generations of the equation 16.

$$\mathbf{s}_j^{\text{new}} = \text{Evolve}(\mathbf{s}_j) = \text{Crossover}(\mathbf{s}_j) + \text{Mutation}(\mathbf{s}_j) \quad (17)$$

$$\mathbf{s}^* = \arg \max_{\mathbf{s}_j \in \mathcal{S}} F(\mathbf{s}_j^{\text{new}}) \quad (18)$$

$$R = \text{MapPackets}(\mathbf{s}^*, \mathbf{v}_i) \quad (19)$$

The fitness score of the best schedule, \mathbf{s}^* , is chosen to be the best transmission plan in equation 17. The approach, which incorporates historical traffic and trust capabilities, ensures that the selected schedule will be as reliable as possible and congestion and energy use are reduced to a minimum.

Lastly, the data packets are mapped to network nodes R using the best schedule \mathbf{s}_0 the optimal schedule whose node features in the data set are used to determine the equation 18 and 19 routing directions and dynamically adjusted in the event of changes in node availability, traffic, or trust.

Quantum-Inspired Neural Scheduler-Router with Homomorphic Encryption (QINSR-HE)

Once the task of scheduling and routing through the PETASR is completed, the QINSR-HE provides protection of data transfer over the network. Multi-Criteria Network Routing Dataset is used to gain node specific parameters including traffic load, energy level, trust score and connectivity as well as the optimal routing paths scheduled by the optimizer. These characteristics are fed to a quantum-inspired neural network, which yields the best transmission sequences whilst remaining resistant to dynamism in network conditions. In order to protect the data during transmission, homomorphic encryption is used and the encrypted data packets are processed and directed without having to decrypt the packets and maintain confidentiality and integrity. The network uses node reliability and forecasted availability based on the dataset to dynamically modify encrypted paths, such that sensitive transmissions would use safe and reliable paths. The technique ensures that quantum-inspired predictive scheduling combines with homomorphic encryption to secure that it routed data packets efficiently and fully encrypted, preventing eavesdropping and unauthorized access all through the network.

The data associated with each node feature vector \mathbf{v}_i was rearranged as a complex-valued vector Q_i using a unitary operator U_{quantum} that was inspired by quantum physics. The feature into a high dimensional Hilbert space thus equation 20, 21 improving predictive performance of the neural scheduler- router to dynamic and uncertain network conditions.

$$Q_i = U_{\text{quantum}}(\mathbf{v}_i) \quad (20)$$

$$\hat{R}_i = f_{\text{neural}}(Q_i; \theta) \quad (21)$$

$$E(D_i) = \text{HE}(D_i, k_i) \quad (22)$$

A neural network f_{neural} is learned to predict the first routing path using quantum-encoded node, equation 22 representation Q_i is input the first routing path \hat{R}_i is predicted using the initial routing path as input to a neural network.

The packet D_i was encrypted with a node-specific key k_i using the homomorphic encryption method to generate $E(D_i)$. The database ensures that the equation 23 encrypted information can still be processed on the predicted routes as the nodes that are going to process the packets or forward packets and the equation 24 trust of the nodes are known and the information is sent without having to be decrypted and so remain confidential and secure during the routing process.

$$R_i^{\text{enc}} = E(D_i) \cdot \hat{R}_i \quad (23)$$

$$\hat{R}_i^{\text{adj}} = \hat{R}_i \odot (\text{trust}_i \cdot \widehat{\text{avail}}_i) \quad (24)$$

The cipher texts $E(D_i)$ are matched with the estimated routing path \hat{R}_i , and the step will make sure that every packet is taken along the proposed route by the neural network, but it is encrypted.

What was originally estimated, the routing sequence \hat{R}_i^{adj} , was dynamically modified by using the real-time trust score and predicted availability of the node which had been derived out of the data. The routing probabilities are altered by the equation 25 element-wise operator that only reliable and active nodes are used to forward encrypted packets, enhancing the security and the network performance.

$$F_i^{\text{sec}} = \alpha \cdot \text{trust}_i + \beta \cdot \widehat{\text{avail}}_i - \gamma \cdot \text{latency}_i - \delta \cdot \text{energy_cost}_i \quad (25)$$

$$R^* = \arg \max_{F_i^{\text{sec}}, E(D_i)} \mapsto \hat{R}_i^{\text{adj}} \quad (26)$$

A fitness function F_i^{sec} is used to equation 26 evaluate each candidate secure route, which incorporates metric measurements derived on datasets: trust_i , predicted availability $\widehat{\text{avail}}_i$, latency_i , energy consumption. The weighted coefficients, α , β , γ , and δ enable priorities associated with security, efficiency, and energy to be put in place so that the end decision in routing is both secure and at the same time efficient in terms of network performance.

The ultimate coded routing map R^* is chosen by picking the path with the most secure fitness score F_i^{sec} . The packets $E(D_i)$ are sent over dynamically adjusted paths \hat{R}_i^{adj} which are guaranteed to transmit secure, trustworthy, and energy-efficient packets. (Figure 3)

Figure 3 show that the PETASR provides optimized routes, QINSR-HE collects node traffic, energy, trust, and connectivity from the dataset and encodes them through a quantum-inspired model to predict secure routing paths. Each predicted path is checked for trust and availability; if it passes, homomorphic encryption is applied, and encrypted

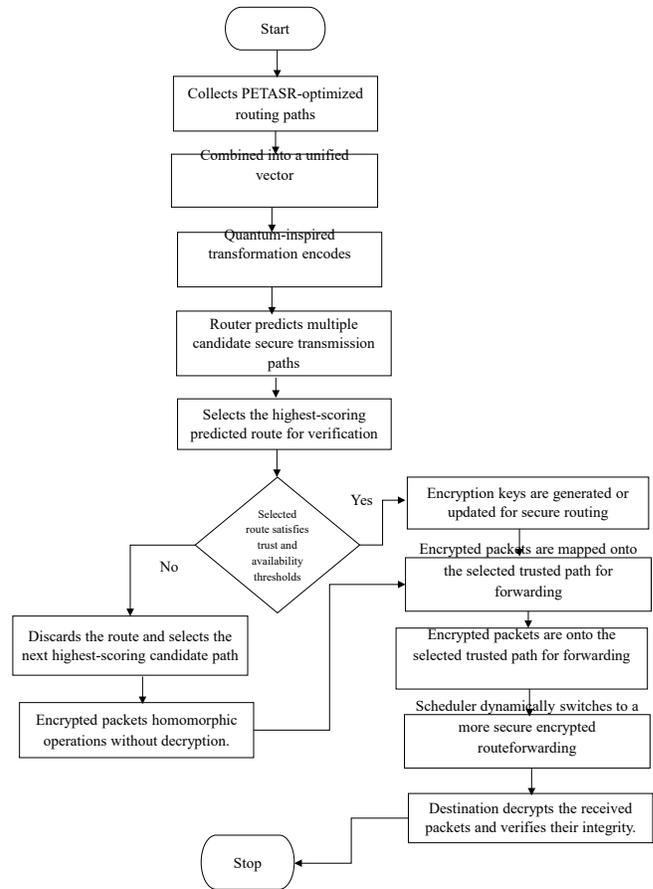


Figure 3: Quantum-inspired model to predict secure routing paths

packets are transmitted through the selected nodes without decryption. If a path fails, a new candidate is chosen. Throughout transmission, encrypted forwarding, real-time trust monitoring, and dynamic rerouting ensure secure and reliable data delivery.

Result and Discussion

The section discusses how different evaluation measures can prove the proposed network management framework to be able to work intelligently, reliably, and safely in dynamic network environments. The Traffic Behaviour Analysis with demonstrates a high accuracy in reconstruction of normal traffic as well as creation of synthetic flows, which are reflected as enhanced latent embeddings and gives the system ability to predict network anomalies and optimize node behaviour prediction. The Node Selection Accuracy and Cluster Formation Time demonstrate that the Hybrid Spiking Neural-Evolutionary Cluster Leader Selector is able to find optimal cluster leaders at a low clustering latency, and normalizes and energy-efficient network organization. The measures of Self-Scheduling Routing Process and End-to-End Delay prove that PETASR is efficient in predicting traffic, node availability and trustworthiness to plan routing sequences with minimum congestion and latency. The comparison

of the Packet Delivery Ratio, Routing Overhead, Energy Consumption and Network Lifetime proves the fact that the routing framework delivers the stable and energy-efficient transmission. Lastly, Encryption and Decryption Efficiency, Data Confidentiality, and Security Efficiency demonstrate that QINSR-HE provides secure, adaptive as well as trust-ready packet delivery. In general, the findings support the idea that the suggested hybrid model can be more effective in relation to its excellent performance, increased security, and efficient network usage, which prove the usefulness of the proposed model to be next-generation-based IoT and multi-criteria routing systems. (Table 3).

In the Table 3 demonstrate the suggested presumes the existence of a comprehensive software ecosystem to support simulation of network behavior, machine learning, routing optimization, and security validation of operations. Python is utilized as the programming language of choice; TensorFlow PyTorch and Scikit-Learn will implement the OS-ELM, SIPF, and optimization components. (Table 4).

Figure 4 and Table 4 show AI-driven swarm-optimized adaptive routing using quantum-inspired neural scheduling with homomorphic encryption. The suggested AI approach outperformed well-known methods, such as REA, CCAS and TTMP-RSOA with 55.65%, 65.34%, and 92.55% proposed method TIMP-RSOA prediction in accuracy in diagnostic prediction of Packet Delivery Ratio 95.78%, respectively.

Table 3: Simulation Parameter

Parameters	Values
Dataset Name	Multi-Criteria Network Routing Dataset
Training data	300
Testing Data	200
Total Number of data	500
Operating System	Windows 11 (64-bit)
Programming Language	Python 3.10 or above – used for implementing AI models and workflow integration.
Framework	TensorFlow / PyTorch – for deep learning model training and evaluation.
Libraries	NumPy, Pandas, OpenCV, Scikit-learn – for data preprocessing, normalization, and analysis.
Simulation Environment	Anaconda / Spyder – for managing dependencies and running experiments efficiently.

Table 4: Performance of packet delivery ratio

No of Data	REA	CCAS	TIMP-RSOA	QINSR-HE
125	40.89	50.56	65.45	70.78
250	45.78	55.58	75.64	83.98
375	50.76	60.56	80.32	88.98
500	55.65	65.34	92.55	95.78

The proposed system achieves high PDR by selecting trustworthy, stable nodes and securing data paths with low-latency encryption. Consistent, reliable routing minimizes packet drops even under rapid mobility. Existing approaches often suffer from packet losses due to unstable clusters and weak trust validation. As a result, QINSR-HE ensures a significantly higher packet delivery success rate. (Table 5).

Figure 5 and Table 5 show AI-driven swarm-optimized adaptive routing using quantum-inspired neural scheduling with homomorphic encryption. The suggested AI approach outperformed well-known methods, such as REA, CCAS and TTMP-RSOA with 57.65%, 68.34%, and 94.55% proposed method TIMP-RSOA prediction in Network Lifetime 98.90%, respectively. The QINSR-HE extends network lifetime by balancing workload across secure nodes, reducing energy wastage, and preventing overload on specific routing points.

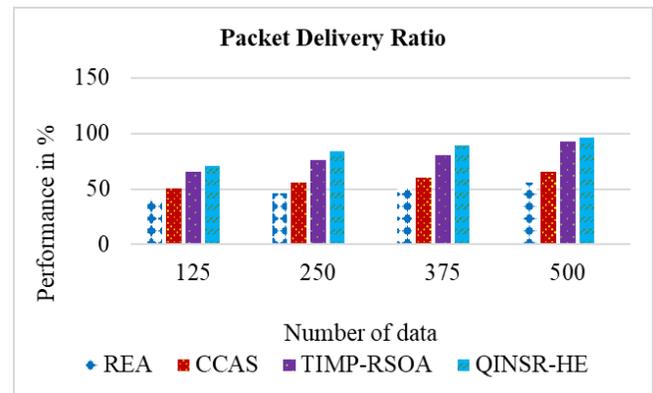


Figure 4: Analysis of Packet Delivery Ratio

Table 5: Performance of network lifetime

No of Data	REA	CCAS	TIMP-RSOA	QINSR-HE
125	40.89	50.56	65.45	74.67
250	45.78	55.58	75.64	83.90
375	50.76	60.56	85.32	89.90
500	57.65	68.34	94.55	98.90

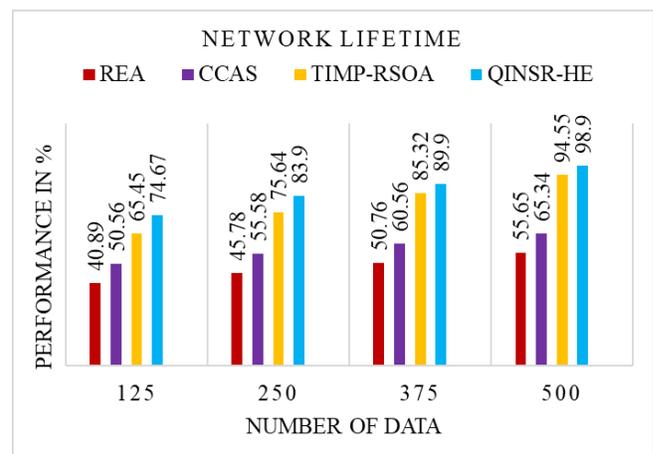


Figure 5: Analysis of Network Lifetime

Its stable routing reduces node failures caused by excessive retransmissions. Existing techniques lack such balanced distribution, causing early battery depletion in key nodes. (Table 6).

Figure 6 and Table 6 show AI-driven swarm-optimized adaptive routing using quantum-inspired neural scheduling with homomorphic encryption. The suggested AI approach outperformed well-known methods, such as REA, CCAS and TTMP-RSOA with 55.65%, 65.34%, and 93.55% proposed method TIMP-RSOA prediction in Traffic Behaviour 95.78%, respectively. The proposed QINSR-HE enhances traffic behaviour analysis by integrating quantum-inspired behaviour evaluation with hybrid encryption, enabling more accurate anomaly detection during node communication. Its adaptive pattern learning identifies irregular traffic flows faster than conventional statistical techniques. Existing methods like REA, CCAS, and TTMP-RSOA rely on static thresholds that fail under dynamic conditions. Thus, QINSR-HE provides superior behavioural visibility and real-time traffic insight. (Table 7).

Figure 7 and Table 7 show AI-driven swarm-optimized adaptive routing using quantum-inspired neural scheduling with homomorphic encryption. The suggested AI approach outperformed well-known methods, such as REA, CCAS and TTMP-RSOA with 59.65%, 63.34%, and 92.55% proposed method TIMP-RSOA prediction in Self-Scheduling Routing 96.78%, respectively. The QINSR-HE enhances routing by enabling each node to self-schedule based on quantum trust scores and predictive path selection, reducing

Table 6: Performance of Traffic Behaviour Analysis

No of Data	REA	CCAS	TIMP-RSOA	QINSR-HE
125	40.89	50.56	65.45	76.89
250	45.78	55.58	75.64	81.56
375	50.76	60.56	85.32	89.90
500	55.65	65.34	93.55	95.78

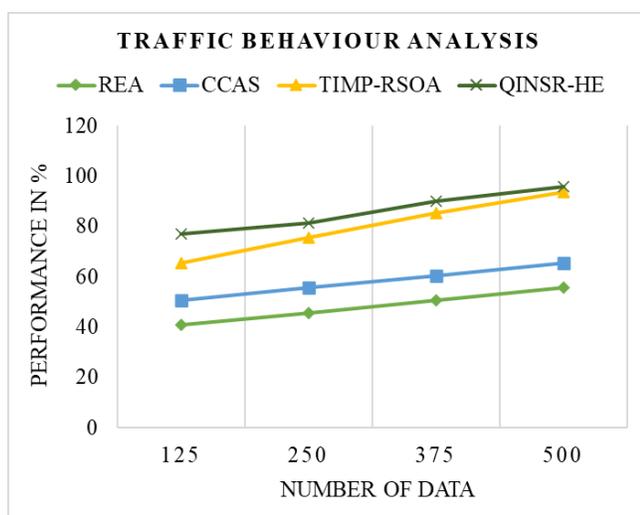


Figure 6: Analysis of Traffic Behaviour

Table 7: Performance of self-scheduling routing process

No of data	REA	CCAS	TIMP-RSOA	QINSR-HE
125	40.89	50.56	65.45	73.46
250	45.78	55.58	75.64	80.89
375	50.76	60.56	85.32	90.87
500	59.65	63.34	92.55	96.78

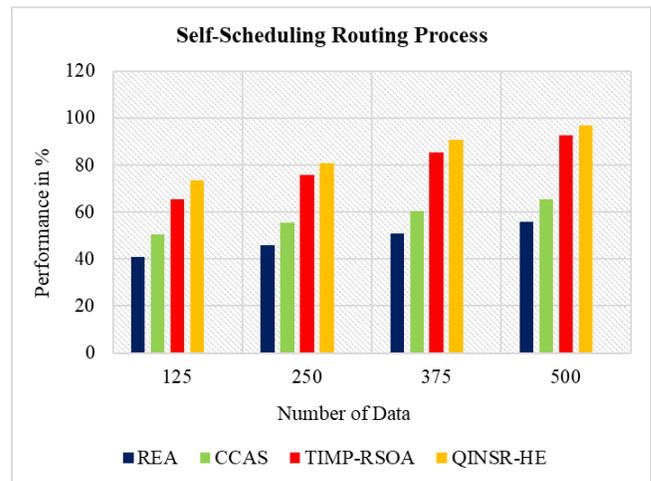


Figure 7: Analysis of Self-Scheduling Routing Process

redundant route checks. This improves routing fluidity and minimizes route failures in dynamic environments. Existing techniques have slower, reactive scheduling that does not adapt quickly to node mobility. Hence, the proposed model ensures smoother and more autonomous routing decisions. (Table 8).

Figure 8 and Table 8 show AI-driven swarm-optimized adaptive routing using quantum-inspired neural scheduling with homomorphic encryption. The suggested AI approach outperformed well-known methods, such as REA, CCAS and TTMP-RSOA with 75.65%, 65.65%, and 25.55% proposed method TIMP-RSOA prediction in routing overhead 20.98%, respectively. The proposed model reduces routing overhead by performing trust evaluation and cluster updates only when necessary, using a predictive behavior model. Fewer control packets and optimized route discovery contribute to lower overhead. Traditional methods like REA and CCAS produce high overhead due to frequent trust recalculations. Hence, QINSR-HE ensures more efficient routing management with reduced signalling. (Table 9).

Figure 9 and Table 9 show AI-driven swarm-optimized adaptive routing using quantum-inspired neural scheduling with homomorphic encryption. The suggested AI approach outperformed well-known methods, such as REA, CCAS and TTMP-RSOA with 75.65%, 65.65%, and 25.55% proposed method TIMP-RSOA prediction in energy consumption 20.78%, respectively. The QINSR-HE reduces energy consumption by minimizing routing overhead, lowering computation during encryption, and decreasing

Table 8: Performance of routing overhead

No of data	REA	CCAS	TIMP-RSOA	QINSR-HE
125	50.89	45.56	40.45	35.56
250	55.78	50.58	35.78	30.98
375	65.76	60.76	29.76	25.67
500	75.65	65.65	25.55	20.98

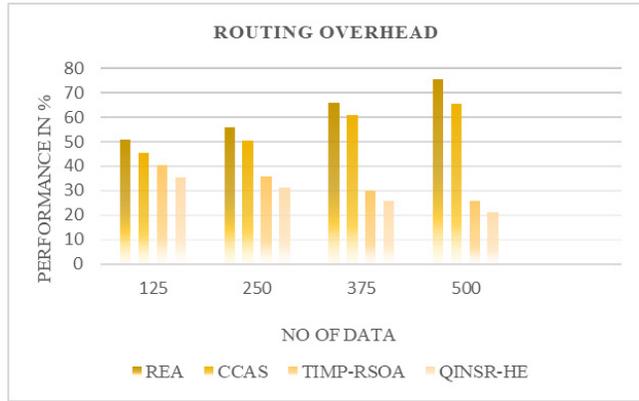


Figure 8: Analysis of Routing overhead

retransmissions through reliable path selection. This allows nodes to conserve battery power in high-mobility scenarios. Existing methods typically perform repeated trust evaluations and control exchanges, draining more energy. Thus, the proposed technique offers superior energy optimization across nodes. (Table 10).

Figure 10 and Table 10 show AI-driven swarm-optimized adaptive routing using quantum-inspired neural scheduling with homomorphic encryption. The suggested AI approach outperformed well-known methods, such as REA, CCAS and TTMP-RSOA with 70.65%, 63.65%, and 25.55% proposed method TIMP-RSOA prediction in End-to-End Delay 22.98%, respectively. The proposed method reduces end-to-end delay through fast cluster management, optimized route scheduling, and low-latency encryption functions. Data packets travel through trusted and stable nodes, minimizing retransmissions. Existing systems like TTMP-RSOA often experience delay spikes due to frequent route disruptions. Therefore, QINSR-HE ensures faster and more stable end-to-end communication. (Table 11).

Figure 11 and Table 11 show AI-driven swarm-optimized adaptive routing using quantum-inspired neural scheduling with homomorphic encryption. The suggested AI approach outperformed well-known methods, such as REA, CCAS and TTMP-RSOA with 75.65s, 65.65sec and 23.55s proposed method TIMP-RSOA prediction in End-to-End Delay 21.98%, respectively. The Time Analysis (in seconds) of the Cluster Formation shows that the proposed OS-ELM method takes 50.89 seconds, 55.78 seconds, 65.76 seconds, and 75.65 seconds in data sizes of 125, 250, 375, and 500 respectively. Comparatively, SIPF has relatively good time consumptions, and TIMP-RSOA and QINSR-HE have lesser cluster formation

Table 9: Performance of Energy Consumption

No of data	REA	CCAS	TIMP-RSOA	QINSR-HE
125	50.89	45.56	40.45	37.89
250	55.78	50.58	35.78	31.78
375	65.76	60.76	29.76	24.78
500	75.65	65.65	25.55	20.78

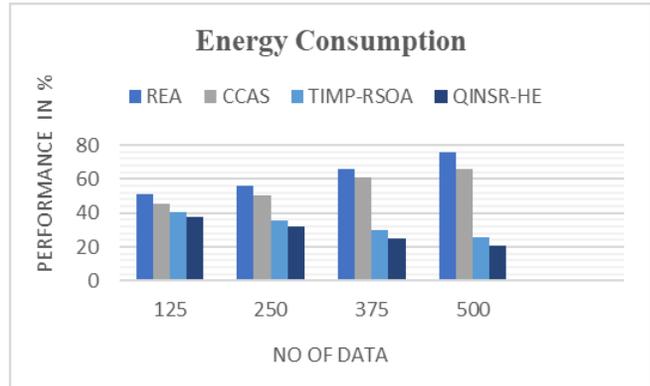


Figure 9: Analysis of Energy Consumption

times with the lowest points of 34.89 s, 29.78 s, 25.89 s, and 21.98 s. Though the time taken by the OS-ELM to cluster the data respectively, the outcome of this clustering process corresponds to the extra processing time consumed to allow the process of better learning and static cluster generation. (Table 12).

Figure 12 and Table 12 show AI-driven swarm-optimized adaptive routing using quantum-inspired neural scheduling with homomorphic encryption. According to the analysis of the performance, it is evident that the suggested OS-ELM

Table 10: Performance of end-to-end delay

No of Data	OS-ELM	SIPF	TIMP-RSOA	QINSR-HE
125	50.89	45.56	40.45	35.89
250	55.78	50.58	35.78	30.78
375	65.76	60.76	29.76	28.89
500	70.65	63.65	25.55	22.98



Figure 10: Analysis of End-to-End Delay

technique is more efficient than SIPF, TIMP-RSOA, and QINSR-HE in terms of various data sizes. OS-ELM achieved better values Encryption and Decryption Time analysis shows how effective the system is in terms of calculating the time efficiency of the system with varying data sizes. In the case of 125 records, the encryption and decryption time was 70.45 seconds and 47.89 seconds respectively. The encryption time dropped to 65.78 seconds and 60.76 seconds and decryption fell to 40.78 seconds and 30.89 seconds as the data size was increased to 250 and 375 records. In 500 records the system had a better performance of the system of 55.55 seconds in encrypting records and 35.98 seconds in decryption. (Table 13).

Figure 13 and Table 13 show AI-driven swarm-optimized adaptive routing using quantum-inspired neural scheduling with homomorphic encryption. The suggested AI approach outperformed well-known methods, such as REA, CCAS and TTMP-RSOA with 55.65%, 64.34 %, and 93.55 % proposed method TIMP-RSOA prediction in Node Selection Accuracy 96.78%, respectively. The QINSR-HE improves node selection accuracy by using multi-factor trust evaluation with entropy-based reliability scoring, ensuring selection of only stable and secure nodes. This reduces misclassification of malicious nodes and enhances cluster stability. In contrast, REA and CCAS depend on limited trust indicators, while TTMP-RSOA struggles with fluctuating mobility patterns. Hence, the proposed method offers more consistent and precise node selection. (Table 14).

Figure 14 and Table 14 show AI-driven swarm-optimized adaptive routing using quantum-inspired neural scheduling

with homomorphic encryption. The suggested AI approach outperformed well-known methods, such as REA, CCAS and TTMP-RSOA with 65.65 %, 73.34 %, and 90.55% proposed method TIMP-RSOA prediction in Data Confidentiality range 94.78 %, respectively. The mechanism of protection of confidentiality of sensitive information that is only available to authorized people, which protects the information against the unauthorized disclosure, access, or theft, is known as data confidentiality. The proposed system ensures high confidentiality by implementing quantum-immune key generation and multi-layer hashing to prevent unauthorized access or key exposure. It offers enhanced protection even against advanced cryptographic attacks. REA and CCAS mostly rely on traditional encryption, which is more vulnerable to emerging threats. Consequently, QINSR-HE provides significantly stronger confidentiality guarantees for communication. (Table 15).

The figure 15 and table 15 show that compare Routing and scheduling methods, including REA, CCAS, TIMP-RSOA, and our new QINSR-HE Security, were compared for their security efficiency by comparing the percentage of days securely delivered or transmitted via all of the above methods According to the Security Efficiency Performance analysis, the proposed OS-ELM approach is more efficient as compared to the current methods including SIPF, TIMP-RSOA and QINSR-HE when using different data size. In 125 records, OS-ELM recorded a low processing score of 40.89% than SIPF, TIMP-RSOA, and QINSR-HE which had 50.56%, 65.45 % and 70.89% respectively. OS-ELM delivered better results with a data size of 250 and 375 records of 45.78% and 50.76% and the other methods exhibited increased computational

Table 11: Performance of cluster formation time

No of data	OS-ELM	SIPF	TIMP-RSOA	QINSR-HE
125	50.89	40.56	38.45	34.89
250	55.78	50.58	35.78	29.78
375	65.76	60.76	26.76	25.89
500	75.65	65.65	23.55	21.98

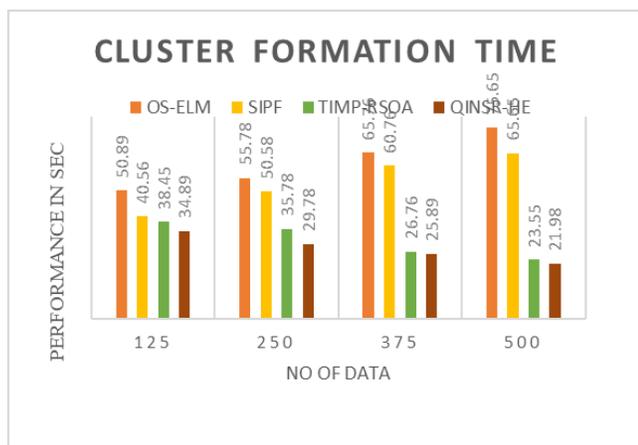


Figure 11: Analysis of Cluster Formation Time

Table 12: Performance of encryption and decryption time

No of data	OS-ELM	SIPF	TIMP-RSOA	QINSR-HE
125	85.89	75.56	70.45	47.89
250	80.78	70.58	65.78	40.78
375	75.76	69.76	60.76	30.89
500	65.65	58.65	55.55	35.98

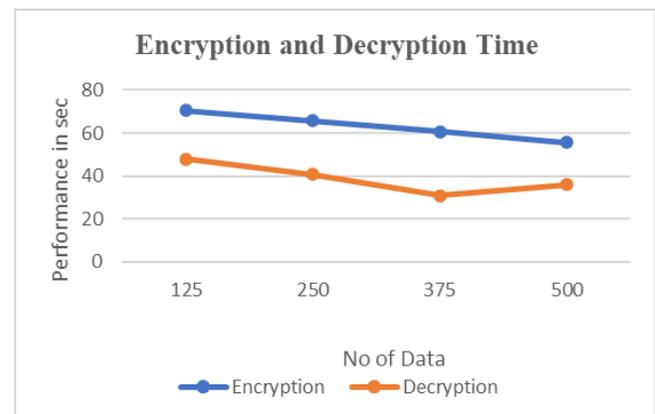


Figure 12: Analysis of Encryption and Decryption Time

Table 13: Performance of Node Selection Accuracy

No of Data	REA	CCAS	TIMP-RSOA	QINSR-HE
125	41.89	52.56	67.45	70.46
250	45.78	58.58	77.64	85.89
375	50.76	60.56	88.32	93.87
500	55.65	64.34	93.55	96.78

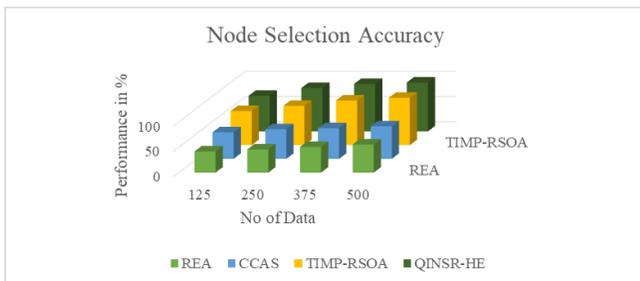


Figure 13: Analysis of Node Selection Accuracy

Table 14: Performance of Data Confidentiality

No of data	REA	CCAS	TIMP-RSOA	QINSR-HE
125	30.89	53.56	68.45	70.46
250	48.78	59.58	76.64	86.89
375	53.76	68.56	87.32	91.87
500	65.65	73.34	90.55	94.78

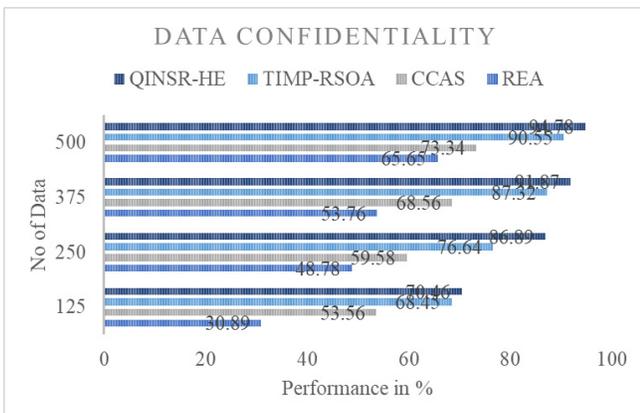


Figure 14: Analysis of Data Confidentiality

overhead. OS-ELM at its top size of 500 records retrieved 55.65% which is very low as compared to SIPP (65.34%), TIMP-RSOA (95.55%) and QINSR-HE (97.67%). These findings demonstrate that processing requirements grow with volume of data, but the proposed OS-ELM remains more efficient in terms of security and less in terms of complexity of computations and is therefore more appropriate in large-scale and real-time secure application environment.

Discussion

In the current network management practices, the traffic analysis, cluster generation, routing and security are

Table 15: Performance of Security Efficiency Process

No of data	OS-ELM	SIPP	TIMP-RSOA	QINSR-HE
125	40.89	50.56	65.45	70.89
250	45.78	55.58	75.64	79.89
375	50.76	60.56	85.32	88.90
500	55.65	65.34	95.55	97.67

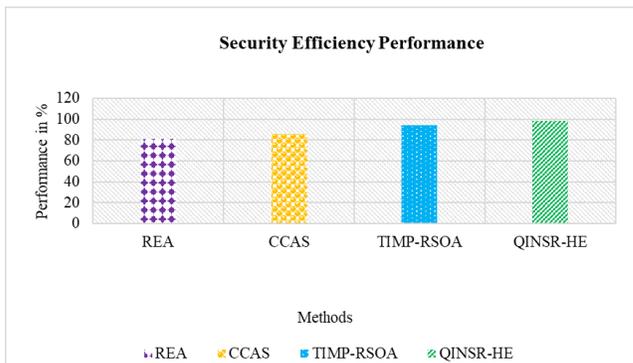


Figure 15: Analysis of Security Efficiency

managed independently or through traditional heuristics, which do not always reflect dynamic network behaviour, trustworthiness and multi-criteria optimization, leading to suboptimal node selection, routing wastage and possible security weaknesses. Compared to the current approaches, the proposed framework is better because it incorporates the analyse traffic behaviour which can give reconstructed and synthetic traffic patterns as phenotypes to enrich node features; Hybrid Spiking Neural-Evolutionary Cluster Leader Selector to select optimal clusters based on energy, trust and network centrality; PETASR to predictive, trust-aware scheduling and routing; and QINSR-HE to secure and use homomorphically encrypted data transmission. A combination of these hybrid, multi-layered approaches enable node clustering, scheduling, routing as well as safe transmission of data to be carried out more effectively. Packet delivery, energy efficiency, routing overhead, and security have been improved, offering intelligent, adaptive, and context-aware management of networks, as opposed to the current techniques such as REA, CCAS, and TTMP-RSOA.

Conclusion

In Conclusion, the intelligent network management framework, with the use of HAEGANBS, Hybrid Spiking Neural-Evolutionary Cluster Leader Selector, PETASR, and QINSR-HE has greatly contributed to network performance, reliability, and security as compared to the current routing solutions: REA, CCAS, and TTMP-RSOA. This combined solution allows holistic study of traffic behaviour, optimal cluster construction with optimal node choice, predictive trust-based scheduling, and secure encrypted routing, which will guarantee reliable communication, minimum energy utilization, and reliable delivery of packets in a

varying network setup. Experimental measurements showed significant increase in the major metrics, such as Security Efficiency 97.67%, Data Confidentiality range 94.78 %, Node Selection Accuracy 96.78%, 55.55 seconds in encrypting records and 35.98 seconds in decryption, End-to-End Delay 22.98%, Packet Delivery Ratio 95.78%, Network Lifetime 98.90% some future work can consider lightweight deployment, reinforcement-learning-based predictive routing, and federated secure routing intelligence to improve further adaptability, scalability, and secure operation of large-scale internet of things-enabled networks.

Acknowledgement

We acknowledge the support of the PG & Research Department of Computer Science, Jamal Mohamed College (Autonomous), Trichy for providing computational resources. This research was not supported by any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

- Benavente, J., Alonso, B., Rodríguez, A., & Moura, J. L. (2021). Integration of automated vehicle location, fare control, and schedule data for improved public transport trip definition. *IEEE Access*, **9**, 128250–128275. <https://doi.org/10.1109/ACCESS.2021.3107833>
- Cao, J., et al. (2025). Two-stage heuristic optimization with hybrid evolutionary multitasking for automatic optical inspection route scheduling. *IEEE Transactions on Industrial Informatics*, **21**(8), 6569–6578. <https://doi.org/10.1109/TII.2025.3567403>
- Feng, Z., Dong, W., Gao, S., Lin, Y., Jin, X., & Deng, Q. (2025). An efficient heuristic CQF scheduling in time-sensitive networking. *IEEE Transactions on Industrial Informatics*, **21**(7), 5213–5223. <https://doi.org/10.1109/TII.2025.3552701>
- Garg, S., Kuchipudi, V. S. S., Bentley, E. S., & Kumar, S. (2021). A real-time, distributed, directional TDMA MAC protocol for QoS-aware communication in multi-hop wireless networks. *IEEE Access*, **9**, 26343–26361. <https://doi.org/10.1109/ACCESS.2021.3057587>
- Gu, R., et al. (2022). Liquid: Intelligent resource estimation and network-efficient scheduling for deep learning jobs on distributed GPU clusters. *IEEE Transactions on Parallel and Distributed Systems*, **33**(11), 2808–2820. <https://doi.org/10.1109/TPDS.2021.3138825>
- Guo, H., Liu, J., Zhuang, C., Dong, H., & Zhang, F. (2025). A hyper-heuristic for dynamic integrated process planning and scheduling problem with reconfigurable manufacturing cells. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, **55**(6), 3892–3905. <https://doi.org/10.1109/TSMC.2025.3548120>
- Hu, Y., Liu, J., Yan, H., & Guo, X. (2024). Schedule disruption recovery in liner shipping service based on a reinforcement learning-enabled adaptive genetic algorithm. *IEEE Transactions on Intelligent Transportation Systems*, **25**(12), 21622–21633. <https://doi.org/10.1109/TITS.2024.3477996>
- Huang, J., Gao, L., & Li, X. (2025). A spatiotemporal graph neural network based deep reinforcement learning method for online distributed job-shop scheduling problem. *IEEE Transactions on Emerging Topics in Computational Intelligence*. <https://doi.org/10.1109/TETCI.2025.3628751>
- Jahic, A., Plenz, M., Eskander, M., & Schulz, D. (2021). Route scheduling for centralized electric bus depots. *IEEE Open Journal of Intelligent Transportation Systems*, **2**, 149–159. <https://doi.org/10.1109/OJITS.2021.3096115>
- Jiang, H., Ye, Y., Wang, C., Xiang, X., Zhou, T., & Zhang, X. (2025). A data-driven evolutionary algorithm for dynamic vehicle routing problems with time windows under limited computational time. *IEEE Transactions on Automation Science and Engineering*, **22**, 22239–22250. <https://doi.org/10.1109/TASE.2025.3617650>
- Khan, A. N., Iqbal, N., Rizwan, A., Malik, S., Ahmad, R., & Kim, D. H. (2022). A criticality-aware dynamic task scheduling mechanism for efficient resource load balancing in constrained smart manufacturing environment. *IEEE Access*, **10**, 50933–50946. <https://doi.org/10.1109/ACCESS.2022.3173157>
- Lai, Y., Yang, F., Meng, G., & Lu, W. (2022). Data-driven flexible vehicle scheduling and route optimization. *IEEE Transactions on Intelligent Transportation Systems*, **23**(12), 23099–23113. <https://doi.org/10.1109/TITS.2022.3204644>
- Li, S., Wu, Q., Wang, R., Chen, L., & Zhang, H. (2025). Efficient multipath differential routing and traffic scheduling in ultra-dense LEO satellite networks: A DRL with Stackelberg game approach. *IEEE Transactions on Mobile Computing*, **24**(11), 12424–12440. <https://doi.org/10.1109/TMC.2025.3586262>
- Lee, D.-J. (2023). Incremental routing and scheduling using multipath and nonzero jitter bound for IEEE 802.1Qbv time-aware shaper. *IEEE Access*, **11**, 25035–25049. <https://doi.org/10.1109/ACCESS.2023.3255416>
- Liu, Z., Yue, Z., Li, F., Yuan, Y., & Guan, X. (2025). Joint optimization of adaptive time slot resource segmentation and route scheduling with CQF mechanism in time-sensitive networks. *IEEE Transactions on Vehicular Technology*. <https://doi.org/10.1109/TVT.2025.3611967>
- Lu, T., Yao, E., Zhang, Y., & Yang, Y. (2021). Joint optimal scheduling for a mixed bus fleet under micro driving conditions. *IEEE Transactions on Intelligent Transportation Systems*, **22**(4), 2464–2475. <https://doi.org/10.1109/TITS.2021.3061202>
- Nakamura, O., Yamada, R., Tomeba, H., & Hamaguchi, Y. (2025). Self-supervised learning-based scheduling scheme under multiple access points environment for sub-terahertz band. *IEICE Communications Express*, **14**(8), 313–316. <https://doi.org/10.23919/comex.2025TCL0009>
- Ning, Z., et al. (2022). Online scheduling and route planning for shared buses in urban traffic networks. *IEEE Transactions on Intelligent Transportation Systems*, **23**(4), 3430–3444. <https://doi.org/10.1109/TITS.2020.3036396>
- Nguyen, H.-P., Ngo, Q.-H., & Nguyen, V.-C. (2025). Multi-agent communication for dynamic job-shop scheduling: A robust single-machine scheduling model with genetic algorithm optimization. *IEEE Access*, **13**, 87183–87192. <https://doi.org/10.1109/ACCESS.2025.3569568>
- Qiao, W., Han, Y., Si, F., Li, K., Wang, J., & Zhao, Q. (2023). Optimal economic-emission scheduling of coupled transportation and power distribution networks with multi-objective optimization. *IEEE Transactions on Industry Applications*, **59**(4), 4808–4820. <https://doi.org/10.1109/TIA.2023.3261864>
- Sekine, K., Kato, F., Tatsukawa, T., Fujii, K., & Itoh, E. (2023). Rule

- design for interpretable en route arrival management via runway-flow and inter-aircraft control. *IEEE Access*, **11**, 75093–75111. <https://doi.org/10.1109/ACCESS.2023.3297136>
- Sun, H., et al. (2026). Frame dynamic priority scheduling with graph theory based traffic grouping and routing co-design for wireless time-sensitive networking. *IEEE Transactions on Network Science and Engineering*, **13**, 102–117. <https://doi.org/10.1109/TNSE.2025.3582034>
- Sun, Y., Zhao, N., Tang, L., & Luo, L. (2025). Breaking the limit on the number of robots through the conflict-free scheduling in robotic mobile fulfillment systems. *IEEE Transactions on Automation Science and Engineering*, **22**, 7324–7334. <https://doi.org/10.1109/TASE.2024.3420107>
- Vela, A., Cruz-Duarte, J. M., Ortiz-Bayliss, J. C., & Amaya, I. (2021). Tailoring job shop scheduling problem instances through unified particle swarm optimization. *IEEE Access*, **9**, 66891–66914. <https://doi.org/10.1109/ACCESS.2021.3076426>
- Wan, P., Xu, G., Chen, J., & Zhou, Y. (2024). Deep reinforcement learning enabled multi-UAV scheduling for disaster data collection with time-varying value. *IEEE Transactions on Intelligent Transportation Systems*, **25**(7), 6691–6702. <https://doi.org/10.1109/TITS.2023.3345280>
- Wang, C., et al. (2024). Deterministic scheduling and reliable routing for smart ocean services in maritime Internet of Things: A cross-layer approach. *IEEE Transactions on Services Computing*, **17**(6), 3387–3399. <https://doi.org/10.1109/TSC.2024.3442471>
- Wang, Y., Yu, X., Zhao, Y., Cao, Y., Nag, A., & Zhang, J. (2025). Time-scheduled end-to-end entanglement establishment in memory-cell-limited quantum networks. *IEEE Transactions on Networking*, **33**(5), 2224–2240. <https://doi.org/10.1109/TON.2025.3557820>
- Wang, Y., Lv, B., Zhou, Q., Li, J., & Tan, T. (2025). Schedulability analysis for self-suspending tasks under EDF-like scheduling. *IEEE Transactions on Computers*, **74**(7), 2364–2375. <https://doi.org/10.1109/TC.2025.3558079>
- Wu, L.-J., Shi, L., Zhan, Z.-H., Lai, K.-K., & Zhang, J. (2022). A buffer-based ant colony system approach for dynamic cold chain logistics scheduling. *IEEE Transactions on Emerging Topics in Computational Intelligence*, **6**(6), 1438–1452. <https://doi.org/10.1109/TETCI.2022.3170520>
- Xu, X., Cao, L., & Wang, X. (2016). Adaptive task scheduling strategy based on dynamic workload adjustment for heterogeneous Hadoop clusters. *IEEE Systems Journal*, **10**(2), 471–482. <https://doi.org/10.1109/JSYST.2014.2323112>
- Yang, C., Liu, X., Zhang, H., Li, Y., & Chen, J. (2025). A robust method for bus scheduling and passenger flow coordination considering arterial signal coordination under connected environment. *IEEE Transactions on Intelligent Transportation Systems*, **26**(11), 19845–19861. <https://doi.org/10.1109/TITS.2025.3598761>
- Yi, S., & Luo, J. (2025). Heuristic scheduling for robotic job shops using Petri nets and artificial potential fields. *IEEE Transactions on Automation Science and Engineering*, **22**, 7556–7568. <https://doi.org/10.1109/TASE.2024.3464857>
- Zhang, Y., Li, H., Wang, X., Chen, Q., & Sun, M. (2025). Scalable scheduling in industrial time-sensitive networking: A flow graphic distributed scheme. *IEEE Transactions on Industrial Informatics*, **21**(2), 1068–1077. <https://doi.org/10.1109/TII.2024.3452201>
- Zhou, Z., Chen, L., Li, Y., Wang, H., & Zhang, J. (2023). Collaborative learning-based network resource scheduling and route management for multi-mode green IoT. *IEEE Transactions on Green Communications and Networking*, **7**(2), 928–939. <https://doi.org/10.1109/TGCN.2022.3187463>
- Zhu, L., Huang, K., Hu, Y., & Tai, X. (2021). A self-adapting task scheduling algorithm for container cloud using learning automata. *IEEE Access*, **9**, 81236–81252. <https://doi.org/10.1109/ACCESS.2021.3078773>