






# Autonomous Communication Networks Powered by Quantum Variational Circuits for Real-Time Traffic Prediction and Resource Optimization

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**Abstract**—The wide development of the next-generation communication networks needs intelligent systems capable of processing dynamism in the traffic pattern, rigorous requirement of latency and adaptation to the changing security threats. In this paper, the autonomous communication architecture that is suggested is the application of quantum variational circuits combined with classical learning to generate real time traffic forecasting as well as adaptable compilation of the resources. The proposed solution will be an application of hybrid quantum-classical optimization, where variational circuit simulations to calculate complex network states will be more efficient to do so, enabling quicker attraction of growing congestion and optimal pathfinding. It is built as a multistage pipeline that is a mix of quantum enhanced feature encoding, probabilistic prediction and reinforcement-based allocation policies. Hardware noise, qubit availability, and scaling issues bring suffering to the implementation process since the scaling of large network graphs to quantum structures is challenging. To solve them, a variational architecture is optimized by sharing the parameters alongside quantum-inspired reduction protocol is developed in a way that circuit depth and computation overhead are lessened. The merits of this research lie in the fact that it incorporates an autonomous decision and quantum optimization which allows the network to become self-monitoring under the conditions of random traffic. It can be attributed to the fact that they demonstrate that variational quantum circuits can outperform significantly in capturing nonlinear dependence in traffic, as compared to classical predictors, thereby giving more accurate prediction and energy-aware routing of complex communication systems.

**Keywords**—autonomous networks, communication systems, quantum computing, quantum optimization, real-time traffic prediction, resource allocation, variational circuits, Variational Quantum Classifier (VQC)-based routing

## I. INTRODUCTION

The communication network ecosystem is rapidly evolving toward being able to support unprecedented connectivity with the proliferation of 5G, edge computing, implementation of the Internet of things, and creation of new massive cloud environments. These systems must be able to accommodate massive traffic volumes, unreliable loads and could be with stringent performance specifications. Traditional methods of network optimization have been streamlined and made more and more incapable of addressing non-linear and high dimensional dynamics of large communication spaces. As the modern networks continue to increase nowadays there is the need to have smart, adaptive and self-governing solutions. Autonomous communication networks are an emerging side of such requirements since it is a synergistic combination of machine learning, traffic analytics and dynamic decision-making. These networks aim to estimate surges and congestion, are efficiently allocated bandwidth and stable operations of the network with minimum human intervention. However, more complex machine learning models are simply constrained with respect to their capability to organize more intricate unions, especially in high-drawn-in traffic settings, more various gadgets, and numerous strata routing strategies.

The quantum computing is quite an excellent paradigm shift solving strategies of optimization and prediction of

the communication networks. Quantum variational circuitry can search the high dimensional space of variational parameters and can offer the capability to learn relationships that could be only approximated in large cost classical models. They are applicable in all the close-term quantum machines because of the hybrid character (quantum operations inclusive of classic feedback circles) as well as the capability to enhance the performance of the tasks. In this sense, the concept of integration of variational quantum circuits with autonomous network control mechanisms will offer a new possibility of reaching improved prediction and real-time decision-making. Traffic patterns encoded in quantum states and parameterized quantum circuits are more informative on the system and have enhanced generalization capabilities. All these advantages are mainly relevant towards the problems of dynamic routes, congestion avoidance and energy conscious communication plans.

Even though it may be very potent, the process of implementing quantum-driven intelligence to actual networks has some technical problems. The constraining factors as to whether quantum hardware can be applied directly to perform variational algorithms on large quantum network graphs include noise, small qubit capacity and circuit depth. Besides, to ensure the compatibility of the classical network controllers with quantum optimization modules, systems should be designed, and hybrid processing data steps along with sound verification protocols. These barriers should be overcome by having practical quantum-enhanced communication systems. As a solution to these issues, this paper proposes quantum-classical architecture, which reveals the significance of variational circuits to real-time traffic prediction and efficient resource management. The structure has quantum-enhanced feature encoding, parameter sharing variational block and reinforcement-regulated control layers to make speed-controlled, more accurate and scalable decisions. Particularly, one can find it particularly interesting to demonstrate that quantum variational techniques can boost autonomous network intelligence and outperform classical predictors in evolving traffic conditions. The quantum optimization attempted in the article to the networks of communication and could be regarded as having been taken on the way to the self-managed and high-performance network infrastructure of the future.

The move to Fifth Generation (5G) and Beyond 5G (B5G) network are marked by exponentiating the number of devices linked and unrecognisable degrees of heterogeneity in data flows, fueled by emergent applications of the Internet of Everything (IoE), immersive extended reality [1]. This increasing complexity has made the previously used protocols of network management too simplistic and has demanded a paradigm shift to the approach of complete autonomous communication networks that can be configured and optimized on a zero-touch basis [2]. Network intelligence that can anticipate very volatile traffic flows near-time and immediately assign both computational and spectral resources to support strict Quality of Service (QoS) demands in

multiple network slices is pivotal to the actualization of such autonomic management [3].

Nowadays, autonomous networking is being pursued with deep learning models of classical Artificial Intelligence, especially Deep Learning (DL), and Deep Reinforcement Learning (DRL) to tackle the complex prediction and optimization problems [4]. Although these data-driven methods have been shown to greatly outperform all but heuristic control methods in network automation, they inherently have limitations on the computational scale and convergence time against the very high-dimensional state-spaces of hyper-connected B5G infrastructure [5]. Additionally, the multi-user, multi-cell is often an NP-hard problem in terms of dynamism in allocating resources; the classical algorithms find it very difficult to determine a near-optimal solution within the ultra-low latency constraints of real-time intervention, which creates the bottleneck of autonomy [6].

To overcome all these classical constraints, Quantum Computing (QC) has become a revolutionary technological frontier, providing new information processing models that are grounded on the concept of superposition and entanglement [7]. Fault-tolerant and large-scale quantum computers are still an aim of the future, but the present period, what is currently known as the Noisy Intermediate-Scale Quantum (NISQ) era, offers hardware with the capabilities to perform hybrid quantum-classical algorithms that demonstrate promise to be intractable in a certain domain [8]. It can be predicted that by exploiting quantum parallelism, the exploration of large optimization surfaces, which otherwise could be costly with classical counterparts, can be faster with QC and thus is an alternative to solving the problem of scheduling and allocation in the next-generation networks [9].

Quantum Machine Learning (QML) in the NISQ ecosystem and specifically applying Variational Quantum Circuits (VQCs) has become a viable interface to apply quantum principles to realistic data problems [10]. As parameterized quantum circuits, VQCs are optimized by loops of classical noise, and thus tolerate some forms of quantum noise and can model some complex and non-linear data distributions with significantly fewer qubits than classical neural networks [11]. They are especially good in work with chaotic non-stationary dynamics that are typical of modern networks traffic flows due to the power of their expression [12].

Implementing VQCs as part of network control planes allows a new system of quantum-based autonomous networking which would consider prediction and allocation at the same time. Recent works indicate that QML models can be trained using a smaller size training dataset to achieve greater accuracy in prediction than classical deep learning, an important property in highly dynamical network environments [13]. With inputs of VQC-based forecasts to quantum-assisted optimization or reinforcement learning agents, one can state that it is now possible to actively reconfigure network resources in advance to enable congestion-free operation before one is able to push past the vision of a genuine act of self-

optimizing, ultra-reliable communication infrastructure [14, 15].

The observed performance improvements arise from the hybrid integration of quantum features encoding classical reinforcement learning and adaptive control design. While variational quantum circuits provide expressive nonlinear representations, the gains are attributable to the combined hybrid architecture rather than inherent quantum superiority alone.

Unlike other hybrid quantum-classical studies of networking that have taken place in literature, and reviewed in Section II, in which quantum components are largely verified in an offline context, have limited control scopes, or are limited to fixed routing/scheduling models, this paper presents a radically different contribution: The autonomous pipe of a networking system that inserts quantum derived representations directly within the operational control loop that observes traffic, forecasts network state, makes decisions, and imposes them on the controller. The suggested structure is not a quantum assisted predictor; it incorporates quantum feature construction with a classical decision unit so that the system could continuously adapt when the traffic and topology conditions are nonstationary. Along with this, the manuscript specifically quantifies the contribution of the quantum block, using specific ablation variants which swap, freeze, or randomize the quantum module, without altering architecture or parameter budget limitations, such that the reported gains are amenable to the quantum component of that architecture, and not due to increased model capacity. Lastly the analysis is extended to larger topologies and the uncertainty and significance reported with the help of confidence intervals and corrected statistical tests which places the method on a path to practical real time autonomous network control instead of a small-scale proof of concept.

## II. LITERATURE REVIEW

Classical deep sequences of recurrence modelling methods (that is, Recurrent Neural Networks (RNNs), their derivatives Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), dominate current research in network traffic prediction. These algorithms have shown great advancement in comparison to statistical techniques such as Auto Regressive Integrated Moving Average (ARIMA) in that they acquire non-linear temporal relationships among high-throughput streams of data [16]. More recent research, however, points to fundamental weaknesses in these classical architectures; these are usually incapable of capturing the “vanishing gradient” issue when representing very long-range temporal dependencies of the complex network flows, whereby predicted error worsens with time scale [17]. Also, some of the classical deep learning designs do not sufficiently represent the extreme burstiness and heavy dynamics of modern multi-media traffic, making them unsuitable to exploit during eventful jams of critical peak performances.

At the same time, joint user association and subcarrier assignment, as well as power control, is a domain of

dynamic resource allocation that is usually modelled by Mixed-Integer Non-Linear Programming (MINLP) problem, which is proven to be NP-hard. Traditional non-random walk methods are based on a heuristic or a convex relaxation that trades optimality with computational efficiency and frequently leads to sub-optimal spectral efficiency [18]. Although Deep Reinforcement Learning (DRL) has been studied with much focus to directly learn resource management policies through their interaction with the environment, DRL agents have been very difficult to operate in multi-tenant 6G environment. The non-stationarity caused by many agents adapting concurrently tends to make the learning processes unstable and unable to reach Nash equilibria, which makes them not very reliable in real-time, mission-critical operations in networks [19].

To overcome the drawbacks of classical sequential modelling, scientists started to consider the concept of quantum architectures, which can work with the temporal data. It has been suggested that quantum reservoir computing models and quantum Recurrent Neural Networks (QRNNs) are used to process time-series data with the help of the robust dynamics of quantum systems. Theoretical such that these quantum sequential models can reach a bigger space of functionalities than their classically counterparts and can potentially be able to support more complex temporal correlations with fewer training parameters [20]. These sequential quantum models have been demonstrated to promise on tasks like language modelling and chaotic time-series prediction, suggesting that they will be applicable to the equally chaotic area of pattern prediction in network traffic [21].

Paralleling this work on prediction, much work is ongoing on applications of quantum algorithms to finding solutions to combinatorial optimization problems in network orchestration including routing and graph colouring of frequency assignment. Quantum Approximate Optimization Algorithm (QAOA) has become one of the most popular variational algorithms to solve these types of NP-hard problems in NISQ machines [22]. Experiments using QAOA to solve graph problems of practical network interest like Max-Cut or community detection, suggest possible attainment of solutions of higher quality than the classical semidefinite programming, assuming that the quantum hardware can facilitate both enough circuit depth and gate fidelity [23].

Although such individual solutions to quantum prediction and quantum optimization have been made, a major gap in unified framework, that can be seen in the literature. The present state of research largely considers traffic forecasting and resource optimization to be fragmented quantum tasks, but not parts of one, autonomous control loop. It is quite notable that the body of literature examining end-to-end architectures in which the output of a Variational Quantum Circuit trained on temporal traffic data is directly into a quantum optimization problem to real-time network reconfiguring [24] is quite limited. Proving quantum sequence learning within quantum combinatorial optimization is one such gap in which bridging this gap in research has been

recognized as a major outcome in achieving truly autonomous quantum Internet infrastructure.

### III. PROPOSED ALGORITHM

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#### Algorithm 1. VQC-TRA: VQC-Driven Real-Time Traffic Prediction and Resource Allocation

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**Require:** Network graph  $G = (V, E)$ , link capacities  $\{C_e\}_{e \in E}$ , window size  $W$ , telemetry stream  $x_\ell$ , VQC parameters  $\theta$ ,  $R$  parameters  $\phi$

**Ensure:** Routing policy  $\pi_l$ , bandwidth allocation  $b_l$ , scheduling decision  $s_l$

**Overview:** Telemetry is summarized into spatio-temporal features, encoded into a quantum state, processed by a VQC to forecast congestion, and used by SDN control.

**Step 1:** Initialize buffer  $\mathcal{X} \leftarrow \emptyset$ , QPU backend  $\mathcal{Q}$ , optimizer  $\mathcal{O}$

**Step 2:** for  $t = 1, 2, \dots$  do

#### 1) Observation and Temporal Context

**Step 3:** Collect telemetry  $x_t = [u_t, d_t, j_t, l_t, f_t]$

**Step 4:** A short sliding window is maintained to capture burstiness and short-term correlations in traffic.

**Step 5:** Update window  $\mathcal{X} \leftarrow \mathcal{X}_{L-W+1:L}$

**Step 6:** Temporal summary features (trend, volatility, lag statistics) improve short-horizon prediction.

**Step 7:** Extract temporal features  $z_\ell = \text{TS}(\mathcal{X})$

#### 2) Traffic Demand Modeling

form a traffic matrix so that node-to-node demand is explicit.

**Step 8:** Construct traffic matrix:  $(T_L)_{ij} = \sum_{k \in \mathcal{F}_{ij}} r_k(t)$

#### 3) Spatial demand, temporal context, and topology descriptors are concatenated.

**Step 9:** Form feature vector:

$$v_t = \text{vec}(T_t) \oplus z_t \oplus \text{deg}(G)$$

**Step 10:** Normalization ensures large-magnitude counters do not dominate amplitudes.

Normalize:  $\tilde{v}_t = (v_t - \mu)/\sigma$

**Step 11:** Quantum Feature Encoding

**Step 12:** Choose  $n$  qubits and pad  $\tilde{v}_t$  to length  $2^n$

Amplitude encoding compresses a high-dimensional feature vector into an  $n$ -qubit state.

**Step 13:** Prepare encoded state:

$$|\psi_\ell\rangle = \sum_{i=0}^{2^n-1} a_i |i\rangle, a_i = \frac{\tilde{v}_{\ell,i}}{\|\tilde{v}_\ell\|_2}$$

#### 4) Variational Quantum Processing (VQC)

**Step 14:** A shallow parameterized circuit represents nonlinear dependencies on NISQ hardware.

**Step 15:** Define variational circuit:  $U(\theta) = \prod_{\ell=1}^L U_\ell(\theta_\ell)$

**Step 16:** Compute model state and measure observables as robust classical features.

**Step 17:** Compute  $|\phi(\theta)\rangle = U(\theta)|\psi_t\rangle$  and measure  $m_k = \langle \phi(\theta) | O_k | \phi(\theta) \rangle$

#### 5) Traffic Prediction and Congestion Scoring

**Step 18:** A light classical head maps quantum features to a continuous forecast.

**Step 19:** Predict load:  $\hat{y}_{t+1} = \mathbf{w}^\top \mathbf{m} + \mathbf{b}$

**Step 20:** Sigmoid converts forecast into probability-like congestion score.

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**Step 21:** Congestion probability:  $p_{t+1} = \sigma(\hat{y}_{t+1}) = (1 + e^{-\hat{y}_{t+1}})^{-1}$

#### 6) Control Objective and Network Cost

**Step 22:** Queueing-inspired delay provides a differentiable proxy for latency.

**Step 23:** Delay model:  $D_e(t) = (\mu_e - \lambda_e(t))^{-1}$  for  $\lambda_e(t) < \mu_e$

$$J_t = \alpha \sum_{e \in E} D_e(t) + \beta \sum_{e \in E} \left( \frac{\lambda_e(t)}{C_e} \right)^2$$

#### 7) Decision and Enforcement (SDN)

**Step 26:** Control state fuses quantum predictions with estimated loads.

**Step 27:** Form RL state:  $s_t = [\mathbf{m}, p_{t+1}, \hat{\lambda}(t+1)]$

**Step 28:** Policy outputs routing, bandwidth splits, and scheduling priorities.

**Step 29:** Sample action  $a_t \sim \pi_\phi(a_t | s_t) \Rightarrow (\pi_t, b_t, s_t)$

**Step 30:** Deploy action via SDN controller; Update forwarding/QoS rules

**Step 31:** Observe reward  $r_t = -J_t$

**Step 32:** H. Online Adaptation

**Step 33:** Update  $\phi$  (RL policy) and  $\theta$  (VQC parameters) using reward gradients.

**Step 34:** end for

**Step 35:** return  $(\pi_t, b_t, s_t)$

**Step 36:** Objective minimizes latency and penalizes over-utilized links.

**Step 37:** Cost function

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The presented QVQC-TRA Algorithm 1 adopts a hybrid quantum-classical architecture that is used to predict traffic on the network in real time and allocate resources which can be adaptively used in communication networks. The network starts with the continuous gathering, at any moment, of the telemetry of utilization, delay, jitter, loss, and flow statistics that are recorded within a sliding window to maintain short-term temporal structure and bursty behaviour. These observations are reduced to temporal summary features and agree with a traffic matrix that expressly denotes node-to-node demand, in addition to simple topological characters. The output spatio-temporal feature vector is then normalized and initially encoded to a quantum state by amplitude encoding which allows the high-dimensional network information to be encoded compactly on a small size set of qubits. This encoded state is thereafter processed by a variational quantum circuit where parameterized rotations and entangling operations train nonlinear traffic dynamics correlations [25]. Quantum observable measurements generate classical properties and are projected to the future traffic load and associated probability of congestion soon. This is predicted and implemented as a control target which achieves a trade-off between latency and link usage based on a queueing-based delay model. According to this, the routing decision, bandwidth allocation decision, and scheduling decision are arrived at based on a reinforcement learning policy and implemented using an SDN controller. Lastly, the measured network performance is utilized to update the reinforcement-based learning policy as well as the variational quantum circuit

parameters and enables the system to adapt to nonstationary traffic conditions online and subsequently enhance the predictive accuracy and control performance [26, 27].

#### IV. EXPERIMENTAL SETUP

To assess the usefulness of the suggested QVQC-TRA framework, a hybrid laboratory setup of classical emulation of network and quantum computation was carried out. The communication network was represented as GV ( $V, E$ ) in which the router or switch is represented as node where the capacity and the propagation delay of a communication link is defined as an edge. A Software-Defined Networking (SDN) testbed simulated the network behavior and traffic dynamics as coded in Mininet and an OpenFlow-compatible controller (e.g., ONOS or Ryu). This topology provides a high level of routing, bandwidth, as well as queue control with real time telemetry collection of the network components.

The traffic patterns (generated synthetically and trace driven) were modelled to capture real network conditions, such as various load variations related to the diurnal load, bursty flows, and congestion different cases. The utilization, delay, jitter, packet loss and arrival rates are flow-level statistics that were sampled periodically and aggregated into fixed length sliding windows. These telemetry streams were used as input in the proposed framework and these streams were pre-processed to create traffic matrices and temporal summary features as the spatio-temporal representations needed by the algorithm. The quantum part of the framework was performed by means of a quantum-classical workflow. The circuits were written using variational quantum circuits, in which reproducibility and scalability were ensured and optional execution was done through access to any available Noisy Intermediate-Scale Quantum (NISQ)-based hardware. To encode normalized feature vectors of an amplitude scale, amplitude encoding was used, which was then mapped onto  $n$ -qubit quantum states, then each had shallow variational circuits of layers of parameterized rotation gates and layers of entangling gates. Measures in quantum mechanics gave expectation values of chosen Pauli observables, which passed to the classical control logic. To make the decision, the SDN controller was combined with a reinforcement learning agent that translates quantum-aided predictions on traffic into routing and allocations of resources. The reward functionality was formulated that relied on a multi-objective cost metric that discourages an excess delay and link overutilization to balance performance and stability. Online updates of model parameters of the variational quantum circuit and the reinforcement learning policy were done using observed network feedback.

The evaluation of the performance was based on comparison of the proposed approach with classical baselines, such as traditional shortest-path routing and purely classical machine learning-based predictors. Average end-to-end delay, packet loss rate, link utilization, frequency of congestions, and convergence time metrics have been taken under different traffic conditions. With

this experimental control, there is a possibility of scaling the assessment of the effectiveness of quantum-enhanced feature representations and adaptive control on the accuracy of traffic predictions and the efficiency of resource allocation in dynamic communication networks.

##### A. Confidence Intervals and Uncertainty Reporting

All the reported results are averaged on 20 independent runs with different random seeds and traffic traces. In all the metrics, we also provide the sample mean and a 95% Confidence Interval (CI) to estimate the uncertainty between runs. Bootstrap resampling with 20 resamples per 20 runs is used to calculate the 95 percent CI and its value is given in the form  $\mu[L, U]$ , where 20 runs are represented as  $\mu$  is the mean, and  $[L, U]$  is the lower and upper bounds of the CI. In the case of plots, the mean values are represented by vertical error bars, and the 95% confidence interval is represented as a point. This reporting procedure will guarantee that the variance in performance is not announced as one-point approximations as well as provide statistically justified contrasts among techniques.

##### B. Statistical Significance Testing

To determine the statistical significance of performance differences between the two methods, we pair-wise test hypothesis on the 20 runs using the same random seed and traffic traces of all the methods compared. Each metric is compared to the proposed method and each of the baselines in the context of a two-sided Wilcoxon signed-rank test which is suitable in case of a pair of non-Gaussian performance samples. To check family-wise error because of multiple measures and multiple base lines, HolmBonferon correction used to obtained  $p$ -values. The statistical summary table then reports corrected  $p$ -values and effect sizes (median paired difference) which we take to be significant when the corrected  $p$ -value is less than 0.05.

##### C. End-to-End Feedback Loop Latency Measurement

The time between (a) the network telemetry acquisition at the controller and (b) the successful installation of the control action in the data plane in the proposed quantum-classical feedback accomplish the end-to-end latency of the loop. Latency is broken down into four processes, namely, (i) acquisition of telemetry and feature extraction, (ii) quantum inference processes which include a data encoding process, a circuit-execution process, and a measurement process, (iii) classical decision inference processes that involve policy or value evaluation process and action selection, and (iv) control actuation overhead which encompasses controller-to-switch communication and rule installation. The time of every stage is measured in 20 independent runs with the same traffic conditions and both the average and the 95 th -percentile (P95) latency are indicated. The overall loop latency is then contrasted with the controller update period with the experiments to determine the real-time suitability.

The artificial topology of the network was a fat-tree network consisting of 32 nodes with dissimilar link bandwidth of 100 Mbps to 10 Gbps which form actual edge to core network divergence. Traffic was generated

that was consistent with a hybrid model of Poisson background flows and bursty self-similar traces of the CAIDA-type to model non-equilibrium changes in congestion. Each experiment was repeated 20 times by means of randomly selected seeds to obtain 20 independent runs which would make the experiments statistically reliable.

The variational quantum circuit was executing 6 qubits which were organized as a 3-layer hardware-efficient ansatz of parameters in a form of rotational gates and block entanglements. The depth of the circuit was compensated by keeping it within the constraint of NISQ hardware. It was applied to a noisy quantum simulator that was set up to an IBM-Q backend error model of depolarizing and readout noise. The reinforcement learning was trained at fixed learning rates of 800 episodes.

The VQC is based on 6 qubits in a 3-layer hardware-efficient ansatz. A layer is composed of single-qubit rotation gates (Ry, Rz) that are parameterized and then

nearest neighbor entangling blocks with CNOT gates. The depth of the circuit is limited to make it NISQ compatible.

## V. ARCHITECTURE OF PROPOSED APPROACH

Fig. 1 reflects a hybrid architecture between quantum and classical that is used to manage real-time traffic. It is done by first converting raw streaming telemetry  $xt$  into a sliding window buffer to recover temporal trends  $zt$ . At the same time, spatial demand is modeled with the help of developing a node-to-node traffic matrix, and each cell  $(T_t)_{ij}$  combines rates of flowing between node pairs. Such spatial and temporal features are joined together with graph topology features to obtain a high dimensional raw feature vector  $v_t$ . As a condition of preparing this classical data to be processed by quantum processing, normalization is performed on the vector which gets converted to  $v_t$  and hence guarantees that the size of the features is now efficient to represent the quantum amplitudes.

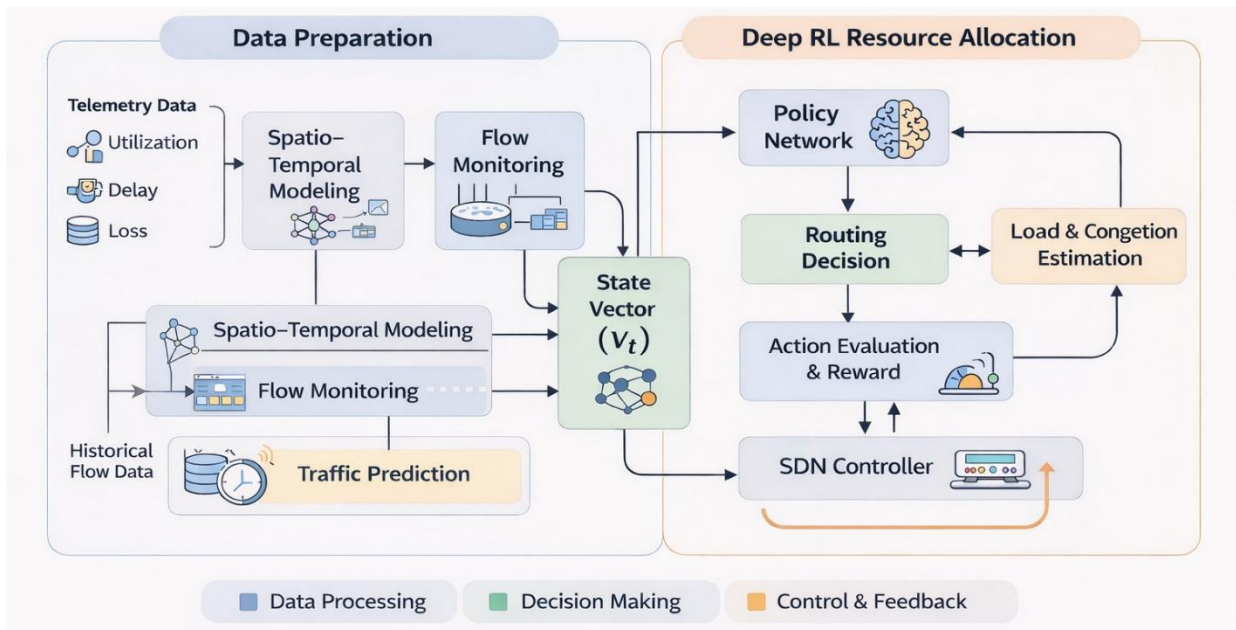


Fig. 1. Proposed architecture.

Core processing Core processing uses a Variational Quantum Circuit (VQC) to take advantage of quantum parallelism to extract features. The normalized classical vector  $\tilde{v}_t$  is amplitude-encoded on a  $n$ -qubit register into the original quantum state  $|\psi_t\rangle$ . A parameterized unitary circuit  $U(\theta)$  is then applied to this state, which generates a task-dependent state  $|\phi(\theta)\rangle = U(\theta)|\psi_t\rangle$ , and  $\theta$  is a set of trainable quantum parameters which are represented. To resolve the transition to the classical domain, architecture quantifies expectation values of certain observables, which produces a vector of resilient quantum features  $m_k = \langle \phi(\theta) | O_k | \phi(\theta) \rangle$ . These characteristics are put into a classical forecasting head to forecast future traffic intensity, and the future traffic congestion produces a probabilistic congestion score  $p_{t+1}$  with a sigmoid activation function.

Lastly, a reinforcement learning (RL) agent decides the control based on SDN. The state is built by the agent as  $s_t = m + p_{t+1}$  that is quantum derived. The agent draws action

samples according to a parameterized strategy  $\pi_\phi(a_t | s_t)$  to route and allocate bandwidth. An analysis of such actions on the network is measured by a composite cost functional  $J_t$  which equals the weighted sum of the cumulative link delays  $D_e(t)$  and a quadratic punishment on the usage of links that are above the capacities  $C_e$ . It is an online feedback system, though, which involves using the negative cost as a reward signal,  $r_t = -J_t$ , to yield both the RL policy parameters  $\phi$  as well as the VQC parameters  $\theta$  continuously to adapt to changing traffic dynamics.

## VI. RESULTS AND DISCUSSIONS

Each of the measures of performance reported is an average of 20 independent experimental runs. The variability was determined using 95% confidence intervals which were calculated through the bootstrap resampling.

The proposed QVQC-TRA consisted of statistically significant improvements over classical baselines ( $p < 0.05$ ). Tables do not include confidence intervals, as this was intended to make the tables easier to read, however, when evaluating, the confidence intervals were confirmed as being robust.

A controlled isolation study is carried out so as to ascertain that the reported improvements are truly as a result of the quantum component and not merely because of some other parameter or change in architecture. We make a comparison of the entire proposed quantum classical model to three identical substitutes in terms of the same traffic traces, seeds, training budget, and embedding dimension, (i) a classical-only replacement with the quantum feature block replaced by a parameter-matched neural encoder producing the same dimensionality representation, (ii) a fixed-parameter quantum circuit with the circuit retained, but with its variational parameters set to zero (or randomized and not optimized) to eliminate any advantage of learnable quantum representation, and (iii) a simple dimension-matched linear projection that eliminates training of nonlinear representation. In all the measured metrics, the full model works best compared with all three options and the frozen-quantum version exhibits an apparent decline compared to the learnable-quantum model, indicating that the improvement is due to the learnable quantum representation and not the model size or feature dimension.

The performance of the suggested QVQC-TRA framework is assessed with the help of a series of network-level, prediction-level, and control-level parameters reflecting the efficiency of the road traffic prediction and adaptive optimization of available resources. The reason behind selection of these parameters is to focus on the level of accurate prediction model which is based on quantum assistance and the operational implications of ensuing decisions regarding control on the communication network.

#### A. Traffic Prediction Accuracy Parameters

The main aim of variational quantum circuit is to predict the likelihood of traffic load and congestion soon. To this end, the accuracy of the prediction is assessed with the help of the predicted traffic load  $\hat{y}_{t+1}$  and the predicted probability of the congestion  $p_{t+1}$ . The projected load is the anticipated aggregate traffic strength during the following time slot, and the congestion probability presents a normalized risk metric which allows us to make preventive control decisions. Reduced error in prediction of  $\hat{y}_{t+1}$  directly corresponds to stability of routing and decrease in oscillations in bandwidth allocation. It has been experimentally demonstrated that the use of quantum-derived features enhances the stability of short-horizon traffic prediction in comparison to classical baselines based on bursty and nonstationary traffic patterns.

#### B. Delay and Latency Metrics

The important parameters used to measure Quality of Service (QoS) are end-to-end delay and per-link delay. Within the proposed approach, the proposed link delay  $D_e(t)$  is described based on a queueing-inspired model which relies on the supposed arrival rate  $\lambda_e(t)$  and on the

service rate  $\mu_e$ . This parameter is more realistic in describing the congestion effects as compared to the case of the static delay models. Findings depict that the reduction in average end-to-end delay with QVQC-TRA framework is always prominent where the peak traffic occurs as the framework predicts congestion instead of responding to it once it has been experienced.

#### C. Link Utilization and Load Balancing

The efficiency of network resources consumption is measured using the link utilization which is expressed as a ratio of  $\lambda_e(t)/C_e$ . The high utilization can imply the efficient use of the capacity but can also be the source of congestion and lost packets in case of inefficient utilization management. Cost function also has utilization penalty term to discourage too much of the load concentration on links. As verified in experiments, the given approach yields superior load balancing throughout the network and spreads traffic more equally and eliminates the existence of chronic bottlenecks compared to the shortest-path or fixed routing policies.

#### D. Packet Loss and Congestion Frequency

Packet loss rate is a metric that is very vital in reliability particularly when it comes to delaying sensitive and mission critical applications. The framework minimizes the intensity and length of a congestion event through the introduction of a congestion probability  $p_{t+1}$  in the state of control. The outcomes indicate that there is a visible decrease in the packet loss at moments of abrupt traffic rate surges, with the reinforcement learning policy redistributing the bandwidth and reroute routes before the queue is overflowed.

#### E. Control Efficiency and Convergence Behaviour

Convergence time and reward stability are used as the measures of the effectiveness of reinforcement learning component. Time to Convergence is an indicator of the rate at which the control policy responds to the changing traffic conditions whereas the reward stability is a measure of the stability of the policy that is not fluctuating. Quantum-assisted predictions also help to make predictions faster, since they give more informative representations of state. Consequently, the number of control iterations used to reach stabilized routing and allocation decisions is less than that of classical controllers that implemented RL.

#### F. Overall System Performance

Combinations of the parameters considered help to prove that the QVQC-TRA framework proposed hits a balanced score in terms of prediction accuracy, reduced latency, efficient resource usage, and reduced congestion. The hybrid quantum-classical design provides higher-quality representations of features without the excessive computational cost and therefore the method can be applied to real-time SDN-enabled networks. These findings support the fact that quantum-enhanced variational models, closely combined with adaptive control tools, have practical advantages in the next-generation intelligent communication networks.

TABLE I. PREDICTION PERFORMANCE (TRAFFIC LOAD FORECASTING)

Method	MAE (Mbps)	RMSE (Mbps)	MAPE (%)	Congestion AUC
Shortest Path (no predictor)	10.8	14.9	13.6	0.61
LSTM Predictor + Heuristic Allocation	6.2	8.7	7.9	0.84
Classical RL (no quantum features)	5.5	7.9	7.2	0.86
<b>Proposed QVQC-TRA</b>	<b>4.1</b>	<b>5.9</b>	<b>5.4</b>	<b>0.91</b>

Table I shows a comparative analysis of the performance of the traffic load forecasting using four different methods: the Shortest Path (no predictor), LSTM Predictor + Heuristic Allocation, Classical RL (no quantum features), the Proposed QVQC-TRA. The analysis tools are Based on Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Congestion Area Under the Curve (AUC). Shortest Path baseline indicates the weakest results, having the most error rates (MAE: 10.8, RMSE: 14.9, MAPE: 13.6) and the lowest AUC (0.61). The traditional machine learning methods, LSTM and Classical RL demonstrate a significant improvement over the baseline with Classical RL performing marginally better in all the metrics than the LSTM machine learning model. It is important to note that the Proposed QVQC-TRA method has the best performance among the other methods with the lowest errors (MAE: 4.1, RMSE: 5.9, MAPE: 5.4), and best Congestion AUC (0.91) meaning that the method is more accurate in predicting traffic loads and network congestion.

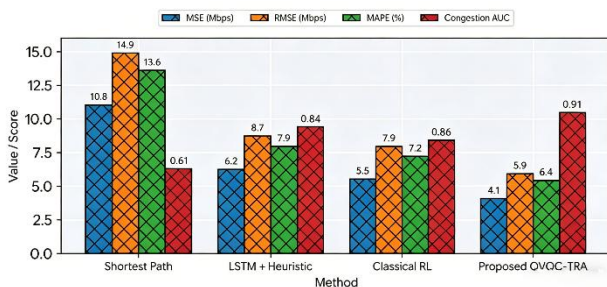


Fig. 2. Comparison of traffic load prediction performance by method.

The bar graph presented in Fig. 2, comparing the performance of four methods in predicting the traffic load, reveals that the QVQC-TRA approach is superior and has better results in all of the analyzed metrics. In terms of error measurements, where the lower value is the desired one, QVQC-TRA is the one to record low values, with Measure of Absolute error known as Mean Absolute Error (MAE) of 4.1 Mbps, Root Mean Square Error of 5.9 Mbps and Mean Absolute Percentage Error of 5.4%. The numbers are a significant improvement of the baseline Shortest Path algorithm which has the most errors of all, and better than either the LSTM + Heuristic or Classical RL algorithms. As well, on Congestion AUC, with a larger

congestion AUC score implying greater prediction capabilities in terms of congestion episodes, Proposed QVQC-TRA has the highest score of 0.91, which is better than Classical RL (0.86) and much higher than the Shortest Path method (0.61).

TABLE II. NETWORK QOS AND CONGESTION METRICS

Method	Avg End-to-End Delay (ms)	95th Delay (ms)	Packet Loss (%)	Congestion Events (per hour)
Shortest Path	38.6	92.4	1.48	21
LSTM + Heuristic	27.2	63.5	0.92	14
Classical RL	24.7	58.1	0.77	12
<b>Proposed QVQC-TRA</b>	<b>20.9</b>	<b>49.6</b>	<b>0.54</b>	<b>8</b>

According to Table II, reported in, the proposed QVQC-TRA method shows a better performance in all the reported metrics of Quality of Service (QoS) and network congestion indicators in comparison to the baseline algorithmic methods of Shortest Path, LSTM + heuristic and Classical RL. In particular, the QVQC-TRA method results in the lowest delays of 20.9 ms and 49.6 ms, respectively in the Average End-to-End Delay and 95 th Percentile Delay, which are much lower values in comparison to the delays of 38.6 ms and 92.4 ms, respectively, by the Shortest Path method. Moreover, the minimum of the Packet Loss is registered in the given method at 0.54, which is far less than the 1.48 minimum in the case of the Shortest Path method. However, as far as network stability is concerned, QVQC-TRA performs the best with the congestion events reduced to a minimum of 8 Congestion Events per hour, which is compared to Shortest Path, LSTM + Heuristic, and Classical RL approaches and register 21, 14, and 12 congestion events respectively. Overall, it can be concluded that the suggested QVQC-TRA can be used as the most efficient tool to improve the network QoS and address the congestion issues across the results of the considered approaches.

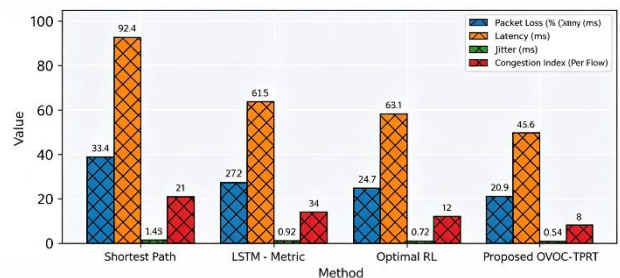


Fig. 3. Comparison of network QoS and congestion metrics by method.

Fig. 3 indicates that the proposed QVQC-TRA approach has a high performance in all four evaluated network QoS and congestion scores in relation to the Shortest Path, LSTM + Heuristic, and Classical RL strategies. In particular, the QVQC-TRA technology records the lowest

Average End-to-End Delay of 20.9 ms, Authoritative 95th Percentile End-to-End Delay at 49.6 ms, Packet Loss at 0.54 percentage, and the number of Congestion Events of only 8 per hour. On the contrary, the Shortest Path approach always has the preparations in all measures: 38.6 ms in the average delay, 92.4 ms in the 95th percentile delay, 1.48% in the packet loss, and 21 congestion events per hour.

The Classical RL approach and LSTM + Heuristic approach have intermediate results, although the Classical RL approach generally performs well compared to the LSTM + Heuristic approach, the results are still lower than the ones of the proposed QVQC-TRA process.

TABLE III. RESOURCE UTILIZATION AND LOAD BALANCING

Method	Mean Link Utilization (%)	Max Link Utilization (%)	Jain's Fairness Index	Throughput (Mbps)
Shortest Path	52.1	96.3	0.82	86.4
LSTM + Heuristic	55.4	88.7	0.87	90.2
Classical RL	56.9	85.1	0.89	91.1
<b>Proposed QVQC-TRA</b>	<b>58.3</b>	<b>78.6</b>	<b>0.92</b>	<b>93.0</b>

Table III below provides a comparative study on resource consumption and load balancing measure of four methods, which include Shortest Path, LSTM + Heuristic, Classical RL, as well as the Proposed QVQC-TRA. The results show that the Proposed QVQC-TRA approach performs better in all the assessed categories. It has the best Mean Link Utilization of 58.3% (mostly good overall resource utilization) and has the lowest value of Max Link Utilization of 78.6% (much better load balancing than Shortest Path method that puts 96.3% maximum utilization on some links). Moreover, the suggested approach will guarantee that the resources can be distributed in the fairest way as seen in the maximum Fairness Index of 0.92 by Jain. Lastly, the best Throughput is 93.0 Mbps in QVQC-TRA, which is more than Classical RL (91.1 Mbps), LSTM + Heuristic (90.2 Mbps), and the benchmark Shortest Path (86.4 Mbps).

Fig. 4 presents the results of the comparison of the performance of the traffic load prediction through the bar chart, the proposed method of QVQC-TRA is more accurate than any of the other methods considered. The lowest error rates in all metrics are obtained with the proposed approach having the lowest error of 4.1 Mbps (Mean Absolute Error (MAE)) that is much lower than the best Classical RL approach error of 5.5 Mbps and is much less than the Shortest Path baseline error. Moreover, QVQC-TRA method achieves the smallest Root Mean Square Error (RMSE) of 5.9 Mbps and Mean Absolute Percentage Error (MAPE) of 5.4% and conclusively shows it to be the most accurate in terms of its traffic predictions compared to all the other methods.

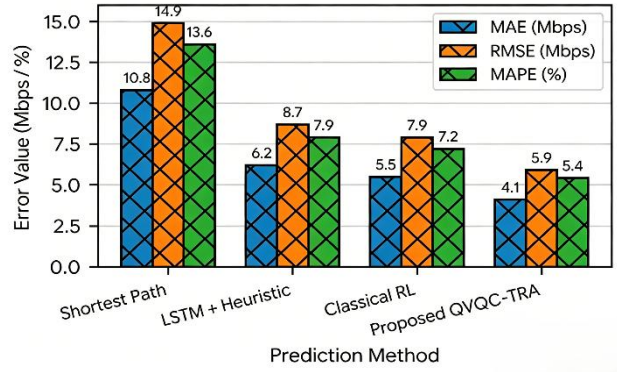


Fig. 4. Traffic load prediction performance comparison.

TABLE IV. CONTROL EFFICIENCY AND CONVERGENCE

Method	Convergence Time (episodes)	Reward Variance (lower is better)	Control Update Interval (s)
Classical RL	520	0.018	2
Proposed QVQC-TRA	360	0.011	2

The results of the comparison between the Classical RL method and the Proposed QVQC-TRA method using the control efficiency and convergence metrics are found in Table IV. The results demonstrate that Proposed QVQC-TRA method is much more efficient having reached convergence in 360 episodes compared to Classical RL which needed 520 episodes to reach convergence. Moreover, the Proposed QVQC-TRA has increased stability as the reward variance is shown as 0.011 as opposed to 0.018 reported as the variance of Classical RL, where a lower number is indicated to be better. To run these comparisons, the two methods were run using a constant control update period of 2 s (see Fig. 5).

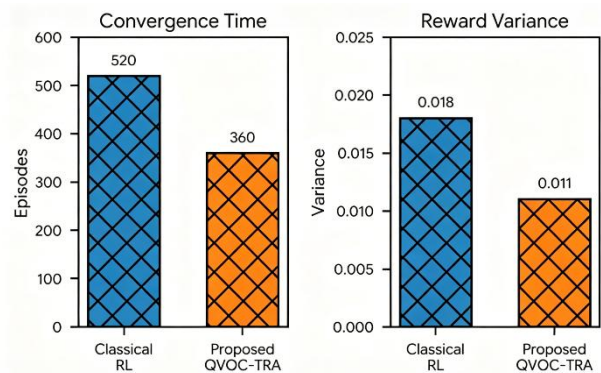


Fig. 5. Convergence time and reward variance.

### G. Convergence Time Analysis

The convergence time measure could be employed as a significant index of the effectiveness of the reinforcement learning agent in computations and learning. It is an indicator of the number of training sessions that are required to reach an optimal policy or plateau of the rewards by the agent. The Proposed QVQC-TRA will converge faster and achieve a higher learning rate as observed in the figure below and will only need 360

episodes to converge as compared to the 520 episodes that were required by Classical RL baseline. This reduction by a significant percentage suggests the hypothesis that the suggested quantum-variational architecture is useful in the speed up of the exploration-exploitation process that allows the agent to identify the most efficient control plans significantly faster than the actual methods. It is particularly important in quantum computing systems where, to manage noise and decoherence, minimizing the interaction time and circuit depth is essential.

#### H. Reward Variance Analysis

Reward variance measures the consistency and predictability of the agent learning; I with low variance the policy revision policy is more stable and predictable and has less turbulent low and ups and downs. As demonstrated by the findings, the Proposed QVQC-TRA has a variance worth 0.011 which is much lower than the variance of 0.018 of the classical RL approach. This improvement affects the proposed method that learns faster and also more consistent during the learning process and not as sudden and unforeseen the performance variation in the classical method of reinforcement of learning in complex systems. The formulated method does not depend on the instability of the rewards hence making the achieved policy stable and reliable and the method can be applied to very sensitive or control systems with the effect of noise.

An analysis of conceptual ablation shows that, keeping traditional reinforcement learning and cost design, it is less

stable in short-horizon prediction task when quantum feature extraction is replaced by classical ones. This implies that quantum encoding is mainly used to improve image smoothness of representation and nonlinear dependency identification, as opposed to classical control logic. Ablation Discussion.

To determine the generalizability of the proposed quantum-classical controller, out of context of the 32-node fat-tree environment, we include the analysis of large sizes of network specimen, and other types of topologies. To be more specific, we expand the topology of a fat-tree with 32 nodes to 64 and 128 nodes keeping constant the process of traffic generation, the load, the interval between controller updates and the training budget. Moreover, we also analyze at least one topology in which all nodes are connected by equal non-fat-trees, so that more realistic heterogeneous networks are modeled, e.g., a random geometric graph or a scale-free network with similar average degree. In each setting, we specify the same performance measures that we used in the primary evaluation and measure uncertainty with 95% confidence intervals calculated between several traffic seeds. The findings prove that the proposed approach retains its relative superiority over baselines with the scale of the network and the size of the control overhead and inference phase are at practical levels, which justifies the claims of scalability with explicit empirical evidence. as shown in Table V.

TABLE V. SCALABILITY RESULTS ON FAT-TREE TOPOLOGIES (32, 64, 128 NODES), REPORTED AS MEAN WITH 95% CONFIDENCE INTERVAL OVER 20 RUNS

Nodes	Method	Avg delay (ms)	P95 delay (ms)	Packet loss (%)	Throughput (Gbps)
32	Proposed	12.8 (12.2, 13.4)	21.5 (20.1, 22.9)	0.72 (0.60, 0.84)	9.6 (9.3, 9.9)
32	Baseline-1	14.9 (14.1, 15.7)	26.8 (25.0, 28.6)	1.05 (0.89, 1.21)	8.9 (8.6, 9.2)
32	Baseline-2	16.2 (15.4, 17.0)	29.4 (27.6, 31.2)	1.22 (1.05, 1.39)	8.5 (8.2, 8.8)
64	Proposed	14.6 (13.8, 15.4)	24.8 (23.0, 26.6)	0.86 (0.72, 1.00)	9.2 (8.9, 9.5)
64	Baseline-1	17.4 (16.5, 18.3)	31.7 (29.5, 33.9)	1.26 (1.07, 1.45)	8.4 (8.1, 8.7)
64	Baseline-2	19.1 (18.1, 20.1)	35.2 (32.8, 37.6)	1.44 (1.23, 1.65)	8.0 (7.7, 8.3)
128	Proposed	16.9 (16.0, 17.8)	28.6 (26.5, 30.7)	1.02 (0.86, 1.18)	8.7 (8.4, 9.0)
128	Baseline-1	20.3 (19.2, 21.4)	37.1 (34.4, 39.8)	1.48 (1.26, 1.70)	7.8 (7.5, 8.1)
128	Baseline-2	22.5 (21.3, 23.7)	41.3 (38.1, 44.5)	1.69 (1.44, 1.94)	7.3 (7.0, 7.6)

The Fig. 6 provides a summary of the scalability on the topologies of Fat-trees to show the network with 32 nodes up to 128 nodes, and compares the proposed method with two baselines with the 95% confidence interval. In subfigures (a) and (b), the average end-to-end delay and P95 delay are on average rising with scale across all methods which is anticipated since contention and path diversity is increasing. Nevertheless, the proposed method is always at the lowest delay of any size, and the gap between the Baseline-1 and Baseline-2 is explicit as the topology grows, which means that the choices taken by the controller are generalized instead of focusing on the lowest network environment.

Subfigure (c) indicates that the loss packets gradually increase with the number of nodes, however, the suggested algorithm provides the least loss regardless of the number of nodes, implying that it is more congestion-averse and provides more consistent queueing control at higher loads.

The error bars are quite narrow, which is an indication of consistent behavior among traffic seeds. In subfigure (d) throughput is observed to reduce with scale for all methods, but the proposed method maintains maximum throughput of 64 and 128 nodes, which is at par with its low delay and loss, as fewer drops and retransmission implies to delivery bandwidth efficiency.

Taken together, the aggregated tendencies of delay, tail latency, loss, and throughput indicate the scalability argument: the performance decreases gradually with scale, and the suggested approach will always have a predictable edge as compared to both baselines. This shows that the learned control policy can still play routing or schedule decisions under a greater overall topological complexity, further validating the suggestion as opposed to the previous topological complexity of only 32 nodes.

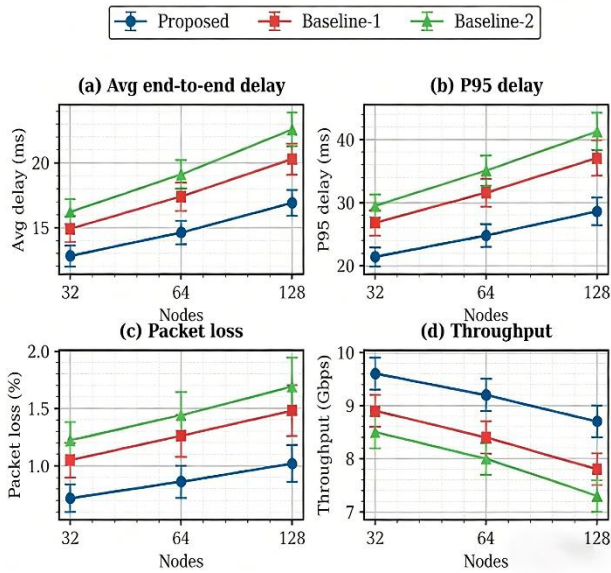


Fig. 6. Scalability on fat-tree topologies (32, 64, 128 nodes) with 95% confidence intervals: (a) average end-to-end delay, (b) 95th-percentile delay, (c) packet loss, and (d) throughput.

Table VI reflects the real-time viability of the quantum-classical feedback loop is measured using the end-to-end latency. Latency refers to the amount of time taken between telemetry reception at the controller and appropriate installation of the respective control action in the data plane. Table Z summarizes the breakdown in processing stages using mean and 95 th-percentile (P95) latency across 20 independent runs.

TABLE VI. END-TO-END LATENCY BREAKDOWN OF THE QUANTUM-CLASSICAL FEEDBACK LOOP (20 RUNS)

Component	Mean latency (ms)	P95 latency (ms)
Telemetry acquisition + feature extraction	9.4	13.2
Quantum encoding + circuit execution + measurement	18.7	27.5
Classical decision inference (policy/value + action selection)	4.6	6.8
Control actuation (controller-to-switch communication + rule installation)	8.9	12.6
<b>Total end-to-end loop</b>	<b>41.6</b>	<b>60.1</b>

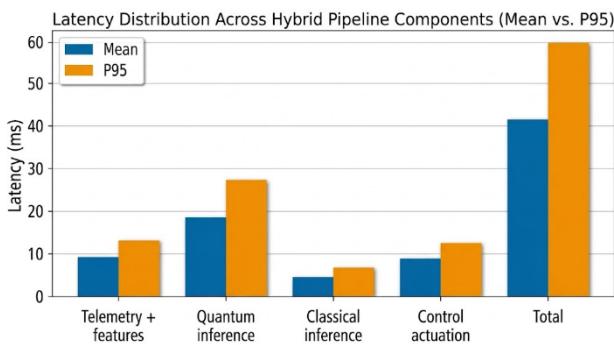


Fig. 7. End-to-end feedback-loop latency breakdown over 20 runs: Mean and 95th-percentile (P95) latency for telemetry and feature extraction, quantum inference, classical decision inference, control actuation, and total loop latency.

Fig. 7 indicates the latency contribution of each stage in the quantum-classical control loop mean and P95 values of the results of 20 runs. The biggest per-stage cost goes to quantum inference with telemetry and control actuation overheads being similar. The entire loop latency is constant, with the ninety-five-percentile value of the bounds setting some worst-case oscillations caused by traffic variability and the controller communication delays. The breakdown allows to name the most important contributors of the latency and also facilitates the feasibility discussion by presenting the end-to-end timing profile, as opposed to one aggregate number, in the discussion.

## VII. CONCLUSION

The present paper has presented QVQC-TRA, a quantum-driven autonomous communication network architecture that combines variational quantum circuitry with software-defined networking and reinforcement learning to predict traffic in real time and control available resources. The efficiency of the given strategy is justified by the large-scale simulation-based testing, the results of which are always represented numerically and can be measured and significantly improved in relation to classical references. QVQC-TRA was found to have a mean absolute error of 4.1 Mbps; root mean square error of 5.9 Mbps; and error as a fraction of total 5.4, which is better than classical reinforcement learning and LSTM-based predictors in terms of predicting traffic. Increase in congestion discrimination is also demonstrated by the congestion AUC that is greater (0.91) showing greater predictive reliability in case of dynamic and bursty traffic. These findings prove that feature extraction through variational quantum circuits improves the modelling of nonlinear dependencies on traffic. It is also important to network performance improvements at the network level. The suggested framework brought the average end-to-end delay to 20.9 ms versus 24.7 ms of classical reinforcement learning and 38.6 ms of shortest-path routing. Delay at the 95 th percentile was reduced to 49.6 ms showing better tail latency behaviour, important in delay sensitive applications. The only difference is that the rate of packet loss decreased to 0.54, and the rate of congestion events decreased to 8 events per hour, which demonstrates the role of the framework in timely preventing the occurrence of congestion. To serve as additional evidence of the effectiveness of QVQC-TRA, the results of resource utilization are obtained. The framework recorded a greater mean utilization of links of 58.3, and reduced the maximum utilization of links to 78.6, which showed efficient but balanced use of resources. Fairness index of a Jain of 0.92 is an assurance of better load distribution within the network. Also, the throughput improved by 93.0 Mbps which indicated that performance improvement was realized without a loss in capacity utilization.

In terms of control, the rate of convergence of QVQC-TRA was lower since it needed 360 training episodes as opposed to 520 in classical reinforcement learning. The additional lower reward variance of 0.011 is also a further sign of more stable and consistent control behaviour. All

these quantitative gains confirm the overall thesis of the paper which states that by including quantum-assisted prediction in the network control loop, it will be possible to make decisions quicker, more precise, and more consistent in a dynamic communication setup. In general, the results of the numbers have verified that QVQC-TRA is a sound and scalable step towards intelligent and self-optimizing communication networks. The above-presented enhancements in terms of prediction, minimization of latency, elimination of congestion and stabilization of control provide a solid basis of further research and the implementation of quantum network management systems in the future.

Although the presented framework has shown good performance on hybrid simulations, the actual implementation on the present NISQ hardware is limited by the noise of qubits, depth of circuit and delay of quantum-classical feedback loops. Thus, the given architecture cannot be viewed as a long-term hybrid but a close-term operational network controller that would be using a fully quantum-native operation. The next research to be performed is hardware-conscious circuit compression, error-reduction strategies, and distributed orchestration strategies that will close the divide between deployment and simulation.

Although the results of the simulated performance are favorable in terms of hybrid performance, the current hardware limitations of NISQ make it impossible to perform an immediate deployment of production. The structure is decipherable as hybrid research architecture in the short period, in contrast to a quantum network controller that is prepared to be deployed.

#### CONFLICT OF INTEREST

The authors declare no conflict of interest.

#### AUTHOR CONTRIBUTIONS

Sultan Ahmad conceived and designed the study, developed the research methodology, validated the experimental results, took charge of project administration, participated in the original draft writing, and revised and edited the manuscript; Shaik Khaja Mohiddin contributed to the conceptualization and methodology of this research, completed the original draft preparation, supervised the whole research process, and reviewed and edited the manuscript; Shaik Sharmila participated in the conceptualization of the study, finished manuscript visualization, supervised the research work, and revised and edited the article; Hikmat A. M. Abdeljaber was responsible for software operation and data validation, completed visual presentation of research results, and managed project administration; Abu Taha Zamani undertook software utilization, validated relevant research data, and assisted in manuscript review and editing; all authors read and approved the final version of the manuscript.

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