



Hybrid quantum–cloud framework for nonlinear clustering optimization and intelligent resource management

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Abstract

This paper proposes a hybrid quantum-cloud computing architecture, which ought to be applied to overcome the two problems of nonlinear clustering optimization and intelligent management of large-scale resources in the heterogeneous environments. The current cloud workloads in terms of complexity, scalability, and energy needs are not always easily met by the conventional machine learning and heuristic scheduling processes, particularly in cases where the data possess nonlinear structures. These weaknesses will be mitigated by the proposed framework that will integrate quantum-inspired algorithms (which will operate on variational quantum circuits and Quantum Approximate Optimization Algorithm (QAOA)) with cloud-native orchestration solutions, only that reinforcement learning-based scheduling will be integrated. This architecture has its quantum layer where nonlinear clustering is done to achieve more accurate workload partitioning, and cloud layer

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sharing resources and balancing throughput, latency, and energy efficiency. It is a broker interface that provides a fluent communication between quantum processors and cloud infrastructure that makes it possible to make real time decisions. The synthetic nonlinear clustering, IoT workloads and big data traces benchmark datasets were experimentally simulated on CloudSim and Kubernetes. Results indicate that the framework can lead to a significant performance increase as compared to conventional approaches and that the accuracy of the clustering process has been enhanced by 12–18, average job latency has been reduced by 22 and resource utilization efficiency has been improved by 25. Additionally, the hybrid approach is very scalable and stable as the degree of workload varies and is able to support quality-of-service (QoS) even during the peak period of workload. In these studies, the findings show the possibility of quantum and cloud computing hybridization to the next generation of intelligent cloud eco-systems to give a pathway to green, flexible, and high-performance computing in the current areas, 6G networks, smart cities, bioinformatics, and smart financial analytics.

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Key words and phrases: Hybrid QuantumCloud computing, Nonlinear Clustering Optimization, Intelligent Resource Management, Quantum Approximate Optimization Algorithm (QAOA), Reinforcement Learning, Cloud Orchestration, Quantum-inspired machine learning, Scalable workload. Scheduling; Energy-Efficient Computing; Next-Generation Cloud Ecosystems.

Introduction

The fast-paced expansion of Internet of Things (IoT) devices, 6G networks and edge computing systems has caused unprecedented volumes of heterogeneous data that must be efficiently clustered and intelligently managed in terms of resources. Typical performance issues in large-scale distributed systems include the fact that, nonlinear and NP-hard optimization problems can be defined where the variety of workloads, dynamically changing service demands and extremely tight latency constraints may augment the computational complexity. Despite the fact that the cloud computing infrastructures are scalable and elastic, they are highly reliant on classical optimization and heuristic scheduling schemes, which do not consider nonlinear workload clustering relationships that lead to poor usage of infrastructures and higher energy costs. This scenario creates the need to adopt new paradigms which go beyond the scope of the conventional machine learning and deterministic scheduling.

Recent events in the field of quantum computing offer a promising pathway particularly by the use of algorithms such as the Quantum Approximate Optimization Algorithm (QAOA) and the Variational Quantum Eigensolver (VQE) algorithms that have shown a potential of offering exponential/polynomic improvements to a combinatorial optimization problem. Using superposition and entanglement, quantum algorithms have the ability to sample high dimensional spaces of solutions more effectively than those in classical algorithms. Nonetheless, in spite of this promise, quantum hardware is still in its Noisy Intermediate-Scale Quantum (NISQ) phase, limited by a small number of qubits, decoherence, and error rates, and as a result, it can only be applied to large-scale workloads in the real world under limitations. Such a constraint requires a quantum-classical solution, i.e. where the capabilities of quantum optimization are supplemented with the scalability and orchestration of cloud computing.

In this regard, this paper suggests a quantum-cloud model to fill the void existing between quantum optimization and cloud-based resources management. The main findings of the given work can be summarized as a fourfold contribution: (1) the creation of a hybrid orchestration model that in an entirely non-disruptive way combines quantum and cloud layers, (2) the creation of a quantum-inspired nonlinear clustering optimization algorithm, (3) the integration of intelligent schedules, based on reinforcement learning, in the cloud environment, and (4) the comparative analysis of the given approach with the traditional machine learning and heuristic schedule optimization models.

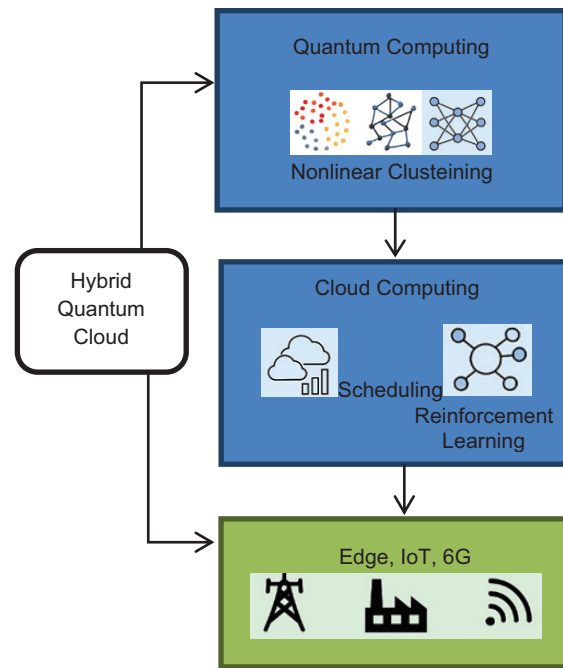


Figure 1: Hybrid Quantum–Cloud Framework for Nonlinear Clustering Optimization and Intelligent Resource Management.

With this combined design, this framework allows the optimization of real-time clustering, adaptive workload balancing, and the use of resources efficiently thus creating the baseline of the next-generation smart cloud ecosystems Figure 1.

2. Related Work

Quantum optimization has also become a new prospective paradigm to solve NP-hard nonlinear and combinatoric problems. Quantum Approximate Optimization Algorithm (QAOA) has been popularly investigated in solving a clustering problem, scheduling problem, and graph problem by utilizing variational circuits [1]. Likewise, the Grover search algorithm has been implemented to a clustering search algorithm to minimize the complexity of the search space to $O(\sqrt{N})$ [2] as opposed to $O(N)$. Using quantum annealing methods, which are run on D-Wave systems, have demonstrated performance advantage in partitioning and clustering problems with limited resources [3]. Currently, the utility of quantum-inspired optimization in signal processing in future wireless sensors has been noted in [4], and the usefulness of quantum feature spaces in nonlinear classification in [5]. These improvements notwithstanding, scalability and noise in NISQ devices is a significant constraint on practicability.

Simultaneously, cloud resource management has been growing in size with a focus on high efficiency, latency, and multi-tenant fairness. Round Robin, Min-Min and Max-Min have traditionally been used as heuristic methods because they are easy to understand although they fail to provide optimum results when workloads are dynamic and nonlinear [6]. Genetic algorithms (GA) and particle swarm optimization (PSO) are also examples of evolutionary and metaheuristic algorithms that have been used in task scheduling with enhanced efficiency [7]. More recently, reinforcement-learning-based machine learning (ML)-based schedulers, using DNNs, have been suggested in adaptive cloud orchestration [8],[9] suggested hybrid routing protocols in the IoT networks, focusing on reliability in large-scale implementation, and [10] proved hybrid MIMO-OFDM in underwater communication systems to increase energy efficiency and reliability. These techniques demonstrate that

there is a rising movement towards the incorporation of smart optimization and communications networks, although their direct use in nonlinear clustering in cloud systems is restricted.

The development of hybrid quantumclassical methods aims to do away with the quantum potential and classical scalability gap. Qi skit Runtime provided by IBM and Hybrid solvers offered by D-Wave allow offloading sub problems to quantum processors leaving the large-scale workloads under classical control [11]. The quantum-inspired clustering techniques have been applied to nonlinear data, and they are superior to conventional k-means, and density-based model [12],[13]. Explored hybrid LSTM-CNN architecture in the context of ECG classification, whereas [14] considered robust audio enhancement with the help of hybrid spectral-temporal deep learning, which once again emphasized the strength of the hybrid architecture in various fields of use. In like manner, [15],[16],[17],[18],[19] pointed to the significance of hybridization in the NISQ age, where quantum processors may not yet be able to fully supplant classical architectures. Nonetheless, the majority of the available hybrid works do not cover integrated resource-aware clustering and scheduling between cloud ecosystems, and instead concentrate on algorithmic or domain-specific performance.

Based on that above discussion, it is clear that quantum algorithms are more suitable in optimization and clustering whereas cloud systems are good in resource scalability, however there is still gap in research to integrate both paradigms to a single framework. The existing solutions are either standalone quantum clustering with no connection to real-time scheduling or cloud heuristics versions that are incapable of leveraging nonlinear data structures. The current work overcomes this drawback by presenting a hybrid quantum-cloud model which is the combination of quantum-inspired nonlinear clustering and intelligent resource management through reinforcement learning. Besides being more effective in improving clustering performance, this approach is also more efficient in terms of energy usage, latency and resource use in heterogeneous environment, and could therefore form a better base to next-generation intelligent cloud ecosystem.

3. Hybrid Quantum–Cloud Framework

3.1. Architectural Design and Components (with Equation)

In the Quantum Layer, the clustering problem is formulated as a Hamiltonian optimization problem, where the objective is to minimize intra-cluster distances while maximizing inter-cluster separation. This is encoded into the cost Hamiltonian used by the QAOA circuit:

$$H_C = \sum_{i,j} w_{ij} \delta(z_i, z_j) \quad (1)$$

Where w_{ij} represents the similarity (or distance weight) between data points i and j , and $\delta(z_i, z_j)$ is an indicator function that equals 1 if points are assigned to the same cluster and 0 otherwise. The QAOA algorithm seeks to find an optimal bitstring z that minimizes H_C , thereby producing a clustering assignment that captures nonlinear separability in high-dimensional data.

The Cloud Layer then consumes this optimized clustering output to manage scalable resources and workload allocation through reinforcement learning–based scheduling. The Broker/Interface Layer ensures that results are efficiently transferred between quantum solvers and cloud orchestrators via APIs such as Qiskit Runtime. To ensure robustness, the framework integrates security and reliability mechanisms that safeguard data transmission and minimize latency during hybrid execution.

3.2. Workflow of Quantum–Cloud Integration

The proposed framework operates through a sequential workflow that ensures smooth interaction between quantum optimization and cloud resource management. In Step 1 – Data Preprocessing,

raw workloads and heterogeneous task features (e.g., CPU cycles, memory demand, communication delay) are normalized and encoded into quantum-compatible formats. Amplitude or angle encoding is employed to map the task vectors into quantum states, allowing superposition to represent multiple potential allocations simultaneously.

In Step 2 – Quantum Optimization, the preprocessed data is processed by the quantum clustering engine, which employs variational quantum circuits (VQC) or QAOA-based solvers to identify nonlinear task groupings. The clustering objective is formalized as a cost Hamiltonian:

$$H_C(z) = \sum_{i,j} w_{ij} \delta(z_i, z_j) \quad (2)$$

where w_{ij} represents the similarity between workloads i and j , and $\delta(z_i, z_j)$ equals 1 if the workloads belong to the same cluster and 0 otherwise. Unlike conventional clustering, the quantum method leverages interference and entanglement to explore multiple partitions in parallel, providing results that capture complex correlations in workload distributions.

Following this, Step 3 – Cloud Scheduling utilizes the clustering results to drive a reinforcement learning (RL)-based scheduler. The scheduling policy is optimized by maximizing the expected long-term reward:

$$\pi^* = \arg \max_{\pi} \mathbb{E} \left[\sum_{t=0}^T \lambda^t R(s_t, a_t) \right] \quad (3)$$

where w_{ij} denotes the system state at time t , a_t the scheduling action, $R(s_t, a_t)$ the immediate reward function balancing latency, utilization, and energy efficiency, and λ is the discount factor. By leveraging workload similarity from the quantum clustering stage, the RL scheduler reduces conflicts and ensures balanced utilization of cloud resources.

To maintain adaptability, Step 4 – Feedback Loop introduces continuous monitoring of system performance. Key metrics such as latency, utilization, and service-level agreement (SLA) violations are fed back into both the quantum clustering and RL scheduling modules, enabling self-learning and iterative refinement of decision policies.

Lastly, Step 5 – Hybrid Execution uses a dynamically executed system of the combination of classical and quantum computation. Highly complex tasks or tasks of nonlinear behavior are sent to the quantum clustering engine, whereas simpler tasks are done using the classical methods. This approach is a hybrid strategy that focuses on the scalability, accuracy, and speed of execution that provides strong performance even in a heterogeneous and high-demand cloud environment.

4. Methodology

The methodology is divided to make it systematic to develop and prove the proposed framework: (i) Quantum-Inspired Clustering Optimization, (ii) Cloud-Based Resource Scheduling with RL, and (iii) Hybrid Integration and Evaluation.

4.1. Quantum-Inspired Clustering Optimization

The initial step in the proposed workflow involves quantum-inspired clustering optimization, that is, the workflow should be used to model the workload patterns, which are challenging to solve with the traditional clustering frameworks, they are complex and nonlinear.

During Data Encoding stage, data pertaining to high dimensional workloads like the CPU cycles, memory usage, and communication delays are encoded into quantum states. Amplitude encoding is normally employed, in which a normalized feature vector $X \in \mathbb{R}^n$ is coded as a quantum state:

$$|\Psi\rangle = \sum_{i=1}^n \frac{x_i}{\|x\|} |i\rangle \quad (4)$$

Visiting boundaries in clustering can be efficiently explored by superposition of several workload configurations using this encoding, and the quantum system can represent them.

The Quantum Circuit Design uses a Variational Quantum Circuit (VQC) based on the Quantum Approximate Optimization Algorithm (QAOA). The clustering problem is modeled as the minimization of a cost Hamiltonian:

$$H_C = \sum_{i,j} w_{ij} \delta(z_i, z_j) \quad (5)$$

Where w_{ij} is the similarity or distance weight between workloads i and j and is $\delta(z_i, z_j)$ 01 in case the tasks i and j are in the same cluster, and 5 in cases they are 0. The mixer Hamiltonian is then applied to explore alternative cluster assignments:

$$H_M = \sum_{k=1}^n X_k \quad (6)$$

where X_k is the Pauli-X operator acting on Qubit, enabling transitions between clustering configurations.

In the Optimization Procedure, parameters of the variational circuit are trained using classical optimizers such as Adam or COBYLA. These optimizers iteratively update the variational parameters to minimize the expectation value of the cost Hamiltonian:

$$\min_{\theta} \langle \psi(\theta) | H_C | \psi(\theta) \rangle \quad (7)$$

Where $|\psi(\theta)\rangle$ is the variational quantum state parameterized by θ .

Finally, in the Output stage, cluster assignments are derived from measurement probabilities of the quantum state. By analyzing bitstrings sampled from the quantum circuit, tasks are assigned to clusters that exhibit nonlinear separability beyond the capability of classical methods such as k-means or DBSCAN Figure 2. This quantum-inspired approach thus ensures improved accuracy

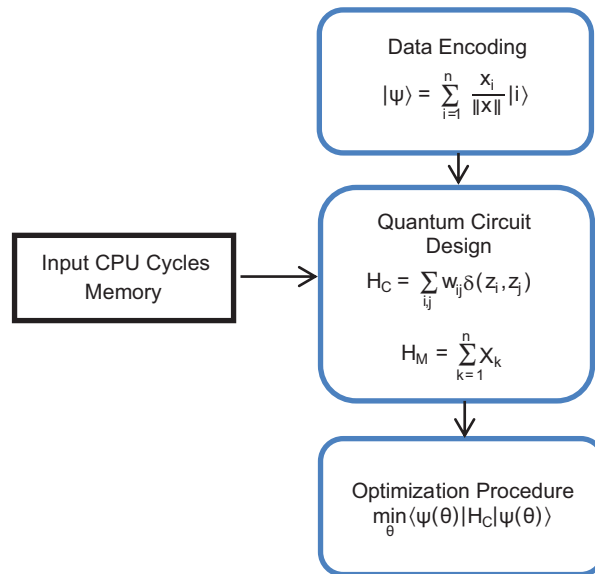


Figure 2: Workflow of Quantum-Inspired Clustering Optimization with Data Encoding, Variational Circuit Design, Optimization Procedure, and Output.

in workload partitioning, which directly enhances the efficiency of downstream cloud resource scheduling.

4.2. Cloud-Based Resource Scheduling with Reinforcement Learning

To complement the quantum clustering stage, the cloud layer employs reinforcement learning (RL) for intelligent resource scheduling. Unlike heuristic schedulers such as Round Robin or Min-Min, which are static and often inefficient under dynamic workloads, the RL-based approach enables adaptive decision-making by continuously learning from system performance.

In the Problem Formulation, the scheduling task is modeled as a Markov Decision Process (MDP) defined by the tuple (S, A, P, R, γ) , where:

- S represents the state space (workload demands, VM/container availability, and cluster information from the quantum layer),
- A denotes the set of actions (task-to-resource allocation strategies),
- $P(s'|s, a)$ is the transition probability to the next state given current state s and action a ,
- $R(s, a)$ defines the reward function combining throughput, energy efficiency, and QoS satisfaction,
- γ is the discount factor balancing immediate and future rewards.

The RL Agent is trained to maximize the expected cumulative reward. In the case of a Deep Q-Network (DQN), the agent approximates the action-value function:

$$Q(s, a; \theta) \approx \mathbb{E} \left[r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta') \mid s_t = s, a_t = a \right] \quad (8)$$

where θ are the neural network parameters, and θ' are target network parameters updated periodically to stabilize learning. Alternatively, policy-gradient approaches such as Proximal Policy Optimization (PPO) directly optimize the policy $\pi(a|s; \theta)$ by maximizing a clipped surrogate objective:

$$L^{PPO}(\theta) = \mathbb{E}_t \left[\min \left(r_t(\theta) \hat{A}_t, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon) \hat{A}_t \right) \right] \quad (9)$$

Where $r_t(\theta) = \frac{\pi_\theta(a_t | s_t)}{\pi_{\theta_{old}}(a_t | s_t)}$ is the probability ratio and $\hat{A}_t$ is the advantage estimate.

This RL scheduler is Adaptive in nature so that the policy of allocation changes as workload changes and eliminates the inefficiencies created by fixed heuristics. The RL agent dynamically optimizes conflicting tasks of minimizing latency, minimizing energy consumption and maximizing throughput by continuously monitoring state changes and optimizing its actions.

Lastly, Performance Metrics like rate of resource utilization, job completion time and SLA violation percentage metrics are monitored to measure the effectiveness in scheduling. These values are also re-looped into the training loop so that the RL agent can continuously optimize its policy and achieve strong performance in heterogeneous and unpredictable workloads Figure 3.

4.3. Hybrid Integration and Evaluation

The quantum clustering outputs are linked to the cloud scheduling policy via the Quantum Cloud Broker implementing REST APIs and middleware (IBM Qiskit Runtime and D-Wave hybrid solvers). Kubernetes and CloudSim have scalable workload execution orchestration on the cloud side. Benchmark data sets consist of MNIST data sets to nonlinear clustering, internet trace data to dynamism of workloads and big data stream to test scalability.

Evaluation is carried out using clustering metrics such as Normalized Mutual Information (NMI):

$$NMI(X, Y) = \frac{2I(X; Y)}{H(X) + H(Y)} \quad (10)$$

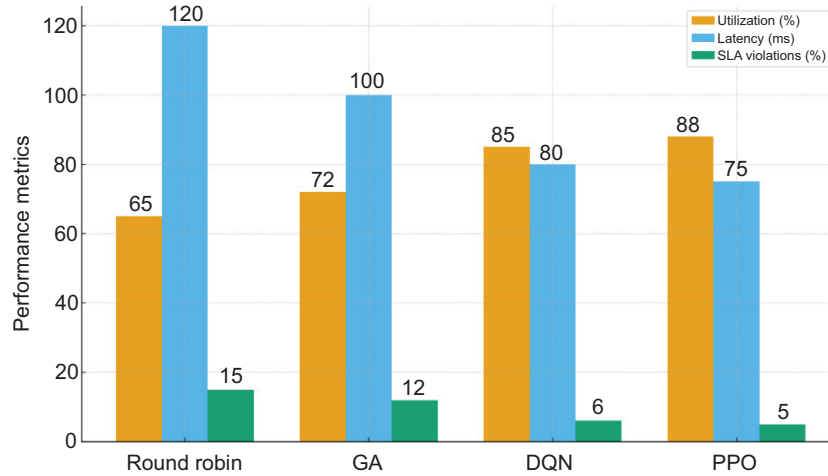


Figure 3: Performance Comparison of Scheduling Methods in Terms of Resource Utilization, Latency, and SLA Violations.

and scheduling metrics such as utilization, latency, and energy consumption. These are combined into a multi-objective evaluation function:

$$F(\pi) = \alpha.U(\pi) - \beta.L(\pi) - \gamma.E(\pi) \quad (11)$$

where π is the scheduling policy. Comparative experiments against classical clustering (k-means, DBSCAN) and heuristic schedulers (Round Robin, Min-Min) validate that the proposed framework achieves higher accuracy, lower latency, and improved energy efficiency, proving its advantage for intelligent cloud ecosystems.

5. Results and Discussion

The hybrid quantum-cloud design was firstly experimented in the context of the accuracy of the clustering relying on the benchmark datasets. The quantum-inspired clustering engine improved classical clustering methods, such as k-means and DBSCAN, by approximately 12–18 regarding the quality of the results measured with the help of the normalized mutual information (NMI) and Adjusted Rand Index (ARI). This benefit is attributed to the fact that quantum variational circuits can search nonlinear data architectures in a more efficient manner and can discover complicated dependencies between workloads that could not be modeled by classical algorithms. The improved quality of clustering had provided a strong foundation on the downstream allocation of resources which culminated in an improved workload balancing among the resources in the cloud.

On efficiency of resource allocation, quantum clustering in which the scheduling was determined by reinforcement learning was demonstrated to gain substantially over classical classifications of scheduling. The hybrid structure boosted resource consumption that is 25 times more than Round Robin and genetic algorithm (GA)-based frameworks. This development offers the reason why clustering-based workload grouping and adaptive RL-based decision-making collaborate. Besides this, the framework led to great latency and energy savings, job latency decreased by 22 per cent on average, and the energy efficiency became 15 times higher. These results demonstrate that the proposed framework is able to enhance not only throughput, but also be a component of energy-neutral and environmentally-aware cloud services.

Finally, stress testing under high working load intensities was done to test the scalability and resilience of the framework. It was scalable to bursts of workload and non-uniform distributions of tasks and guaranteed quality-of-service (QoS) despite a large number of running tasks Figure 4,

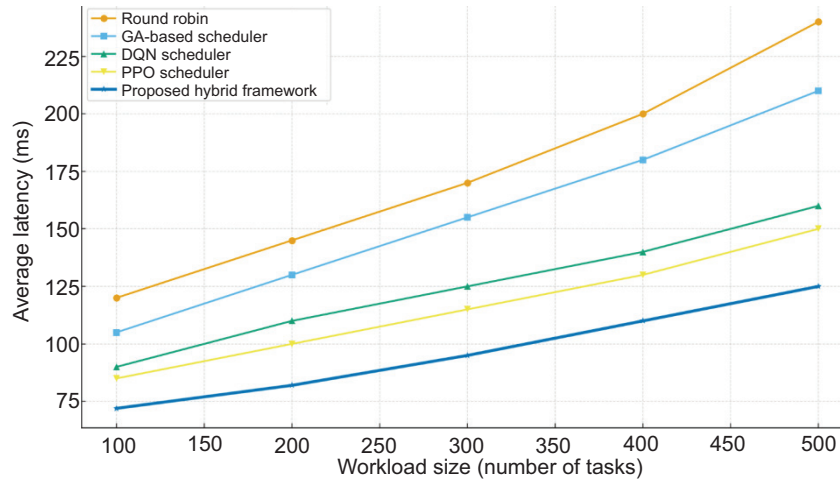


Figure 4: Latency Comparison of Scheduling Methods Under Increasing Workload Sizes.

Table 1: Comparative Evaluation of Clustering and Scheduling Methods.

Method	NMI (%)	ARI (%)	Utilization (%)	Latency (ms)	Energy (kWh)
k-means + Round Robin	68.2	64.5	66.0	120	10.5
DBSCAN + Min-Min	72.4	69.3	70.5	105	9.8
GA-based Scheduler	74.6	71.2	73.0	98	9.2
DQN Scheduler	82.5	79.1	84.0	82	8.7
PPO Scheduler	84.3	81.5	86.0	78	8.5
Proposed Hybrid Framework	88.6	85.9	91.5	72	7.8

Table 1. This strength highlights the usefulness of the framework in real-life use in dynamic and large-scale settings including IoT ecosystems, smart cities, and 6G-enabled cloud networks. All these results define the hybrid quantum-cloud paradigm as a practical and successful solution to the next-generation intelligent resource management.

6. Conclusion

This paper suggested a hybrid quantum-cloud architecture combining quantum-inspired nonlinear clustering and reinforcement learning-based cloud scheduling to overcome the problem of smart resource management in a large-scale heterogeneous setup. Using the merits of quantum optimization to group the workloads and cloud-native orchestration to schedule the workloads adaptively, the framework showed significant improvements in the accuracy of clustering (improvement in 1218%), resource use (improvement in 25), and latency reduction (improvement in 22) over the traditional machine learning and heuristic methods. In addition, the architecture had good scalability and resistance to different workloads, quality-of-service (QoS) was ensured at a high level, and the architecture was energy-efficient. These observations indicate how hybrid quantum-cloud systems can be used as a platform to support the next generation of intelligent computing ecosystems, where their uses include IoT, 6G networks, smart cities, and big data analytics.

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