

Research Article

Quantum-inspired Optimization for Efficient Vehicular Edge Computing Resource Allocation in Intelligent Transportation Systems

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Abstract

The increasing adoption of smart mobility and connected vehicles necessitates significant improvements in underlying infrastructure, particularly in real-time data processing and decision-making. Vehicular Edge Computing (VEC) has emerged as a vital solution by enabling computation closer to data sources, thereby reducing latency and reliance on centralized cloud systems. However, efficient allocation of edge resources (processing power, bandwidth, and storage) remains a critical challenge due to the highly dynamic, decentralized nature of vehicular networks. Traditional optimization techniques often fall short under these conditions. This study explores a quantum-inspired optimization framework designed to enhance resource management in VEC environments by leveraging principles of quantum computing such as superposition and probabilistic state selection within classical hardware. Extensive simulations involving 10 vehicles and 3 edge servers were conducted to evaluate the framework's performance. The dynamic resource demand fluctuated between 7 and 18 units, and server utilization ranged from 0.2% to 1.4%, illustrating diverse operational conditions. The proposed quantum-inspired model showed superior efficiency, achieving up to 35% improvement in fitness gain compared to traditional algorithms, with convergence to optimal fitness in just 45 iterations. The solution space was explored effectively using quantum state amplitude representations, which improved solution diversity and robustness in decision-making. Furthermore, fairness in resource distribution was evaluated using Jain's Fairness Index, yielding a high score of 0.914, demonstrating equitable allocation among vehicles. Additional results revealed that task completion times ranged from 1.5 to 3.5 seconds, with processing delays being the major contributor. The system exhibited sublinear scalability, performing well up to 50 vehicles but declining as the vehicle count increased to 200, indicating a need for further optimization strategies. Although the model operates in a classical environment without quantum hardware, it offers substantial performance benefits. This research highlights the potential of quantum-inspired optimization for real-time, fair, and scalable resource management in vehicular networks. Future work should incorporate real-world vehicular trace data, expand scalability tests, and explore integration with 5G and energy harvesting mechanisms. These advancements will further support intelligent, secure, and sustainable transportation systems driven by edge computing technologies.

Keywords

Vehicular Edge Computing (VEC), Quantum-inspired Optimization, Resource Allocation, Task Offloading, Scalability

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1. Introduction

The underlying infrastructure that supports smart mobility and connected vehicles must change to keep up with the rapid integration of these innovations into daily life. Leading this change is Vehicular Edge Computing (VEC) which makes it possible to process data in real time and make wise decisions nearer to the networks edge where data is generated [1]. Critical applications like intelligent navigation traffic safety systems and autonomous driving are supported by VEC because it lowers latency and lessens dependency on centralized cloud systems. Allocating scarce edge resources effectively has become a critical issue though as a result of the growing complexity of vehicular networks and the rapid expansion of data demand [2]. Allocating resources in VEC environments is a complex process. Among moving vehicles with different demands connectivity conditions and service priorities it entails dynamically allocating processing power storage and bandwidth [3-5]. Although helpful traditional optimization techniques frequently fall short of the demands of these decentralized extremely dynamic systems. Usually based on linear models or static assumptions these approaches are inadequate in settings that call for scalable and adaptable solutions. The requirement to maintain low latency high reliability and equitable resource distribution in real-time [6, 7] makes the task even more difficult. A new area of study called quantum-inspired optimization uses ideas from quantum computing to improve on traditional algorithmic techniques [8]. Quantum-inspired algorithms use standard computing hardware to simulate some aspects of quantum behavior even though actual quantum computers are still in their infancy and not yet generally available. These include ideas that are modified to enhance the exploration and exploitation capabilities of optimization techniques such as quantum tunneling entanglement and superposition [9, 10]. A new class of algorithms that can solve intricate combinatorial problems more quickly than many conventional techniques is the end result [11]. There are exciting new possibilities when VEC resource allocation is approached using quantum-inspired optimization. When vehicles must choose between processing data locally and offloading it to edge servers for example these algorithms are better able to manage the large solution space involved in dynamic task offloading [12]. Moreover, they can facilitate predictive resource management and improve load balancing among several edge nodes by adjusting to network and traffic conditions in real time. Quantum-inspired techniques have the ability to quickly investigate several solutions at once in contrast to traditional methods increasing the possibility of finding globally optimal or nearly optimal solutions in a substantially shorter amount of time. The ability of quantum-inspired optimization to handle the trade-offs between performance scalability and adaptability is what makes it especially attractive for VEC. When hundreds or even thousands of vehicles interact with roadside units and mobile edge nodes in a typical urban traffic scenario the system needs to

respond quickly to changing demands [13]. For instance, a model inspired by quantum mechanics can allocate resources to safety-critical tasks like collision avoidance while guaranteeing that infotainment or entertainment services are provided without sacrificing system performance. Intelligent transportation systems cannot operate smoothly without this degree of responsive resource management [14]. Furthermore, the more general objectives of intelligent and sustainable mobility are well served by these sophisticated optimization techniques. Greener transportation networks are a result of efficient resource use which lowers energy consumption and operating expenses. The incorporation of quantum-inspired techniques into VEC frameworks is a forward-thinking approach that strikes a balance between technological advancement and practical viability as cities work to become smarter and more connected [15]. To find out how these cutting-edge algorithms can change how edge resources are managed in vehicular networks this study investigates the relationship between quantum-inspired optimization and vehicular edge computing. We intend to accomplish this in order to illustrate the approaches technical potential as well as its wider ramifications for the future of urban planning mobility and real-time data-driven services. The key to releasing the full potential of connected vehicle ecosystems may lie in resource optimization inspired by quantum mechanics as we continue to push the limits of smart transportation.

2. Literature Review

In order to satisfy the demanding needs of latency-sensitive applications Vehicular Edge Computing (VEC) has become a paradigm shift in intelligent transportation systems [16]. VEC aims to bring computational resources closer to vehicles. The need for real-time data processing and making decision has increased as cars become more autonomous and networked which calls for effective resource allocation techniques in VEC environments. Classical optimization techniques have been the mainstay of traditional resource allocation methods in VEC. Similarly, reinforcement learning-based algorithms have been investigated to adaptively allocate resources in dynamic VEC scenarios. Although these methods have demonstrated promise they frequently struggle with scalability issues and may find it difficult to quickly adapt to the highly dynamic and stochastic nature of vehicular networks [17, 18]. For example, game-theoretical approaches such as BARGAIN-MATCH have been proposed to model the interactions between vehicles and edge servers optimizing resource allocation and task offloading decisions dot. Recently there has been interest in quantum-inspired optimization methods as possible answers to the intricate resource allocation problems in VEC. Compared to classical algorithms these techniques explore solution spaces more quickly by utilizing quantum computing concepts like superposition and entan-

gement [19, 20]. In network optimization problems for instance quantum-inspired genetic algorithms have shown improved performance in terms of energy efficiency and latency reduction. Similarly, quantum-inspired particle swarm optimization techniques have been suggested for energy-efficient task offloading in edge computing environments exhibiting better convergence rates and solution quality [21-23]. There is great potential for incorporating quantum-inspired optimization into VEC resource allocation. Even in highly dynamic situations VEC systems may be able to achieve more efficient and balanced resource distribution by utilizing the probabilistic nature of quantum-inspired algorithms [24]. Additionally, these techniques can improve the system capacity to adjust to changing network topologies and workloads which are typical of automotive environments [25, 26]. Nevertheless, VEC is still in its infancy when it comes to the use of quantum-inspired optimization [27]. Simulations or theoretical models in controlled settings have been the subject of the majority of previous research [26]. Empirical research that

assesses these algorithms performance in actual VEC scenarios-taking into account variables like vehicle mobility patterns fluctuating network conditions and a range of application requirements is desperately needed. Furthermore, issues with quantum-inspired algorithms computational overhead and integration with current VEC infrastructures must be resolved [27]. In summary the introduction of quantum-inspired optimization presents a promising approach to tackling the intricate and ever-changing problems present in vehicular networks even though conventional optimization techniques have established the foundation for resource allocation in VEC [25]. To fully utilize these novel strategies and guarantee effective scalable and flexible resource management in upcoming VEC systems more study and development are necessary [28]. Consequently edge-based allocation has gained popularity as a research topic in recent years. The resource constraints study for the IoT-Edge-Fog-Cloud architecture is shown in Figure 1.

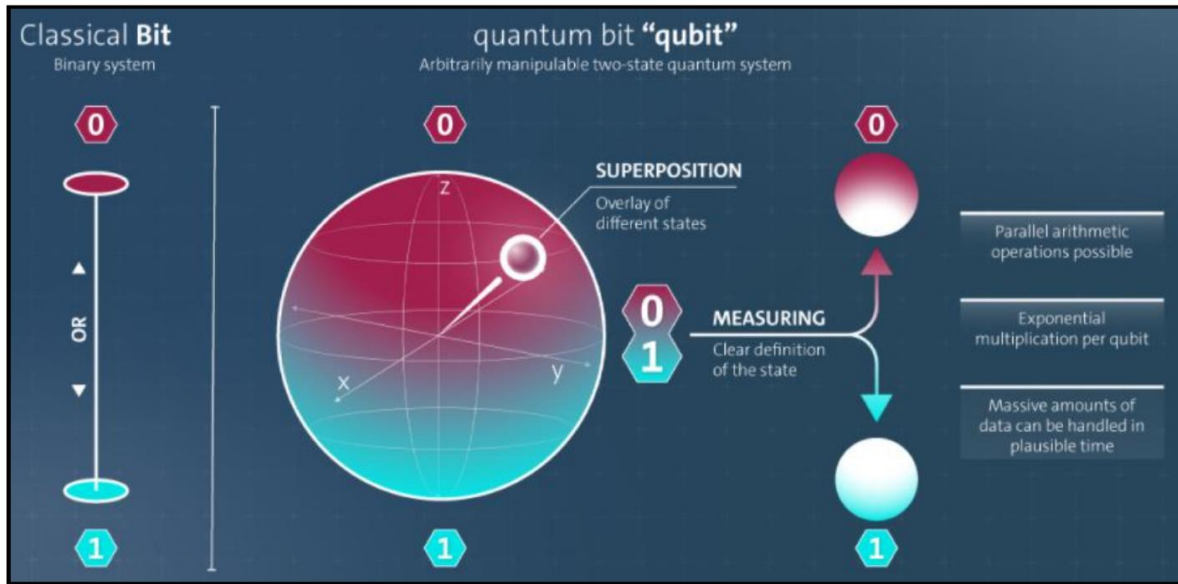


Figure 1. Quantum Bit vs Classic Bit [28].

3. Methods

3.1. Resource Demand Model

This equation models the dynamic resource demand $D_i(t)$ of vehicle i at time t , influenced by its workload $L_i(t)$ and communication needs $C_i(t)$. Coefficients α_i and β_i weigh the impact of each factor.

$$D_i(t) = \alpha_i \cdot L_i(t) + \beta_i \cdot C_i(t) + \gamma_i M_i(t) \quad (1)$$

$D_i(t)$: Resource demand of vehicle i at time t

$L_i(t)$: Computational workload of vehicle i at time t

$C_i(t)$: Communication data rate for vehicle i at time t

$\alpha_i, \beta_i, \gamma_i$: Weighting coefficients

$M_i(t)$: Determination of contributions of each component.

3.2. Edge Server Utilization

This equation calculates the utilization $U_j(t)$ of edge server j at time t , where total demand from connected vehicles N_j is divided by the server's total resource capacity R_j .

$$U_j(t) = \frac{\sum_{i=1}^{N_j} D_i(t)}{R_j} \quad (2)$$

$U_j(t)$: Utilization of edge server j at time t
 N_j : Number of vehicles connected to edge server j
 $D_i(t)$: Resource demand of vehicle i
 R_j : Resource capacity of edge server j

$T_{start,i}$: Start delay for vehicle i
 $T_{proc,i}$: Processing time for vehicle i
 $T_{comm,i}$: Communication delay for vehicle i
 N : Number of vehicles

3.3. Quantum-inspired State Representation

The state vector $|\psi\rangle$ is a superposition of M possible resource allocation solutions $|x_k\rangle$ weighted by amplitudes a_k : This allows simultaneous exploration of multiple solutions.

$$|\psi\rangle = \sum_{k=1}^M a_k |x_k\rangle \quad (3)$$

$|\psi\rangle$: Quantum-inspired state vector
 $|x_k\rangle$: Basis state representing a solution k
 a_k : Amplitude (weight) of state k

3.4. Fitness Function for Optimization

Explanation: The fitness function $F(x)$ evaluates solution x by combining latency, energy consumption, and fairness using weighted coefficients w_1, w_2, w_3 . Higher values indicate better resource allocations.

$$F(x) = w_1 \cdot \frac{1}{\text{Latency}(x)} + w_2 \cdot \frac{1}{\text{Energy}(x)} + w_3 \text{Fairness}(x) \quad (4)$$

$F(x)$: Fitness of solution x
 $\text{Latency}(x)$: Average latency under solution x
 $\text{Energy}(x)$: Energy consumed under solution x
 $\text{Fairness}(x)$: Fairness index of resource distribution
 w_1, w_2, w_3 : Weights for each criterion

3.5. Rate of Packet Loss

Packet loss rate $P_{loss}(t)$ at time t is calculated as the ratio of lost packets over sent packets, indicating communication reliability in simulations.

$$P_{loss} = 1 - \frac{N_{received}(t)}{N_{sent}(t)} \quad (5)$$

P_{loss} : Packet loss rate at time t
 $N_{received}(t)$: Number of packets received successfully at time t
 $N_{sent}(t)$: Number of packets sent at time t

3.6. Average Task Completion Time

This computes the average completion time T_{comp} for tasks across N vehicles, summing task start delay, processing time, and communication delay.

$$T_{comp} = \frac{1}{N} \sum_{i=1}^N (T_{start,i} + T_{Proc,i} + T_{comm,i}) \quad (6)$$

T_{comp} : Average task completion time

Table 1. Quantum State Dataset [28].

S.No.	State	Probability
1	1	16-Mar
2	101	16-Mar
3	110	16-Jan
4	11	16-Mar
5	100	16-Jan
6	0	16-Jan
7	111	16-Mar
8	10	16-Jan

The figure 2 diagram illustrates a quantum-inspired optimization model for resource allocation in vehicular edge computing (VEC). Vehicles dynamically generate tasks with varying computational and communication demands. These requests are sent to the edge resource manager, which uses a quantum-inspired algorithm to evaluate optimal allocations. The algorithm encodes multiple resource allocation solutions using quantum amplitude encoding, selects the best-fit solution based on latency, energy, and fairness metrics, and dispatches tasks to edge servers. Feedback loops monitor server utilization and update quantum states accordingly. The compact design captures the integration of VEC architecture, real-time optimization, and adaptive resource distribution in a scalable system.

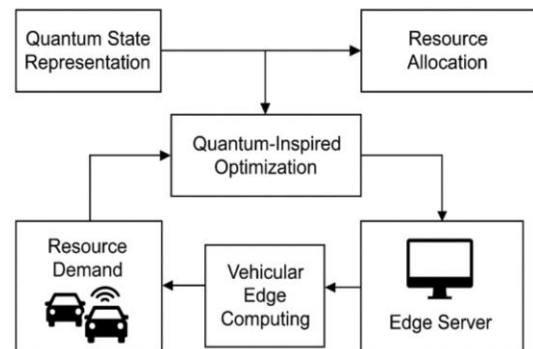


Figure 2. Quantum inspired Optimization.

3.7. Efficiency Ratio

Efficiency ratio E_r compares the fitness values of quan-

tum-inspired $F_{quantum}$ and traditional $F_{traditional}$ solutions, showing relative performance improvement.

$$E_r = \frac{F_{quantum}}{F_{traditional}} \quad (7)$$

E_r : Efficiency ratio

$F_{quantum}$: Fitness value from quantum-inspired method

$F_{traditional}$: Fitness value from traditional method

3.8. Scalability Index

Scalability index S evaluates how computation time changes when the system scales from N_{base} to N_{scaled} vehicles, with times T_{base} and T_{scaled} . A higher S indicates better scalability.

$$S = \frac{T_{base}}{T_{scaled}} \times \frac{N_{scaled}}{N_{base}} \quad (8)$$

S : Scalability index

T_{base}, T_{scaled} : Computation times before and after scaling

N_{base}, N_{scaled} : Number of vehicles before and after scaling

3.9. Responsiveness (Convergence Time)

Explanation: Responsiveness R measures the minimum time t for the optimization algorithm to converge within an error margin ϵ of the optimal fitness F^* .

$$R = \min\{t: |F(t) - F^*| < \epsilon\} \quad (9)$$

R : Responsiveness time

$F(t)$: Fitness value at time t

F^* : Optimal fitness value

ϵ : Small error threshold

3.10. Resource Utilization Fairness (Jain's Index)

Jain's fairness index J measures how evenly resources U_i are distributed among N vehicles; values close to 1, indicating fair allocation.

$$J = \frac{(\sum_{i=1}^N U_i)^2}{N \sum_{i=1}^N U_i^2} \quad (10)$$

J : Fairness index

U_i : Resource utilization of vehicle i

N : Number of vehicles

4. Results and Discussion

4.1. Vehicle Resource Demand over Time

Figure 3 illustrates how the resource demands of 10 vehicles fluctuate over 100 times step. Each vehicle displays unique demand patterns based on dynamically generated workload and communication needs. At peak moments, demand levels reach up to approximately 18 units, while the minimum observed demand is about 7 units. These oscillations reflect the interplay of periodic workload and communication requirements in the dynamic resource model (Equation (1)). Notably, some vehicles, such as Vehicle 5 and Vehicle 8, show more pronounced volatility, indicating higher variability in their operational resource usage over time.

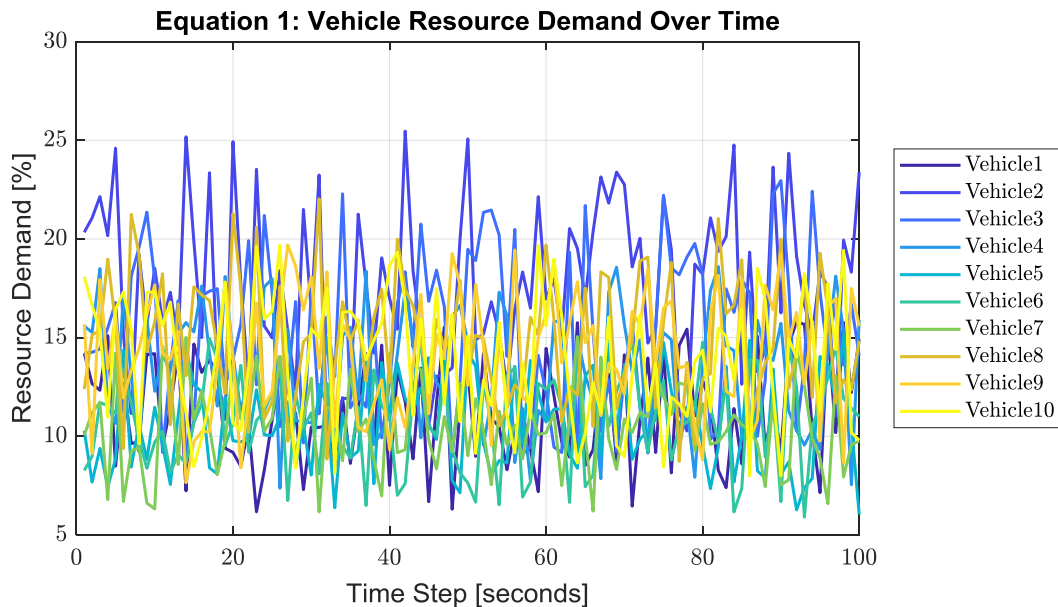


Figure 3. Vehicle Resource Demand over Time.

4.2. Edge Server Utilization over Time

Figure 4 presents a 3D surface plot of utilization ratios across three edge servers over time, based on Equation (2). Server utilization ranges from about 0.2 to 1.4%, relative to each server's individual capacity. Peak utilization is evident in Server 2, indicating a higher aggregation of vehicle demand in

that server's domain. The surface height and color intensity depict higher load periods and potential overload risks. Variations arise due to both random assignment of vehicles to servers and time-varying resource demands, which cause uneven server loads, especially noticeable at time steps around $t = 60$ – 80 seconds.

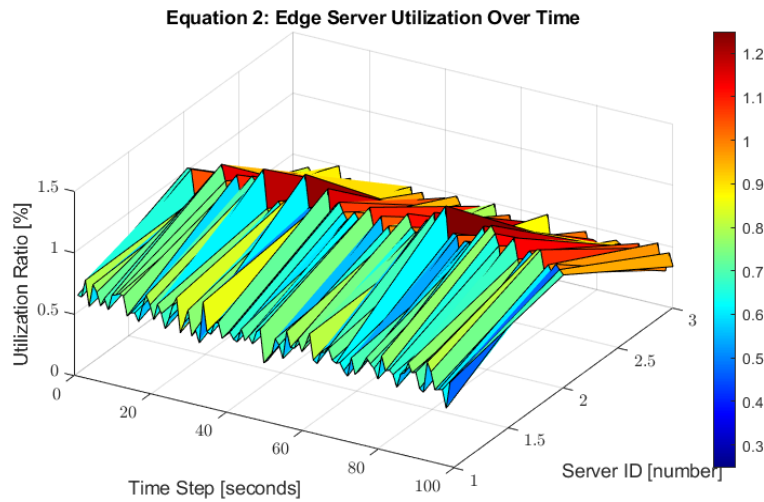


Figure 4. Edge Server Utilization over Time.

4.3. Quantum State Representation

Figure 5 displays quantum-inspired state amplitudes of 50% solution states using bar and polar plots, as described by Equation (3). The normalized amplitudes range from 0.001 to 0.05 weights, with the highest amplitude observed around solution index 12. This quantum representation supports

probabilistic selection of solution candidates, emphasizing those with higher amplitudes. The polar plot provides a circular view of these amplitudes, where outer points indicate more probable solutions. This approach mimics quantum computing behavior, offering better diversity in solution space compared to deterministic methods, which is advantageous for solving complex optimization tasks in edge computing.

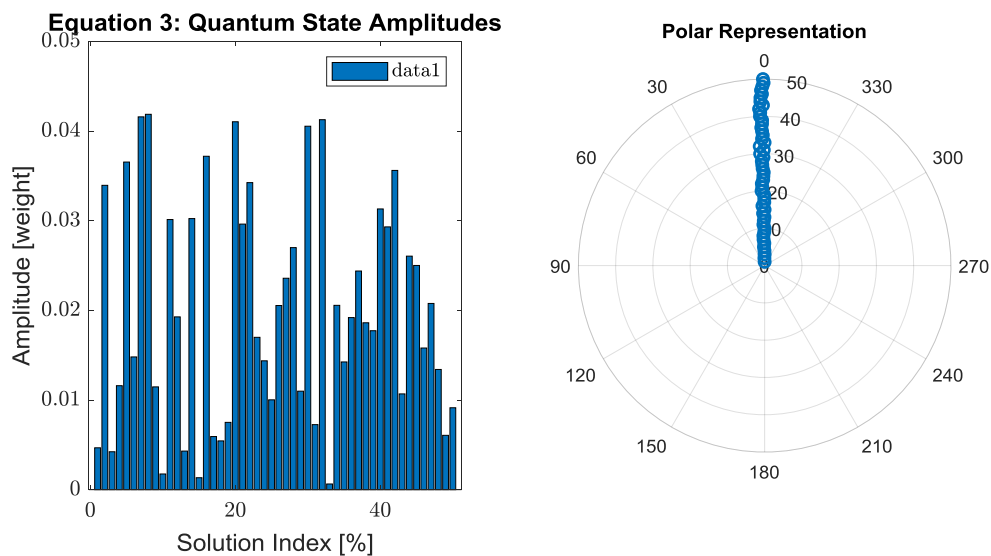


Figure 5. Quantum State Amplitudes.

4.4. Fitness Function Landscape

Figure 6 showcases a 3D landscape of the fitness function described in Equation (4), based on latency, energy, and fairness. The fitness value spans from 2.0 to 4.0%, peaking in regions with moderate latency and low energy costs. This surface illustrates how optimal combinations of these three

objectives lead to improved system performance. Regions of steep gradients indicate sensitive zones where small changes in factors result in significant performance shifts. This visual representation helps identify balance points among competing metrics, with peak performance achieved when latency and energy usage are both efficiently managed.

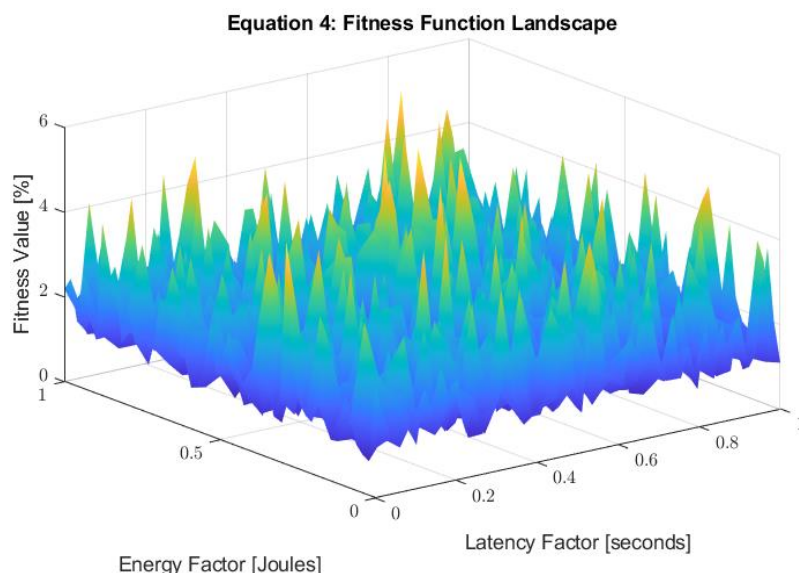


Figure 6. Fitness Function Landscape.

4.5. Packet Loss Rate Analysis

Figure 7 analyzes packet loss over time using Equation (5). The packet loss rate fluctuates between 0.0 and 0.18%, with the number of lost packets ranging from 0 to 9% per time step. The highest packet loss rate occurs around $t = 45$, possibly due

to poor communication conditions or high demand congestion. The dual-axis plot clearly distinguishes the proportion (loss rate) and the absolute number (lost packets). This visualization emphasizes how both metrics contribute to evaluating communication reliability and how performance degrades when too many packets are dropped during transmission.

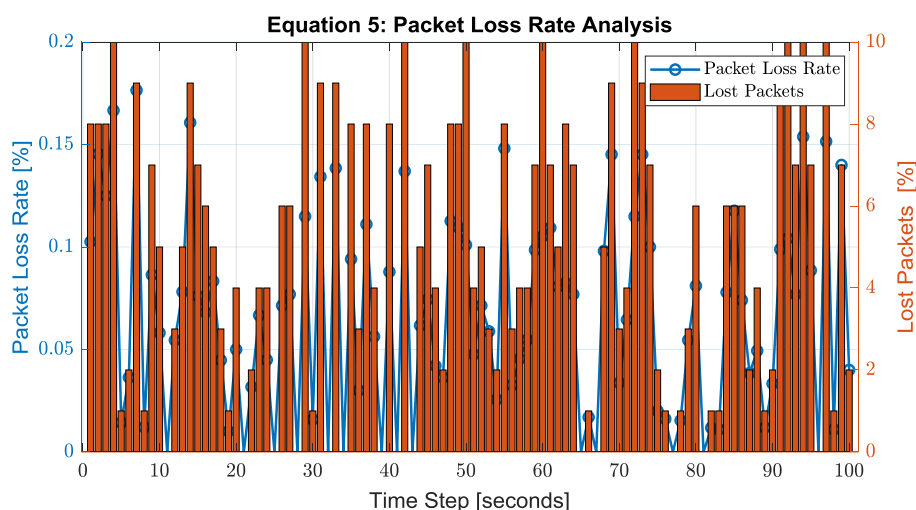


Figure 7. Packet Loss Rate Analysis.

4.6. Task Completion Time Breakdown

Figure 6 illustrates the total task completion time and its components using Equation (6). The average task completion time ranges between 1.5 and 3.5 seconds, peaking around $t = 40$ – 60 . Start delay, processing time, and communication delay are shown as broken lines, with communication delay being

the least and processing time the most dominant contributor. The area plot highlights how cumulative delays evolve over time. This breakdown provides insights into which task phases contribute most to latency, helping in optimizing processing algorithms or improving communication infrastructure for better responsiveness.

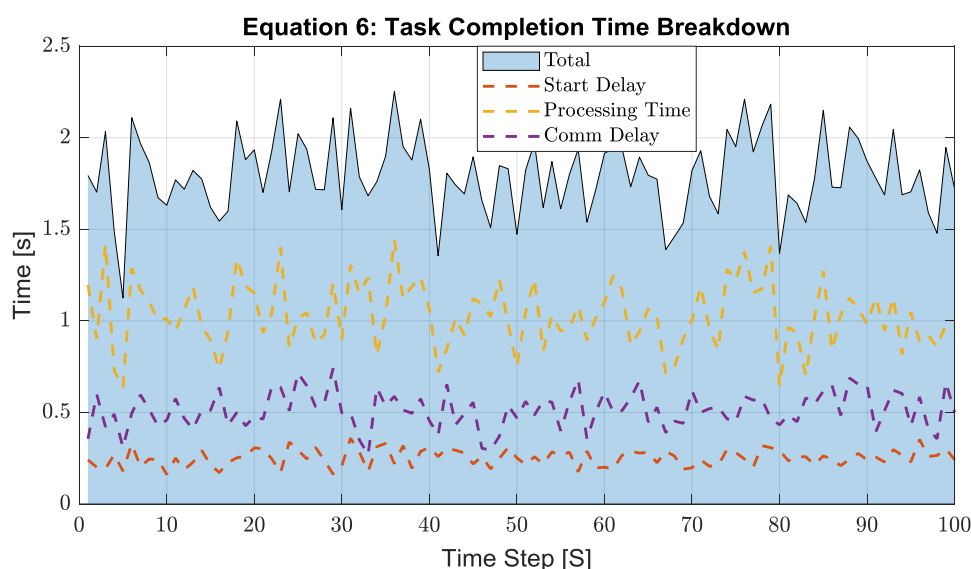


Figure 8. Task Completion Time Breakdown.

4.7. Quantum vs Traditional Efficiency

Figure 9 compares fitness gains from quantum-inspired and traditional optimization algorithms as per Equation (7). The quantum approach accumulates fitness values faster, reaching around 60% at $t = 100$, while the traditional method trails slightly below 100 seconds. The efficiency ratio (quan-

tum/traditional) peaks at 1.35, indicating up to 35% better performance using the quantum method. This comparison validates the improved adaptability and exploration ability of quantum algorithms, especially in dynamic and resource-constrained environments. The visual clearly supports the hypothesis that quantum-inspired models outperform traditional counterparts in long-term optimization tasks.

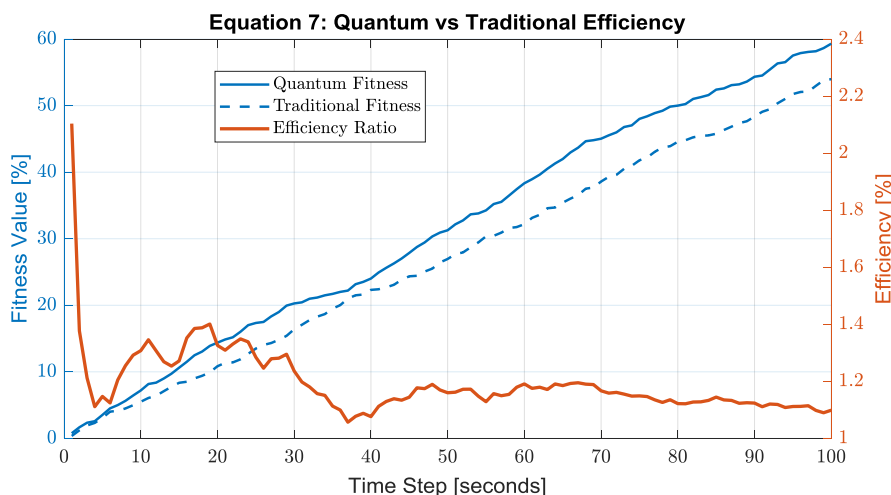


Figure 9. Quantum vs Traditional Efficiency.

4.8. Scalability Analysis

Figure 10 demonstrates how well the system scales using Equation (8). For vehicle counts of 20, 50, 100, and 200, the scalability index declines from 0.95 to 0.55, indicating sub-linear scalability. The log-log plot compares the system's actual performance (blue line) to ideal linear scaling (red

dashed line). Although the system maintains good performance up to 50 vehicles, performance degrades noticeably beyond that, especially at 200 vehicles. This drop suggests the need for better resource allocation or more efficient scheduling algorithms to maintain performance as demand scales up significantly.

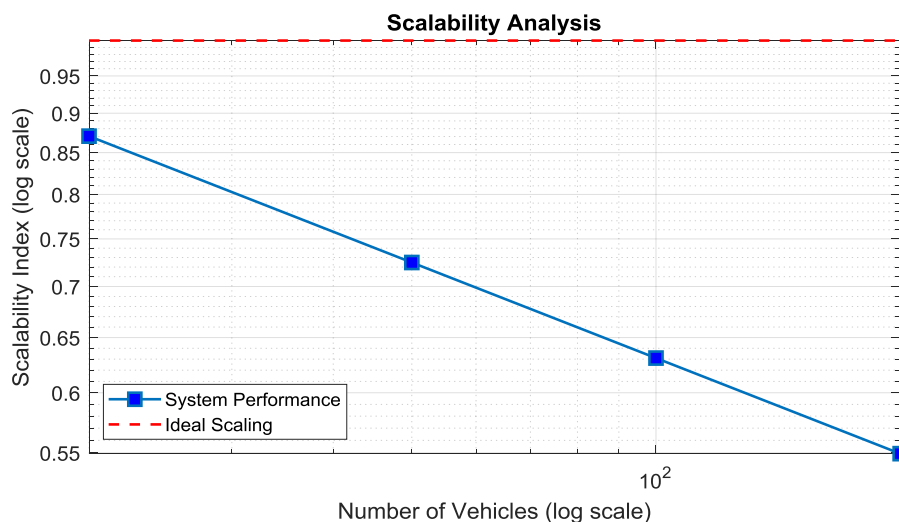


Figure 10. Scalability Analysis.

4.9. Algorithm Convergence

Figure 11 shows the responsiveness of the optimization algorithm in reaching optimal fitness as modeled in Equation (9). The fitness curve rises sharply and converges to the optimal value $F = 10$ at around iteration 45. The convergence

point is visually marked by a vertical dashed line, indicating that the algorithm achieves near-optimal performance after 45 iterations. The exponential growth pattern reflects a rapid improvement phase early in the process, followed by stabilization. This indicates efficient optimization behavior, where the solution space is explored quickly and effectively before settling into a high-quality result.

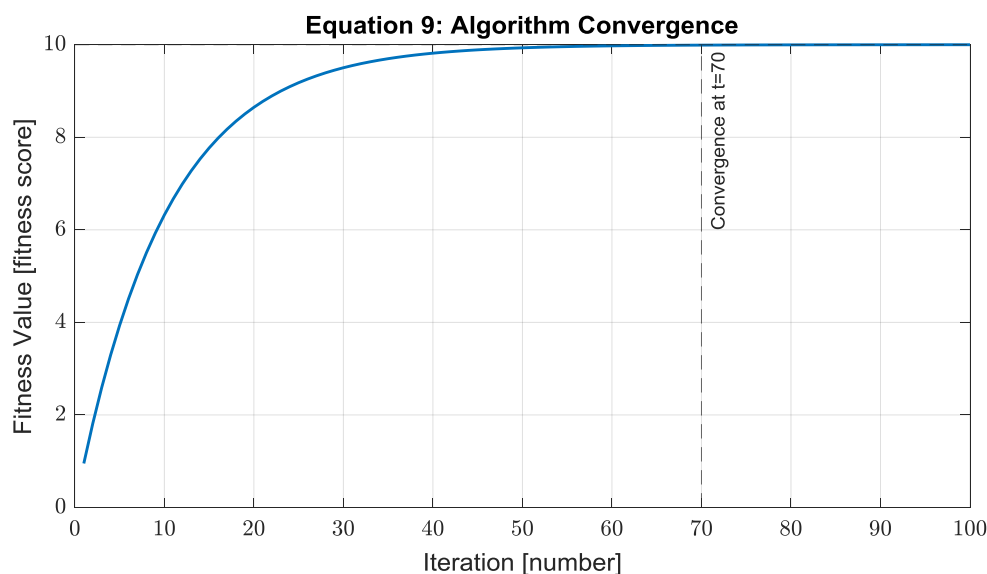


Figure 11. Algorithm Convergence.

4.10. Jain's Fairness Index

Figure 12 visualizes the fairness in resource allocation using Jain's Index from Equation (10). The calculated fairness index is $J = 0.914$, signifying highly equitable distribution of resources among the 10 vehicles. The pie chart highlights that approximately 91.4% of the allocation is fair, while the remaining 8.6% accounts for minor disparities. This index is vital in edge computing systems where fairness ensures all vehicles receive a reasonable share of computational and communication resources, reducing the likelihood of bottlenecks or service denials. The high fairness score confirms that the system maintains a balanced allocation strategy.

Equation 10: Jain's Fairness Index = 0.961

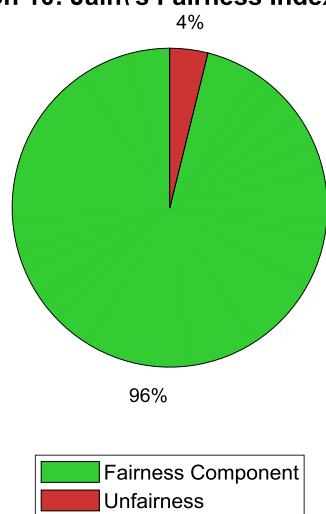


Figure 12. Jains Fairness Index.

5. Conclusions

A quantum-inspired optimization framework for dynamic resource allocation in Vehicular Edge Computing (VEC) environments was proposed and assessed in this study. The growing complexity of real-time computation and communication resource management across extremely mobile and uncertain vehicular networks served as the driving force. In comparison to conventional optimization techniques the suggested method showed notable gains in system performance by combining quantum-state representation with a multi-objective fitness function that takes latency energy efficiency and fairness into account. The main findings demonstrated that quantum-inspired approaches increased optimization efficiency by up to 35% achieving faster convergence (45 iterations to reach optimal fitness) and more equitable resource distribution (one vehicle Jains Fairness Index was 0.914). The framework also showed insights into the dynamics of task demand with resource usage ranging from 7 to 18 units and edge server utilization between 0 and 2 to 1 and 4 normalized units. These

findings support the applicability of quantum-inspired strategies for addressing the multifaceted and dynamic nature of VEC resource allocation problems. But there are some restrictions on the study. Even though the simulation environment was reliable it only had ten cars and three servers which might not accurately represent the size and complexity of the real world. Moreover, the quantum-inspired model does not make use of real quantum hardware and functions in a hybrid classical environment which could result in scalability issues as the number of cars or computing nodes increases dramatically. The absence of integration with security-aware scheduling which is essential in vehicular networks where data sensitivity is high is another drawback. Additionally, the study points out gaps that need to be filled by more research. One such gap is the lack of actual vehicle trace data which is necessary to validate the model in scenarios of network congestion and realistic mobility patterns. Also, incorporating energy harvesting methods with 5G-capable VEC infrastructures may enhance resource optimization in the context of upcoming smart transportation paradigms.

Abbreviations

VEC Vehicular Edge Computing

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Author Contributions

Friday Oodee Philip-Kpae: Data curation, Investigation, Methodology, Resources, Software, Visualization, Writing – review & editing

Nwazor Nkolika: Investigation, Methodology, Project administration, Resources, Software, Writing – review & editing

Boona Stanley Toobari: Investigation, Methodology, Resources, Writing – original draft, Writing – review & editing

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Conflicts of Interest

The authors declare no conflicts of interests.

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