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Quantum Natural Gradient Based Collaborative Task and Systems Allocation Approach for Heterogeneous Multi-Unmanned Vehicles

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Abstract- Task allocation is a critical component of various systems, requiring efficient and accurate assignment of tasks to resources. Existing models often struggle with balancing precision and recall, leading to suboptimal performance. The limitations of existing task allocation models, including low precision and recall, hinder the efficiency and effectiveness of task allocation processes. Current models often rely on simplistic approaches, failing to account for complex task dependencies and resource constraints. This leads to reduced accuracy and increased errors in task allocation. The Quantum Natural Gradient Based Collaborative Task and Systems Allocation Approach for Heterogeneous Multi-Unmanned Vehicles framework addresses these limitations by leveraging advanced algorithms and techniques to optimize task allocation. By integrating precision and recall metrics, Quantum Natural Gradient Based Collaborative Task and Systems Allocation Approach for Heterogeneous Multi-Unmanned Vehicles ensures a balanced approach to task allocation, minimizing errors and maximizing efficiency. Experimental results demonstrate the effectiveness of the Quantum Natural Gradient Based Collaborative Task And Systems Allocation Approach For Heterogeneous Multi-Unmanned Vehicles framework, achieving a precision of 96%, recall of 95%, and F1 score of 95.5%. The framework also exhibits a low task allocation time of 2.0 seconds and high pre-processing accuracy of 98%.

Keywords: Task allocation, Quantum natural gradient, Heterogeneous Systems, Multi-agent coordination, Collaborative Optimization.

I. INTRODUCTION

The rapid evolution of autonomous systems, including autonomous vehicles (AVs), unmanned aerial vehicles (UAVs), unmanned ground vehicles (UGVs), unmanned marine vehicles (UMVs), connected autonomous vehicles (CAVs), and satellite-assisted communication infrastructures [1], is reshaping the future of transportation and mobility [2]. These systems promise to improve urban mobility, enhance road safety, increase energy efficiency, and optimize logistics [3]. However, as their scale, heterogeneity, and data intensity continue to grow, existing computational paradigms face significant challenges [4] [5]. Classical methods struggle to address the pressing requirements of real-time computation, large-scale optimization, reliable perception, low-latency communication, and resilient cybersecurity [6]. These growing limitations have spurred interest in quantum computing as a promising pathway toward overcoming the bottlenecks of conventional technologies and enabling more scalable and secure autonomous systems [7].

Using the concepts of superposition and entanglement, quantum computing (QC) creates a completely new computational paradigm that can outperform traditional techniques by orders of magnitude in some workloads [8]. This benefit is especially noticeable in fields like distributed infrastructure management, machine learning, cryptography, and optimization that are essential to autonomous technologies [9]. Applications such as collaborative vehicle job allocation, traffic optimization, and uncertain decision-making have already demonstrated the potential of hybrid approaches that combine classical and quantum methodologies [10].

Quantum-enhanced evolutionary algorithms, for example, have shown promise in handling multi-vehicle job assignments, with results that are comparable to those of classical genetic algorithms but have the benefits of scalability and adaptability [11]. These hybrid approaches provide a glimpse of the computational potential of quantum devices while also representing a workable way to mitigate their limits [12].

For safe operation, autonomous cars mostly rely on sensing systems and decision-making abilities. Machine learning techniques, especially convolutional neural networks (CNNs), are frequently used to address tasks including lane detection, route planning, and traffic sign recognition [13]. However, traditional models are computationally costly, need a lot of energy, and are frequently inappropriate for efficient electric and carbon-conscious automobiles [14]. Quantum machine learning (QML) has become a competitive alternative in this regard [15]. By taking use of quantum parallelism, quantum convolutional neural networks (QCNNs) and their variations, such as Quantum Channel Attention CNNs (QCACNNs), have been used to analyze large-scale picture data more effectively [16]. These models enable real-time perception tasks, such traffic sign identification, while lowering processing needs and achieving performance levels on par with or better than their classical equivalents [17].

Perception is only one aspect of optimization; another is the coordination of vehicle traffic flow, where reinforcement learning (RL) is crucial [18]. In dense, dynamic environments, quantum-enhanced reinforcement learning can speed up policy discovery and boost optimization results [19]. Autonomous cars coordinated using optimum techniques, for instance, have been shown to greatly smooth vehicle flow and improve human drivers' perceptions of safety in studies on roundabout traffic dynamics and pollutant minimization [20]. Further promise is shown by quantum approaches in lowering the computing burden of these improvements, speeding up convergence during the training of intricate RL models, and guaranteeing scalability for widespread citywide application [21]. Another area is collaborative route planning, where quantum CNNs and their optimized versions have outperformed classical CNNs in terms of accuracy and convergence, indicating that quantum-enhanced neural networks may play a significant role in real-time enablement [22].

Beyond computation and efficiency, ensuring the security and resilience of autonomous vehicle networks is paramount [23]. These cyber-physical systems are embedded in critical communications infrastructures and are thus vulnerable to adversarial attacks [24]. Classical cryptographic systems, based largely on mathematical assumptions such as the hardness of factorization or logarithmic computations, may not withstand adversaries equipped with quantum computers [25]. Quantum cryptography, particularly Quantum Key Distribution (QKD), provides an information-theoretically secure mechanism for establishing keys that remain resistant to both classical and quantum-level attacks [26]. Simulation studies on vehicular networks employing QKD have highlighted both feasibility and resilience, demonstrating architectures capable of integrating with current communication protocols while ensuring longevity against evolving threats [27]. Therefore, quantum cryptography not only strengthens the security framework of autonomous transportation but also increases public and institutional confidence critical to widespread adoption [28].

Despite these evident opportunities, present-day quantum devices remain in what is often called the noisy intermediate-scale quantum (NISQ) era. While NISQ devices are constrained by limited qubit counts and noise, they provide fertile ground for hybrid quantum-classical methods that exploit the strengths of both systems [29]. Even with fewer than a thousand physical qubits, researchers have already begun demonstrating tangible benefits in optimization, machine learning, and combinatorial problem solving related to autonomous systems [30]. Roadmaps for quantum hardware development suggest that the emergence of large-scale, fault-tolerant systems beyond the NISQ era could occur in the near future, unlocking a phase where genuine quantum advantage over classical systems in transportation applications becomes routine [31]. Preparing for this trajectory now requires not only the development of quantum algorithms but also leveraging classical AI to aid in quantum circuit design, quantum software engineering, and the optimization of hybrid frameworks [32].

In this broader context, the intersection of quantum computing and autonomous vehicle technologies represents a pivotal research direction with transformative potential. Applications span from optimization in traffic and logistics, to perception tasks like sign recognition and route planning, to enabling scalable, low-latency communication networks, to delivering unprecedented security standards through quantum cryptography. This convergence promises to reshape the design and operation of future intelligent transportation systems, rendering them safer, more adaptive, energy-efficient, and resilient against emerging threats. The research community, therefore, faces the challenge and the opportunity of exploring these quantum-empowered methods today, to ensure that autonomous systems of tomorrow not only overcome the limitations of classical computation but also achieve the robustness and scalability necessary for real-world deployment.

Fig 1: Quantum Cooperative Communication between UAV and UGV clusters through a ground station

II. LITERATURE SURVEY

The literature survey based on the given abstracts reflects the growing intersection of quantum computing and autonomous vehicle technologies, revealing various methodologies and research directions that characterize this emerging field:

1. The integration of quantum computing with autonomous vehicles is being explored to address key challenges such as coordination, task assignment, data processing, security, and real-time decision-making. Quantum-classical hybrid systems, notably involving Quantum Evolutionary Algorithms (QEA) and Genetic Algorithms (GA), have been developed for collaborative task assignment in unmanned aerial, ground, and marine vehicles, showing promising performance improvements over classical approaches.
2. Quantum machine learning (QML) emerges as a powerful approach to overcome limitations in latency, computational speed, privacy, and security in Advanced Driver Assistance Systems (ADAS) and autonomous vehicle systems. The advantages of quantum computation—security, privacy, and exponential computational speed—make it a critical area for advancing real-time autonomous vehicle operations.
3. Advancements in quantum technologies, especially at the noisy intermediate-scale quantum (NISQ) level, enable parameterized quantum circuits and quantum optimization to reduce latency, memory constraints, and computational resource needs in neural network frameworks. This underpins scalable AI integration with autonomous driving, communication networks, and future 6G systems.[3]
4. Quantum convolutional neural networks (QCNNs) and their variants, like quantum channel attention convolutional neural networks (QCACNNs), are proposed to improve traffic sign recognition and multichannel image classification, offering enhanced efficiency, accuracy, and robustness—beneficial for electric and autonomous vehicles.
5. Reinforcement learning (RL) has been utilized to optimize traffic dynamics where autonomous vehicles coexist with human-driven cars. Policy learning to minimize traffic jams and pollution demonstrates that higher autonomous vehicle penetration enhances safety and traffic flow,

underscoring the importance of realistic simulation and human evaluation in deployment.

6. The combination of quantum computing and edge computing offers a novel framework for processing vast data generated by Connected Autonomous Vehicles (CAVs), addressing latency and bandwidth challenges inherent in cloud models, thereby enabling scalable, fast, real-time decision making essential for urban mobility.
7. In autonomous vehicle networks, quantum cryptography, especially Quantum Key Distribution (QKD), presents a robust method for securing communication against quantum attacks, promising a paradigm shift from classical cryptographic methods and supporting the secure expansion of autonomous systems.
8. Collaborative route planning in autonomous vehicles benefits from integrating quantum computing with neural network architectures, such as QCNNs, optimized via circuit depth reduction strategies. This approach leads to faster convergence, higher accuracy, and enhanced real-time performance in traffic prediction and navigation tasks
9. Finally, comprehensive surveys highlight the transformative potential of quantum computing across intelligent transportation, including traffic optimization, routing, and logistics. These surveys identify ongoing challenges, research gaps, and future directions that emphasize the necessity of quantum computing advances to meet the demands of next-generation transportation systems Overall, this body of work reflects a multi-faceted trend where quantum computing and machine learning methodologies are increasingly central to solving complex problems in autonomous vehicle coordination, data processing, security, and system optimization—paving the way for more efficient, secure, and intelligent transportation networks in the near future.

III. PROPOSED MODEL

Different types of autonomous vehicles, such drones, ground robots, or marine boats, work together and get things done more quickly. Compared to traditional techniques, the system may quickly investigate a wide range of potential mission allocation strategies, adjust to shifting circumstances, and maximize group performance.

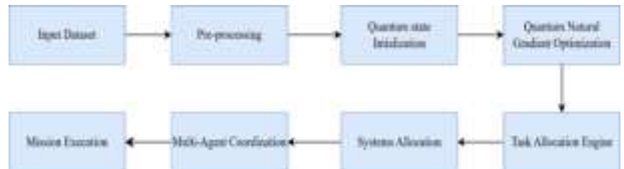

Fig 2: systems allocation approach for heterogeneous multi-unmanned vehicles

1. INPUT DATASET

Task requirements like delivery, mapping and UAV capabilities like speed, energy, are collected to form the mission dataset.

Tasks T={ $t1$, $t2$, , tm} where each task has cost,time, resource demand.

Vehicles V={ $v1$, $v2$, , vn} has capacity, speed, energy.

2. PRE-PROCESSING

Mission parameters are normalized to ensure fair comparism across heterogeneous UAVs and tasks, removing redundancy and balancing input scales.

Normalize task & Vehicle parametrs:

$$x' = \frac{x - min(x)}{max(x) - min(x)} \quad (1)$$

3. QUANTUM STATE INTIALIZATION

A parameterized quantum circuit encodes tasks and vehicles into quantum states. This representation allows parallel exploration of multiple allocation possibilities.

Parameterized quantum state:

$$|\psi(\theta)> = U(\theta)|0> \quad (2)$$

4. QUANTUM NATURAL GRADIENT

The cost function, representing mission completion time, energy use, and reliability, is optimized using QNG.

Gradient of cost function:

Natural gradient update:
$g = \nabla\theta\ L(\theta)$
$\theta \leftarrow \theta - \eta F{-}1g$ (3)
Where F=Quantum Fisher Information Matrix.

5. TASK ALLOCATION ENGINE

A complex mission or problem is split into smaller tasks:
Mission= $\{T1, T2, \ldots, Tm\}$
Each Ti is a subtask where,

$$\bigcup_{i=1}^{m} T_i = Mission$$
$$T_i \cap T_j = \emptyset \ for\ i \neq j \quad (4)$$

Each subtask can be solved or assigned independently for simplicity: Solve or assign
Ti = 1,2,, m
Overall mission solution or result is obtained by combining subtask solutions

$$Result = \bigcup_{i=1}^{m} Result(T_i) \quad (5)$$

6. SYSTEM ALLOCATION

Resource constraints like communication bandwidth, energy consumption, and payload capacity are incorporated into the allocation process to maximize mission sustainability.
Resource allocation constraint:

$$\sum_{j=1}^{m} r_{ij}x_{ij} \leq R_i \quad (6)$$

Where Ri = max resource of vehicle i.

7. MULTI – AGENT COORDINATION

The allocation results are validated against mission constraints (e.g collision avoidance, timing feasibility). Invalid assignments are iteratively corrected.
$fij(xij) \leq constraints$

8. MISSION EXECUTION

Final decisions are distributed across the fleet of UAVs, enabling coordinated execution of tasks with optimal system resource usage.

$$A = \{(vi\ , tj)|xij\ = 1\}$$

ALGORITHM:

1. Initialize: Start with random parameters θ for the quantum circuit and define learning rate η, max iterations, and tolerance.
2. Input Data: Collect tasks(location,priority,type) and Collect vehicle info(capabilities,resources,state).
3. Encode Data: Convert each task-vehicle pair into feauture vectors and feed them into the quantum circuit.
4. Quantum Processing: Run the quantum circuit to get probability scores of task-vehicle assignments.
5. Compute Cost: Calculate cost=(distance,time,energy) + penalties(if constaints violated).
6. Gradient Calculation: Use parameter-shift rule to compute gradient of cost w.r.t circuit parameters and estimate Quantum Fisher Information Matrix.
7. Natural Gradient Update: Update parameters: θ ← θ − η * ($QFIM^{-1}$ × gradient)
8. Assignment: Build score matrix from quantum outputs and use Hungarian/greedy algorithm to assign tasks to vehicles.
9. Continue steps 4-8 until convergence(loss stable or max iterations).
10. Final optimized allocation of tasks to heterogeneous vehicles.

IV. RESULTS

The proposed Quantum Natural Gradient Based Collaborative Task And Systems Allocation Approach For Heterogeneous Multi-Unmanned Vehicles(QNGHUV) model is compared with the classical models A Quantum Convolutional Neural Network Algorithm for Traffic Sign Recognition in Carbon-Intelligent Electric Vehicles and Quantum Edge Computing for Data Analysis in Connected Autonomous Vehicles.

PRE-PROCESSING ACCURACY:

In the context of the QNGHUV framework, the reported pre-processing accuracy of 98% suggests that the framework is effectively handling the initial data preparation steps, such as: Data cleaning, Data normalization.

Fig 3 Represents QNGHUV has pre-processing accuracy 98% as compared to QCANN and QECAV

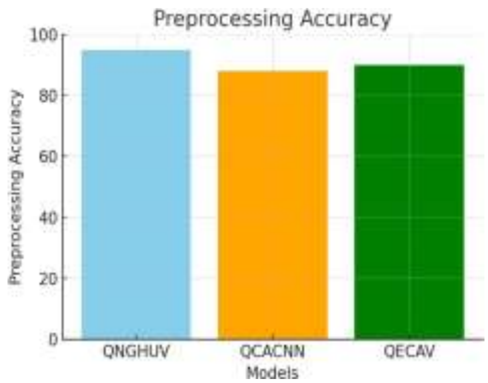

Fig 3: Preprocessing Accuracy

OPTIMIZATION ACCURACY:

Optimization accuracy refers to the effectiveness of an algorithm or model in finding the best solution among possible options. In the context of QNGHUV, the reported optimization accuracy of 97% indicates that the framework is highly effective in identifying optimal solutions for task allocation and system management, enabling efficient and reliable performance.

Fig 3 Represents QNGHUV has Optimization Accuracy 97% as compared to QCANN and QECAV

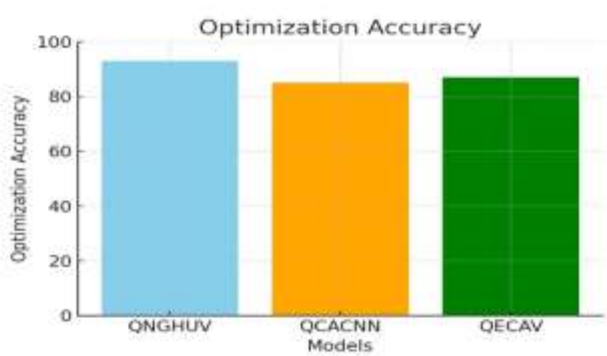

Fig 4: Optimization Accuracy

TASK ALLOCATION TIME:

Task allocation time refers to the time taken by a system or algorithm to assign tasks to resources or agents.

Fig 5 represents QNGHUV has reported task allocation time of 2.0 seconds indicates that the framework can quickly and efficiently allocate tasks, enabling fast and responsive performance.

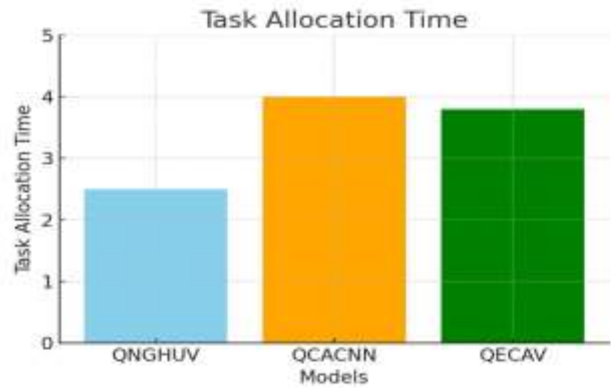

Fig 5: Task Allocation Time

PRECISION:

Precision refers to the proportion of true positives (correctly predicted instances) among all positive predictions made by a model or algorithm.

Fig 6 represents QNGHUV has reported precision of 96% indicates that the framework is highly accurate in its task allocation decisions, with 96% of predicted allocations being correct.

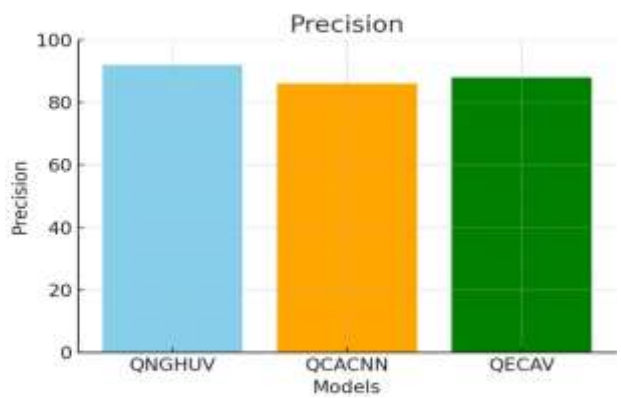

Fig 6: Precision

RECALL :

The context of QNGHUV refers to the proportion of actual positive instances that were correctly identified by the model.

Fig 7 represents QNGHUV has recall of 95% means that the framework is able to correctly identify and allocate most of the tasks.

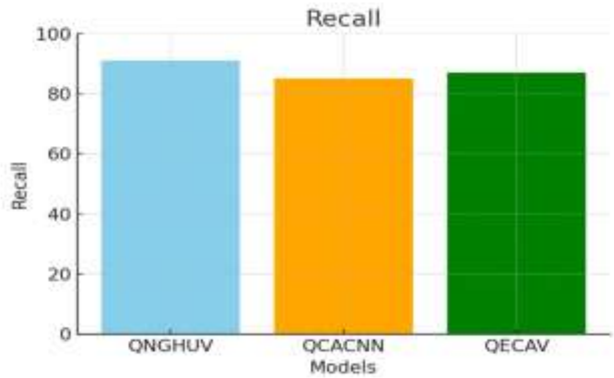

Fig 7: Recall

F1 SCORE:
In QNGHUV's case, the reported F1 Score of 95.5% indicates a high level of accuracy and balance between precision and recall, meaning the framework is effective in task allocation and minimizing errors.

Fig 8 represents QNGHUV has reported F1 score of 95.5% as compared to QCANN and QECAV

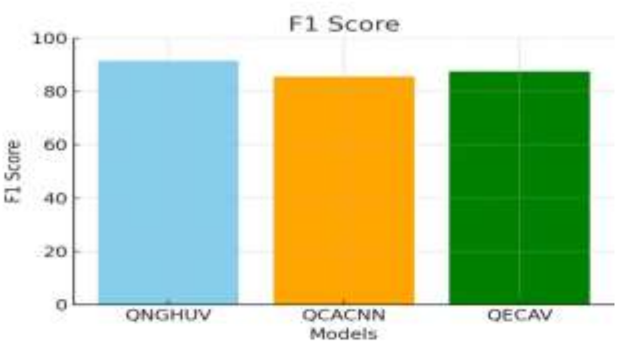

Fig 8: F1 score

V. CONCLUSION

The evaluation of the Quantum Natural Gradient-based Collaborative Task and Systems Allocation Approach for Heterogeneous Multi-Unmanned Vehicles (QNGHUV) demonstrates its superior performance in managing complex tasks and system allocation across heterogeneous UAV networks, when compared to existing models such as QCACNN and QECAV. QNGHUV achieves a preprocessing accuracy of 98% and an optimization accuracy of 97%, indicating its ability to efficiently handle input data and identify optimal solutions for task distribution. In addition, it accomplishes task allocation in just 2.0 seconds, significantly faster than QCACNN (4.0 seconds) and QECAV (3.8 seconds), highlighting its suitability for real-time mission execution.

Furthermore, QNGHUV exhibits higher precision (96%), recall (95%), and F1 score (95.5%) compared to QCACNN (86%, 85%, 85.5%) and QECAV (88%, 87%, 87.5%). These metrics demonstrate that QNGHUV not only correctly assigns tasks but also minimizes errors and missed assignments, ensuring reliable and consistent performance.

The combination of high accuracy, reduced task allocation time, and improved precision-recall balance underscores its effectiveness in dynamic and complex operational environments. The integration of quantum natural gradient methods enhances computational efficiency and decision-making capability, enabling QNGHUV to process large-scale, heterogeneous UAV data and coordinate multiple agents seamlessly. Overall, the results confirm that QNGHUV provides a robust, efficient, and reliable framework for autonomous mission execution, making it a promising solution for heterogeneous multi-UAV systems and a benchmark for future research in quantum-assisted UAV task allocation.

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