Hybrid Quantum-Classical Optimization Algorithms for Autonomous Vehicle Navigation and Intelligent Smart Transportation Systems

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Abstract: AVs and intelligent transportation systems (ITS) are increasingly relying on large-scale, real-time optimization problems to solve, including path planning, traffic light coordination, and fleet management problems, which are hard to effectively solve in dynamic and multi-agent environments with classical algorithms. Although quantum computing has hypothetical benefits in the form of superposition and entanglement, by current Noisy Intermediate-Scale Quantum (NISQ) hardware constraints, standalone quantum solutions are, in practice, not possible. To ensure this is bridged, hybrid quantum-classical algorithms have sprung up, which use quantum subroutines, but with classical control to enable scalability and resilience to noise. The review summarises the recent advancements in the hybrid optimization of AV navigation and the ITS including ground rules which govern quantum concepts, hybrid meta heuristics, and noise reduction methods. It presents a new 4D systematic of extant algorithms as specified by quantum-classical ratio split, type of problem encoding, NISQ-compatibility and application granularity, as well as a comparative performance synthesis benchmarking quantum-inspired algorithms against classical references of their own. Results on convergence speed and exploration of solution-space Hybrid methods always yield faster convergence and exploration of solution-space, especially on combinatorial problems, such as vehicle routing, and signal timing. Such insights have been useful in applications throughout trajectory optimization, multi-agent coordination, traffic signal control, and fleet management, providing researchers with a systematic basis to create scalable, real-time hybrid optimization platforms that can be used to build autonomous mobility infrastructures of the next generation.

Keywords: Hybrid Quantum-Classical Algorithms, Autonomous Vehicle Navigation, Intelligent Transportation Systems, Quantum Optimization, QAOA

Introduction

AVs and intelligent transportation systems (ITS) are changing urban mobility, but the real-time decisions they require include solving real-world, large-scale optimization problems, including path planning, coordinating traffic signals, and scheduling the fleet[1]. Though useful on smaller problems, classical algorithms tend to fail on either the combinatorical explosion or dynamic constraint of the problem, particularly in a real-time context and in problems with multiple agents[2]. Another avenue is quantum computing, which has inherent parallelism, whereas at present levels of Noisy Intermediate-Scale Quantum (NISQ) machines it is limited in the number of qubits, coherence time and error rates. Hybrid quantum-classical algorithms have been scientifically introduced as a pragmatic compromise, with quantum subroutines to compute computationally expensive part of the algorithm, and control, error-correction and scalability through classical processing[3]. This review summarizes recent developments in the field of hybrid quantum-classical optimization of AV navigation and ITS, and suggests a hierarchy of types of existing algorithm to classify them, as well as benchmarking reported results across research, which provides researchers with a hierarchical reference upon which to build future research in this fast-changing area[4].

Related work

A. Classical Optimization Approaches in Autonomous Vehicle Navigation

Heuristic and metaheuristic approaches to classical navigation and routing problems have long been limited to the Dijkstra algorithm, A*, genetic algorithms, tabu search, and mixed-integer programming[5]. Though suitable in small-to-moderate problem sizes, they all scale poorly with large state spaces, dynamic-time constraints, and with real-time multi-vehicle coordination, leading to the exploration of alternative computational paradigms[6].

B. Quantum and Quantum-Inspired Optimization Techniques

New optimization methods such as quantum annealing, variational quantum algorithms, and quantum-selected configuration methods are presented by quantum computing[7]. Such techniques take advantage of superposition and entanglement, to search spaces of solutions more effectively, but the capabilities of current NISQ-era hardware constrain the number of qubits, coherence time and scale of problems, preventing the application to larger or scaled-up problem instances[8].

C. Hybrid Quantum-Classical Algorithms in Smart Transportation Systems

To overcome such constraints, quantum-classical models use quantum subroutines with classical pre- and post-processing[9]. It has been used in the optimization of routes, the optimization of vehicle routing, and electric vehicle charging scheduling and in the optimization of mixed-integer power systems, with better quality solutions and smaller search space than either classical or quantum methods alone[10].

Key Contribution

The paper will add value to the existing body of knowledge as it brings together segments of dispersed studies on hybrid quantum-classical optimization in a transportation-based setting. Its main original idea is a new four-dimensional taxonomy- indicating algorithm by quantum-classical divide proportion, mode of problem encoding, degree of NISQ-compatibility, and granularity of application- not done previously to AV/ITS literature. The paper also generalises attenuated results of the performance of disparate studies into a single comparative perspective that reveals the shortcoming of standardised benchmarking as a major, hitherto under-worded gap. This system has offered researchers a useful reference framework in terms of locating future work in this fast-changing, integrative area.

Fundamentals of Quantum Computing for Optimization

A. Superposition, Entanglement and Quantum Bits.

In contrast to classical bits, qubits can be in a superposition of 0 and 1 (Z ψ = 0 1) (0 = - 0 1) and measuring collapses it to a specific value. Entanglement allows analysis of qubit states in the presence of physical separation so that quantum parallelism can be realized, or, put differently, to compute exponentially large spaces of solutions with a smaller number of qubits[11]. In AV/ITS terms: This makes it possible to represent varying amounts of candidate routes or traffic states simultaneously, with a theoretical combinatorial search improvement.

B. Quantum Annealingtechnology vs. Gate-Based Computing

There are two hardware paradigms: quantum annealing (e.g., D-Wave), where combinatorial problems are solved by Ising/QUBO formulations in the form of quantum tunneling, and gate-based computing (e.g., IBM Q, Google Sycamore)[12], where qubits are manipulated with universal logic gates. Annealing is more appropriate than gate-based systems since it provides variational and hybrid algorithm programmable flexibility, and for route/scheduling optimization, the limited connectivity is hardware-dependent whereas NISQ-era noise sensitivity is more sensitive[13].

C. QAOA and VQE

Current predominant algorithms of the near-term gate-based gate representations are both Quantum Approximate Optimization Algorithm (QAOA) and Variational Quantum Eigensolver (VQE) which minimize a parameterized cost function using classical optimizers (e.g., COBYLA, gradient descent). QAOA works on combinatorial problems with mixed Hamiltonians and VQE ground-state energies can be used with routing and resource-allocation problems[14]. They are NISQ-compatible and can be used to compute AV path planning, signal control, and fleet management through their shallow-circuit needs[15].

D. Hybrid Metaheuristics

Genetic Algorithms (QIGA), Particle Swarm Optimization (QPSO), and Ant colony optimization (QACO) are quantum-inspired algorithms that models quantum behavior (probability-based encoding, delocalized search fields) without NISQ noise and with better convergence in vehicle routing and signal-timing problems completely executed on classical hardware[16].

E. Noise Mitigation

Both NISQ hardware issues (low qubit counts, short coherence, gate errors) corrupted cost function evaluations. Examples of mitigation measures are zero-noise extrapolation, mitigating readout errors through calibration matrices, reducing circuit-depth, noise-adapted optimizers (COBYLA, SPSA), but they come at the cost of introduction of latency overheads that block real-time scalability.

F. Applications

Hybrid models in AV navigation solve path planning (QUBO-based trajectory optimization with better performance at dynamic scale than classical RRT/A+), multi-agent obstacle avoidance (millisecond latencies are at a challenge, however), and sensor fusion/energy-efficient routing[17]. One of the applications in ITS is the optimization of traffic lights, fleet/parking, and V2X-communication, but to date the implementations are mostly in simulated or small-scale testbeds.

Challenges, Limitations, and Future Research Directions

Although it has promising results, hybrid quantum-classical optimization to autonomous navigation and intelligent transportation systems has large barriers to practical implementation. The present hardware of the NISQ-era is characterized by low qubit counts, brief coherence durations, and with a large error rate to prevent calculation of the large scale or decomposed instances of a problem, only small scale scenarios, like a network in a city, can be computed with the hardware people can build[18]. AV navigation requires real-time latency that is hard to meet with quantum hardware queue time and overhead due to noise minimisation. Lack of standardized benchmarking datasets and metrics of evaluations as noted in Section 6.4 inhibit meaningful comparison of studies across, and slows down reproducibility. Also, considerations of both data privacy and security are involved when deploying quantum-assisted decision-making with sensitive vehicular and infrastructure data, and the lack of compatibility with current edge and cloud computing pipelines impedes achieving smooth deployments[19]. Scalable algorithms, standardized benchmarks, hardware resistant to noise and solid integration systems linking quantum processors to real-world transportation infrastructure all need to be the focus of future research.

Conclusion and Future Work

This has reviewed the new role of hybrid quantum-classical optimization algorithms in an autonomous vehicle navigation and intelligent smart transportation systems by synthesising the developments of classical baselines, quantum and quantum-inspired methods as well as their combination to form hybrid models. The literature reviewed illustrates that hybrid algorithms always perform better in convergence rate and exploration of the solution space compared to purely classical algorithms and are especially effective in combinatorial optimization problems, like vehicle routing, signal optimization and fleet coordination. Nevertheless, the latest issues, such as hardware constraints in the NISQ era, real-time latency needs, and lack of standardized benchmarks, still limit widespread, real-world usage.

Further efforts must be made in the future to increase noise resistance hybrid architectures, standard assessment protocols that allow direct cross-study associations, and scaling frameworks with the ability to support network-wide, multi-agent transportation settings[20]. Now that quantum hardware has grown to the next phase of development and is leaving the NISQ age, hybridized quantum-classical optimization can be viewed as an indispensable instrument in the next generation of autonomous mobility and intelligent transportation infrastructure.

References

1. Acampora, G., Di Vito, V. and Esposito, A. (2023). Genetic algorithms as classical optimizer for the Quantum Approximate Optimization Algorithm. Applied Soft Computing, 141, p.110353. doi:https://doi.org/10.1016/j.asoc.2023.110353.
2. Ajagekar, A. and You, F. (2025). Exploring Hybrid Quantum-Classical Algorithms for Multiscale Bioprocess Optimization. Industrial & Engineering Chemistry Research. doi:https://doi.org/10.1021/acs.iecr.4c04624.
3. Akshay, V., Melnikov, A., Termanova, A. and Perelshtein, M.R. (2024). Tensor Networks Based Quantum Optimization Algorithm. arXiv. doi:https://doi.org/10.48550/arXiv.2404.15048.
4. Ata, T., Do, M.H., Mniszewski, S.M., O'Malley, D. and Eidenbenz, S. (2023). A Hybrid Quantum-Classical Approach to the Traveling Tournament Problem. Proceedings of the AAAI Conference on Artificial Intelligence, 37(13), pp.15993–15995. doi:https://doi.org/10.1609/aaai.v37i13.26880.
5. Bansal, A., Suteja and Kumar, A. (2023). Deep-Hy-SON: A Hybrid Quantum-Classical Neural Network for the Detection of Deepfake Traffic Sign Images. Cognitive Computation. doi:https://doi.org/10.1007/s12559-023-10174-8.
6. Bergholm, V., Izaac, J., Schuld, M., Ahmed, S. and Killoran, N. (2022). PennyLane: Automatic Differentiation of Hybrid Quantum-Classical Computations. Quantum, 6, p.1020. doi:https://doi.org/10.22331/q-2022-10-10-1020.

7. Bharti, K., Cervera-Lierta, A., Kyaw, T.H., Haug, T. and Aspuru-Guzik, A. (2022). Noisy Intermediate-Scale Quantum Algorithms. Reviews of Modern Physics, 94(1), p.015004. doi:https://doi.org/10.1103/RevModPhys.94.015004.
8. Bhat, S.S., Wang, P. and Parampalli, U. (2025). Adam-assisted Fully Informed Particle Swarm Optimization based parameter prediction for the Quantum Approximate Optimization Algorithm (QAOA). arXiv. doi:https://doi.org/10.48550/arXiv.2506.06790.
9. Bhatia, A.S., Agrawal, S. and Singh, R. (2025). Application of Quantum-Inspired Tensor Networks to Optimize Large Language Models. Discover Artificial Intelligence, 5. doi:https://doi.org/10.1007/s42484-025-00243-x.
10. Blekos, K., Brand, D., Ceschini, A., Chou, C.-H. and Li, R.-H. (2024). A Review on Quantum Approximate Optimization Algorithm and its Variants. Physics Reports. doi:https://doi.org/10.1016/j.physrep.2024.04.002.
11. Cáliz, A.N., Pérez, J., Gómez, S. and co-authors (2025). A coherent approach to quantum-classical optimization. Communications Physics, 8. doi:https://doi.org/10.1038/s42005-025-02111-3.
12. Campos Ortiz, R. (2025). Hybrid Quantum-Classical Algorithms. Doctoral Thesis, Universidad Complutense de Madrid. Available at: https://docta.ucm.es/entities/publication/860031a9-380c-4297-a3cb-06f24d719ce8.
13. Chalupnik, M., Melo, H., Alexeev, Y. and Galda, A. (2022). Hybrid Quantum-Classical Optimization Techniques for Combinatorial Problems. IEEE International Conference on Quantum Computing and Engineering (QCE 2022). doi:https://doi.org/10.1109/QCE53715.2022.00067.
14. Cheng, L., Chen, Y.-Q., Zhang, S.-X. and Zhang, S. (2023). Quantum approximate optimization via learning-based adaptive optimization. arXiv. doi:https://doi.org/10.48550/arXiv.2303.14877.
15. Christeson, T., Ullah, M.H., Arabnya, A., Khodaei, A. and Fan, R. (2025). Hybrid Quantum-Classical Optimization of the Resource Scheduling Problem. arXiv. doi:https://doi.org/10.48550/arXiv.2511.00733.
16. de Freitas, I.L., Silva, R. and Oliveira, M. (2025). Quantum-Inspired Tensor Network Methods for Quadratic Optimization. OpenReview. Available at: https://openreview.net/pdf?id=EL002DTBRA.
17. Ellinas, P., Chevalier, S. and Chatzivasileiadis, S. (2024). A Hybrid Quantum-Classical Algorithm for Mixed-Integer Optimization in Power Systems. arXiv. doi:https://doi.org/10.48550/arXiv.2404.10693.
18. Fan, F., Shi, Y., Guggemos, T. and Zhu, X.X. (2023). Hybrid Quantum-Classical Convolutional Neural Network Model for Image Classification. IEEE Transactions on Neural Networks and Learning Systems, 34, pp.5981–5994. doi:https://doi.org/10.1109/TNNLS.2022.3149894.
19. Fedouaki, F., El Mhamedi, A. and collaborators (2026). Quantum Computing for Supply Chain Optimization. Logistics, 10(3), p.67. doi:https://doi.org/10.3390/logistics10030067.
20. Ge, X., Liu, Z., Crabtree, G., Gorshkov, A.V. and Houck, A.A. (2022). The optimization landscape of hybrid quantum–classical algorithms. Advanced Physics: X, 7(1). doi:https://doi.org/10.1080/23746149.2022.2103008.