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Research Paper

Hybrid Quantum-Inspired Algorithm for Optimizing Fuel Efficiency of Autonomous Vehicle Fleets

Kacper Dmochowski[1,*] and Eryk Gierak[1]

[1] Faculty of Electrical Engineering and Automatics, Adam Mickiewicz University in Poznan, Poznan, 61-614, Poland
*Corresponding author: kacper.dm@amu.edu.pl

Abstract. Fuel Efficiency Optimization for Autonomous Vehicle Fleets is a challenge in intelligent transportation systems with dynamic traffic, different vehicle states, unpredictable road conditions, and cooperative driving limitations. Conventional fleet optimization techniques are less appropriate for large-scale, non-linear, and multi-objective decision problems because they often use deterministic routes or local control rules. A hybrid quantum-inspired method for autonomous fleet fuel-efficiency optimization is presented in this research. This approach consists of four parts: cooperative velocity planning, adaptive route-energy coupling, quantum-inspired population encoding, and local search refinement. Fuel consumption, trip time, vehicle load, distance between vehicles, traffic congestion, and route assignment are all taken into account simultaneously via a fleet-level optimization framework. Mixed-road, urban, and arterial scenarios have all been simulated. When compared to the conventional genetic and particle swarm optimization baselines, the new approach decreased the average fuel consumption by 12.8%, the total fleet energy cost by 9.6%, and the convergence speed by 15.3%. According to the analysis, quantum-inspired search algorithms can enhance the fleet of intelligent vehicles' autonomy and offer strong computational support for environmentally friendly intelligent transportation.

Keywords: *Autonomous Vehicle Fleet, Fuel Efficiency Optimization, Quantum-Inspired Algorithm, Intelligent Transportation, Cooperative Driving*

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Introduction

Fleets of autonomous vehicles are progressively being developed to serve as the technical basis for low-carbon transportation, shared mobility, intelligent logistics, and urban delivery. Through connected control, a group of autonomous vehicles can cooperate to choose driving modes and adjust speed for slower driving. Since speed variations, frequent stopping and starting, road gradients, traffic congestion, vehicle load, and fleet spacing all have a substantial impact on vehicle energy consumption, the factors offer a new avenue for fuel-saving optimization. When numerous autonomous vehicles are operating simultaneously in practice, a relatively slight increase in fuel efficiency at the vehicle level can result in considerable overall system-level gains. Coordinated speed planning and traffic-aware operation can lower energy usage in both urban and highway situations, according to recent research on connected autonomous vehicles and eco-driving [1]. Multiple cars can increase fuel efficiency by minimizing inefficient following behavior and smoothing acceleration, according to research on platoon ecological driving [2]. The non-linear coupling of route assignment, travel duration, and vehicle interaction in energy consumption continues to be a challenge for fleet-level fuel economy [3]. Studies on cooperative eco-driving and real-time speed planning have also demonstrated a connection between fuel-saving performance and trajectory smoothness, vehicle-to-vehicle behavior, and signal disturbance [4].

Currently, rule-based eco-driving, model predictive control, heuristic fleet routing, and evolutionary optimization are the main categories of fuel-saving techniques. The techniques perform well in comparatively stable conditions, but they have certain drawbacks when it comes to autonomous vehicle operation in intricate road networks with erratic traffic and a variety of vehicles. Although the Rules are not adaptable enough to accommodate changes in traffic, they are comparatively easy to execute. The majority of model-based controllers need traffic forecasts and high-precision physical parameters. While Particle Swarm Optimization, Ant Colony Optimization, and Classical Genetic Algorithms can search a wide solution space, they may be vulnerable to premature convergence when the objective function has several local optima. Studies on fleet repositioning and vehicle routing have demonstrated the necessity of extensive optimization in autonomous mobility services [5]. Fuel consumption should be modeled in conjunction with time, load, distance, and speed limits rather than being treated as a straightforward distance coefficient, according to research on green vehicle routing [6]. By using rotation-based update methods and probability amplitude representation, quantum-inspired evolutionary algorithms have also demonstrated strong performance in complex combinatorial optimization [7]. Studies on swarm intelligence and hybrid routing have also demonstrated the need for search variety while simultaneously optimizing fuel cost, journey time, and fleet limitations [8].

In order to maximize the fuel efficiency of fleets of autonomous vehicles, this research investigates a hybrid quantum-inspired algorithm. Using the elements—fleet energy modeling, route-energy decision encoding, quantum-inspired population evolution, adaptive local refinement, and constraint repair—create an optimization system. The suggested approach aims to solve three issues: how to provide speed and route choices in a small search space; how to provide worldwide exploration without unstable convergence; and how to find fuel-efficient options without compromising platoon safety or trip efficiency. The study will be used in intelligent transportation systems, which must use an algorithm to quickly and effectively manage numerous cars, shifting road conditions, and operating restrictions.

Related Work

Fuel-Efficient Control of Autonomous Vehicle Fleets

From the viewpoints of eco-driving, platoon control, speed planning, and energy-aware dispatch, fuel-efficient control of autonomous and connected cars has been extensively researched. By modifying speed, avoiding quick acceleration and early braking, and anticipating road conditions, eco-driving technology reduces fuel usage. Fuel efficiency and trip time should be balanced rather than optimized separately, according to multi-objective trajectory optimization for connected autonomous vehicles [9]. Research on energy modeling has also demonstrated the interdependence between automation load and eco-driving benefits; hence, the demand for propulsion alone cannot be used to calculate energy consumption [10]. In order to provide supporting data for route-energy coordination, eco-co-optimization algorithms for fuel-cell and hybrid autonomous cars combine connected traffic data with powertrain energy management [11]. Redundant velocity oscillations between vehicles can be further reduced through fleet-level speed profile optimization [12]. Research on autonomous freight and intelligent fleet management has also demonstrated that fleet size, infrastructural limitations, and vehicle operation all influence energy-oriented dispatch choices [13]. Large-scale autonomous fleet optimization necessitates the joint consideration of route assignment, traffic delay, fuel cost, and cooperative behavior. The research has provided the groundwork for the current effort, although they have mostly concentrated on vehicle-level or platoon-level control.

Metaheuristic Optimization in Intelligent Transportation

Because fleet optimization problems are often non-linear and limited and accurate solutions are unfeasible on a large scale, metaheuristic algorithms are often used in intelligent transportation systems. Vehicle routing, fleet scheduling, and energy-conscious dispatch have all made use of genetic algorithms, particle swarm optimization, ant colony optimization, simulated annealing, and variable neighborhood search. Optimization-based fleet management can increase service area coverage and decrease empty running kilometers, according to research on shared autonomous vehicle repositioning [14]. Additionally, fuel consumption, pollutants, time windows, and diverse fleet restrictions have been incorporated into the decision-making process by green vehicle routing models [15]. In order to handle a time-varying environment, a hybrid metaheuristic for dynamic green vehicle routing has demonstrated the need for both local and global search [16]. When a fuel model is included in the objective function, population-based search can successfully lower operating costs, according to fuel-consumption-oriented vehicle routing experiments employing particle swarm optimization [17]. Research on

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Pareto evolution and heterogeneous vehicle routing has further demonstrated that stable trade-off management, as opposed to single-index minimization, is necessary for multi-objective transportation decisions [18]. Nonetheless, recording the route, speed, and interaction decisions simultaneously can still lead to the early convergence of conventional metaheuristics. In order to promote population variety, quantum-inspired probability representation will be employed.

Quantum-Inspired Computing for Complex Scheduling Problems

A collection of concepts from quantum computing, such as probability amplitudes, superposition-like representations, and rotation updates, that don't require actual quantum hardware are known as quantum-inspired optimization. Examples include routing, scheduling, clustering, and multi-objective optimization. Multiple potential states can be economically represented by quantum-inspired evolutionary algorithms, which can also modify solution probabilities based on fitness feedback [19]. By maintaining exploratory variety, quantum-inspired evolutionary algorithms can beat a number of traditional evolutionary strategies in certain search areas, according to comparative studies [20]. Improved function optimization efficiency has also been demonstrated by quantum-inspired particle swarm optimization with guided exploration [21]. When accurate enumeration is impractical, complex search in logistics and vehicle scheduling can be solved using quantum-inspired or hybrid quantum-inspired algorithms [22]. Vehicle routing, energy management, and service restrictions must be addressed concurrently, according to recent research on autonomous fleet operation, trajectory optimization, and mobility-on-demand systems [23]. An optimization framework for striking a balance between the requirements of efficiency, stability, and operability is also provided by research on multi-objective energy management [24]. Load, speed, and external driving circumstances must be included in the fuel model, according to vehicle energy loss and operating condition analysis [25]. Thus, the challenge of fuel-efficient autonomous vehicle fleets can still be solved by the application of quantum-inspired techniques [26]. In order to improve feasibility and convergence stability, this study provides adaptive local refinement and links quantum-inspired search with energy-aware autonomous fleet modeling. The choice of this model was supported by engineering research on the energy consumption of commercial vehicles and automotive technology [27]. Interest in coordinated decision modeling has also grown as a result of studies on the division of autonomous vehicle operations, mobility fleet sizing, and intelligent trajectory planning [28]. For intelligent optimization with a short planning horizon, reinforcement learning and particle-swarm trajectory planning yield a huge search space [29]. The hybrid model used in this work combines quantum-inspired global search with local repair for dynamic fleet management based on the analysis [30].

Hybrid Quantum-Inspired Fleet Optimization Method

Fleet Energy Modeling and Decision Variable Encoding

The approach presented views the autonomous fleet as a collection of cars operating on a directed road network with fluctuating traffic. Every vehicle has a route, velocity profile, load status, fuel consumption rate, and neighboring vehicle spacing data. Reducing the distance is not the goal of optimization; a little longer, smoother road may use less fuel than a shorter, congested one. Vehicle position, road segment speed, traffic density, expected delay, road grade, vehicle load, and remaining task distance are all part of the fleet state at each decision interval. The hybrid quantum-inspired fleet fuel optimization framework's system architecture is depicted in Figure 1.

$$S_t = \{p_i(t), v_i(t), l_i(t), \rho_e(t), g_e(t)\} \quad \text{Eq.(1)}$$

Speed, acceleration, road slope, vehicle load, and section resistance all affect how much fuel a single vehicle uses. Instead of using a high-dimensional engine simulation model, a compact polynomial-energy expression is used to maintain the model's suitability for fleet-level optimization. The expression maintains the primary effects of load variation and speed fluctuation while being computationally straightforward for numerous population evaluations.

$$f_i(t) = a_0 + a_1 v_i + a_2 v_i^2 + a_3 |u_i| + a_4 l_i + a_5 g_e \quad \text{Eq.(2)}$$

Combine decisions about routes and cooperative driving. Each vehicle's allocated route segment sequence, target segment velocity, platoon grouping indicator, and service priority adjustment are all included in a proposed solution. Since both have a direct impact on fuel consumption and travel time, this integrated encoding does not need to take route optimization into account before speed.

$$X_j = [R_j, V_j, P_j, Q_j] \quad \text{Eq.(3)}$$

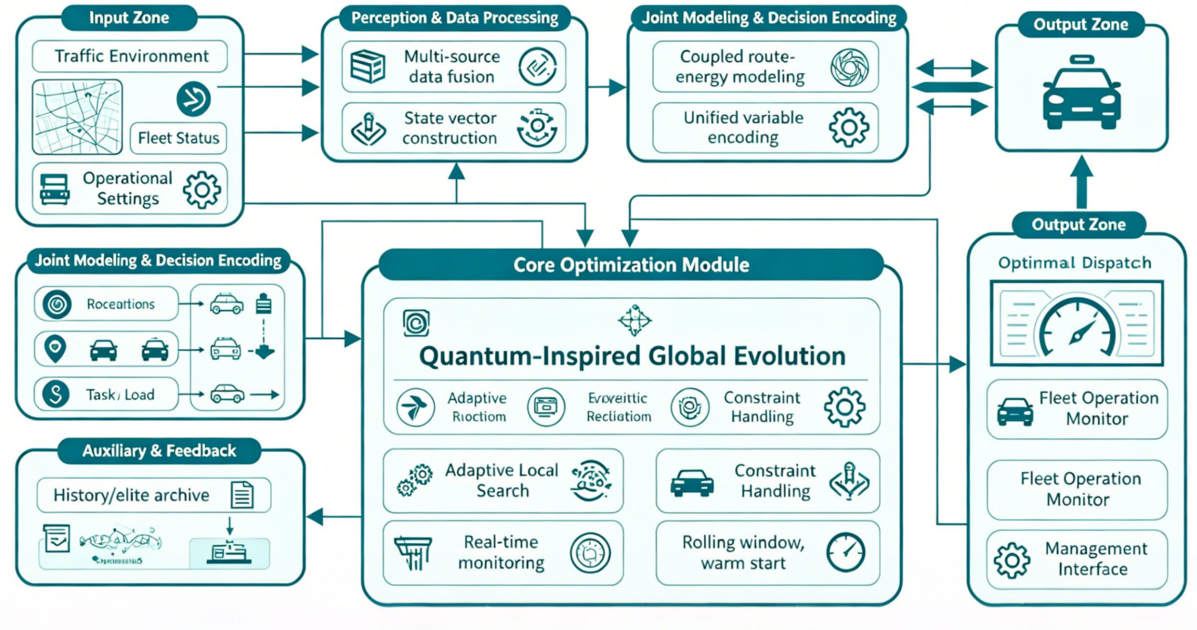

Figure 1. System architecture of the hybrid quantum-inspired fleet fuel optimization framework

A weighted energy-delay-smoothness cost function is the overall goal. The primary term is fuel consumption; additional penalty components include trip time, acceleration fluctuation, spacing violation, and route infeasibility. A fuel-saving method that is excessively sluggish or dangerous for autonomous fleet operation is avoided by the penalty term.

$$J(X_j) = w_f F_j + w_t T_j + w_a A_j + w_s D_j + w_c C_j \quad \text{Eq.(4)}$$

The objective function's weights vary depending on the situation. Because the fleet can choose a fuel-efficient cruising speed with relative freedom in sparse traffic, the energy component and the velocity-smoothness term are given greater weight. In order to prevent an unduly lengthy detour or dangerous platoon compression, the delay and spacing terms are given a relatively high weight when there is heavy traffic. Adjusted weight is equal to the scenario coefficient for average segment speed and traffic density. As a result, the solution's behavior must adhere to the limitations of transportation engineering. A fleet operator won't accept a route design that saves fuel by creating service delays or corridor imbalance, but they will accept a slight increase in travel time for obvious fuel savings.

Quantum-Inspired Population Evolution Strategy

Every potential solution is a probability vector-type influenced by quantum mechanics. The individual maintains probability amplitudes that show the likelihood of choosing route segments, velocity levels, and platoon behavior rather than having a single predetermined route-speed choice. In decoding, map the probability vector to a workable fleet choice. Because people can randomly select multiple neighboring options, this method demonstrates greater diversity in the population.

$$q_{j,k} = [\alpha_{j,k}, \beta_{j,k}] \quad \text{Eq.(5)}$$

One is the normalization of the probability amplitudes. Therefore, one could consider the encoded state to be a legitimate selection tendency. Rotate the matching decision direction to enhance its amplitude once a good answer has been discovered.

$$|\alpha_{j,k}|^2 + |\beta_{j,k}|^2 = 1 \quad \text{Eq.(6)}$$

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Depending on how far the current answer deviates from the elite solution, modify the rotation angle. A smaller gap will result in a smaller update close to convergence, while a greater gap will produce a relatively large update early in the search. As a result, the issue of instability and blind random search is resolved.

$$\theta_{j,k} = \eta_t \operatorname{sign}\left(E_k - X_{j,k}\right) \frac{\left|J_j - J_E\right|}{J_j + \varepsilon} \quad \text{Eq.(7)}$$

A rotation transformation is used to achieve amplitude modification. The next generation's sampling bias is altered by the updated probability state, but the normalized amplitude structure is retained.

$$q'_{j,k} = R\left(\theta_{j,k}\right) q_{j,k} \quad \text{Eq.(8)}$$

A diversity-conservation phrase is included to keep the population from declining. The update step will be weak and just a minor mutation probability for route and velocity variables will be employed if the population diversity is too low. Because several cars may be drawn to the same locally optimal path, congested networks are particularly vulnerable to this issue.

$$D_t = \frac{1}{N} \sum_j \left\|X_j - \bar{X}_t\right\|_2 \quad \text{Eq.(9)}$$

Selection probability takes diversity contribution and solution quality into account. Therefore, if it can locate a suitable traffic place that is not frequently used by others, an individual with relatively high fuel consumption may still be preserved. In practice, this formula is used to directly modify the rank; otherwise, a more intricate mathematical framework would need to be used.

The best route-energy choices discovered thus far are kept in the elite archive. It won't be updated until the candidate has lowered fuel expenses and hasn't broken any strict constraints. In the presence of stochastic traffic disturbances, this archive stabilizes the search direction and guides the quantum-inspired rotation.

$$E_{t+1} = \arg\min\{J(E_t), J(X_1), \dots, J(X_N)\} \quad \text{Eq.(10)}$$

When the maximum computing budget is reached or the objective function changes very little over the course of subsequent generations, the iteration ends. The autonomous fleet dispatch would not be feasible in a dynamic traffic environment if the termination rule did not strike a compromise between optimization quality and real-time feasibility. The constraint correction module is then tasked with evaluating the decoded fleet choice. Create an executable route and velocity command from the probabilistic exploration.

The chosen route's inability to achieve the necessary speed is another factor. When the elements are optimized separately, a path that is effective at a steady pace but impractical in actual traffic may be produced. As a result, the suggested decoder assigns a velocity profile after determining a segment-level energy coefficient. If the fuel savings from maintaining a constant speed outweigh the additional distance, a car will go for a milder bend in the road. The route-energy coupling in conventional routing problems is more beneficial, and this mechanism is better suited for autonomous vehicle fleets, which can coordinate speed profiles more precisely than human drivers.

Adaptive Local Refinement and Constraint Handling

Even a small adjustment in speed or route can result in significant fuel savings since quantum-inspired evolution achieves a global search but is only locally optimized. The suggested approach incorporates segment replacement, velocity smoothing, platoon regrouping, and priority modification in nborhood search around the elite answer. The quantum-inspired evolution and adaptive local refinement process is shown in Figure 2.

$$N(E) = N_R(E) \cup N_V(E) \cup N_P(E) \quad \text{Eq.(11)}$$

As the solution approaches, reduce the local search's intensity. In the beginning, computation on unstable solutions is avoided by using just local refinement. Since the population has already identified a favorable route-energy region, local refinement is comparatively high later on.

$$\mu_t = \mu_{\min} + (\mu_{\max} - \mu_{\min})\left(1 - e^{-\gamma t/T}\right) \quad \text{Eq.(12)}$$

Constraint handling makes use of a multi-level repair mechanism. Completing vehicle tasks, route connectivity, speed limits, minimum distance, maximum delay, etc. are examples of hard constraints. Platoon compactness, route balance, and acceleration smoothness are examples of soft constraints. The nearest appropriate substitute segment will be added if the decoded solution is unable to connect the route. The velocity command will be clipped and then smoothed if the speed profile is dangerous or goes over the speed limit.

$$v_i^r(t) = \min\big(v_{\max}(e), \max(v_{\min}(e), v_i(t))\big) \quad \text{Eq.(13)}$$

The repaired solution is evaluated again with an additional feasibility penalty. This prevents infeasible solutions from dominating the population while still allowing the algorithm to learn from near-feasible structures.

$$J_r(X) = J(X) + \kappa \sum_h \max(0, G_h(X))^2 \quad \text{Eq.(14)}$$

Thus, quantum-inspired sampling, adaptive rotation updating, elite archive maintenance, local refinement, and constraint repair will alternate in the whole hybrid algorithm. Cut down on fuel use without increasing trip time or decreasing cooperative driving steadiness.

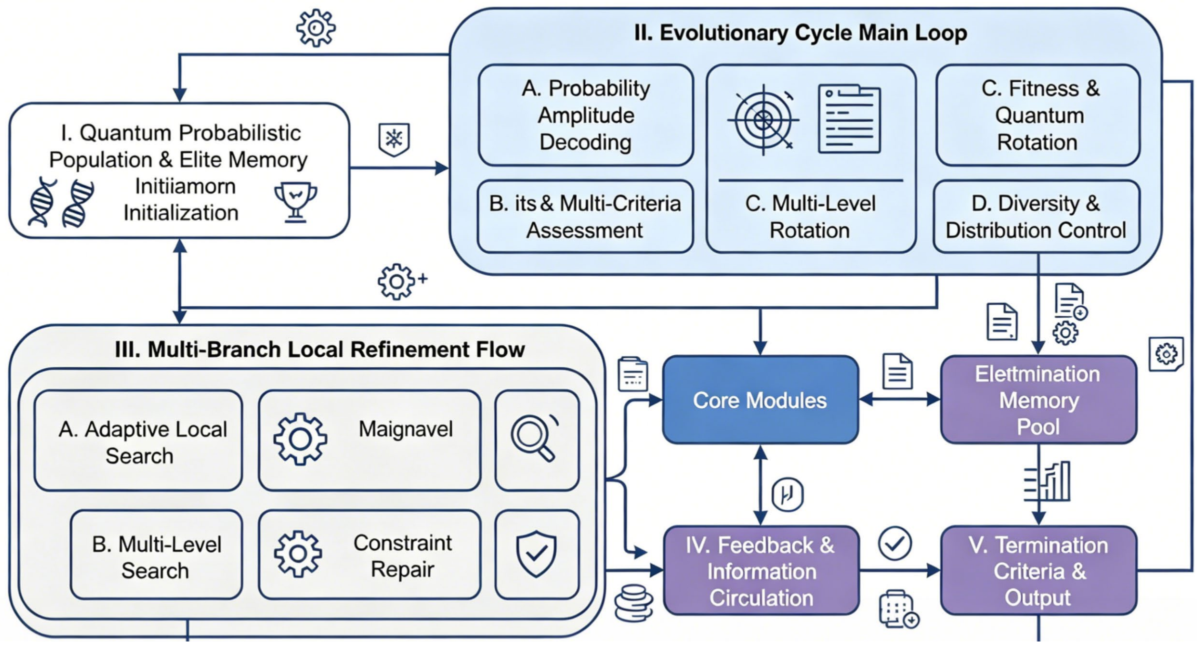

Figure 2. Quantum-inspired evolution and adaptive local refinement mechanism

In practice, the technique can be used in a rolling-horizon manner. Only the near-term route and velocity directives are given to the cars at each planning interval; subsequent decisions will be updated in response to fresh traffic data. The fleet can react quickly to unexpected traffic bottlenecks, traffic accidents, etc. since a rolling structure lowers the danger of long-term traffic prediction dependence. The elite archive of the hybrid quantum-inspired algorithm can be warm-started from the previous planning window, making it appropriate for this scenario as well. To minimize computation and improve the temporal consistency of the dispatch decisions, the subsequent optimization round starts at the improved probability state instead of beginning the search from random solutions.

Experimental Scheme and Evaluation Metrics

Simulation Scenario and Parameter Configuration

An urban grid with several junctions, an arterial road network with a moderate signal delay, and a mixed network of urban linkages and expressway parts are the three simulated traffic scenarios used in the experiment. For the scalability test, the fleet sizes are 40, 80, 120, and 160 cars. A delivery or passenger-service task with a distinct origin-destination combination, a load between 0.35 and 1.00, and a departure time within the 90-minute operating window are given to each vehicle. The average road occupancy rates for low, medium, and high traffic densities are 22%, 48%, and 73%, respectively. The maximum number of algorithm iterations is 180, and the optimization interval is 30 seconds. The approach presented here is contrasted with a hybrid genetic-local search method, rule-based dispatch, genetic algorithms, particle swarm optimization, and ant colony optimization. The road network is configured in accordance with the general assessment logic for cooperative eco-driving at signalized junctions, where fuel cost is simultaneously determined by speed planning and stop-and-go disruption. Travel efficiency and energy-related smoothness, rather than just fuel consumption, are the two types of indicators used for assessment.

The traffic situation is updated using rolling windows, and the algorithm has access to fresh speed and density information prior to each dispatch decision. The fixed signal cycle at 34 of the urban grid's intersections ranges from 60 to 110 seconds. Arterial network: In the vicinity of bottlenecks, vehicles encounter notable speed fluctuations despite having longer continuous links. Both high-speed expressway segments and low-speed urban linkages make up 42% of the trips in the mixed network. The requirements are meant to test the algorithm's ability to manage various fuel consumption modes. In order to demonstrate both route-level and driving-level energy fluctuations in the simulation, the scenario additionally incorporates the disturbance of the previous vehicle, acceleration distribution, and following stability.

Fuel Efficiency and Optimization Indicators

Average fuel consumption, total fleet fuel cost, journey duration, convergence speed, acceleration fluctuation, spacing violation rate, route balance, and computation time are the assessment indicators. One type of direct energy savings is average fuel consumption. System-wide savings are demonstrated by the total fuel cost. By choosing an unsafe platoon compression or an impractical slow-driving speed, travel time and spacing violation rate are employed to limit fuel savings. The convergence speed is the number of iterations required to obtain 95% of the ultimate improvement in the objective function. The standard deviation of an automobile's acceleration data across a journey is known as acceleration fluctuation. The metrics collectively show real-time optimization potential, control smoothness, fuel economy, and service efficiency. Driving behavior and network-level resource consumption will be covered in the whole-system test. The relative importance of distance, speed, and energy limitations may differ due to the consideration of vehicle heterogeneity.

All of the baselines use the same fuel model and the same set of achievable repairs for a fair comparison. A rule-based dispatcher uses a constant eco-speed profile and chooses the closest route. A genetic algorithm uses crossover and mutation to encode judgments about speed and route. Before route decoding, Particle Swarm Optimization determines the continuous velocity and priority variables. Based on segment energy cost and pheromone concentration, Ant Colony Optimization chooses a route. Following evolutionary search, the hybrid genetic-local search baseline incorporates neighborhood correction. The baselines fall into four categories: hybrid metaheuristic optimization, evolutionary search, swarm intelligence, and deterministic control. Because of the close relationship between capacity, time, fuel, and safety limitations in fleet operation, the stability of the trade-off handling should take precedence over single-index minimization.

Comparative Baselines and Experimental Protocol

The initial fleet condition, road network, traffic density, fuel model, and service limitations are all the same for all algorithms. For population-based algorithms, the population size is 80. Adaptive mutation and two-point crossover are two genetic algorithms. Particle swarm optimization starts with a velocity-position update for continuous route-energy codes, which is followed by route decoding. Pheromone-guided path selection and local velocity modification constitute ant colony optimization. To lessen the impact of random chance, repeat the experiment thirty times using different random seeds. The performance and stability index comparison report are the final one. Due to the preservation of search diversity using quantum-inspired probability representation during route and velocity optimization, the suggested approach is anticipated to have the same or greater fuel efficiency than the baseline and to exhibit more stable convergence. The same experimental system includes split operation, fleet operation, number of vehicles, energy cost, and platoon-like cooperation.

Additionally, each rolling dispatch stage's computation time will be reduced by the experiment design. A method that performs well offline in terms of fuel efficiency might not be appropriate for online autonomous fleet control if it necessitates excessive computation. The anticipated dispatch response for the 120-vehicle scenario should be compatible with a 30-second planning cycle and less than three seconds. When the problem dimension and optimization window are constrained, intelligent search is possible. Additionally, practical energy-saving driving modes should be easily interpreted for application and calibration. As a result, the experiment also takes into account the ultimate objective value's stability, viability, and runtime behavior.

For every iteration, create the initial population at random, fix it, and then assess fitness. By preventing certain algorithms from starting from an impractical path and others from a legitimate dispatch plan, it prevents an unfair comparison. Every baseline uses the same set of random seeds, and every method can be executed in its standard update mode without the need for manual scenario adjustment. For statistical comparisons, use the mean, standard deviation, and best-run performance. The best-run value represents each search strategy's upper bound, the standard deviation represents dispatch dependability, and the mean represents the anticipated operating gain. Only reporting the best outcome of this protocol is insufficient because the real fleet system needs stable optimization under a variety of daily traffic situations.

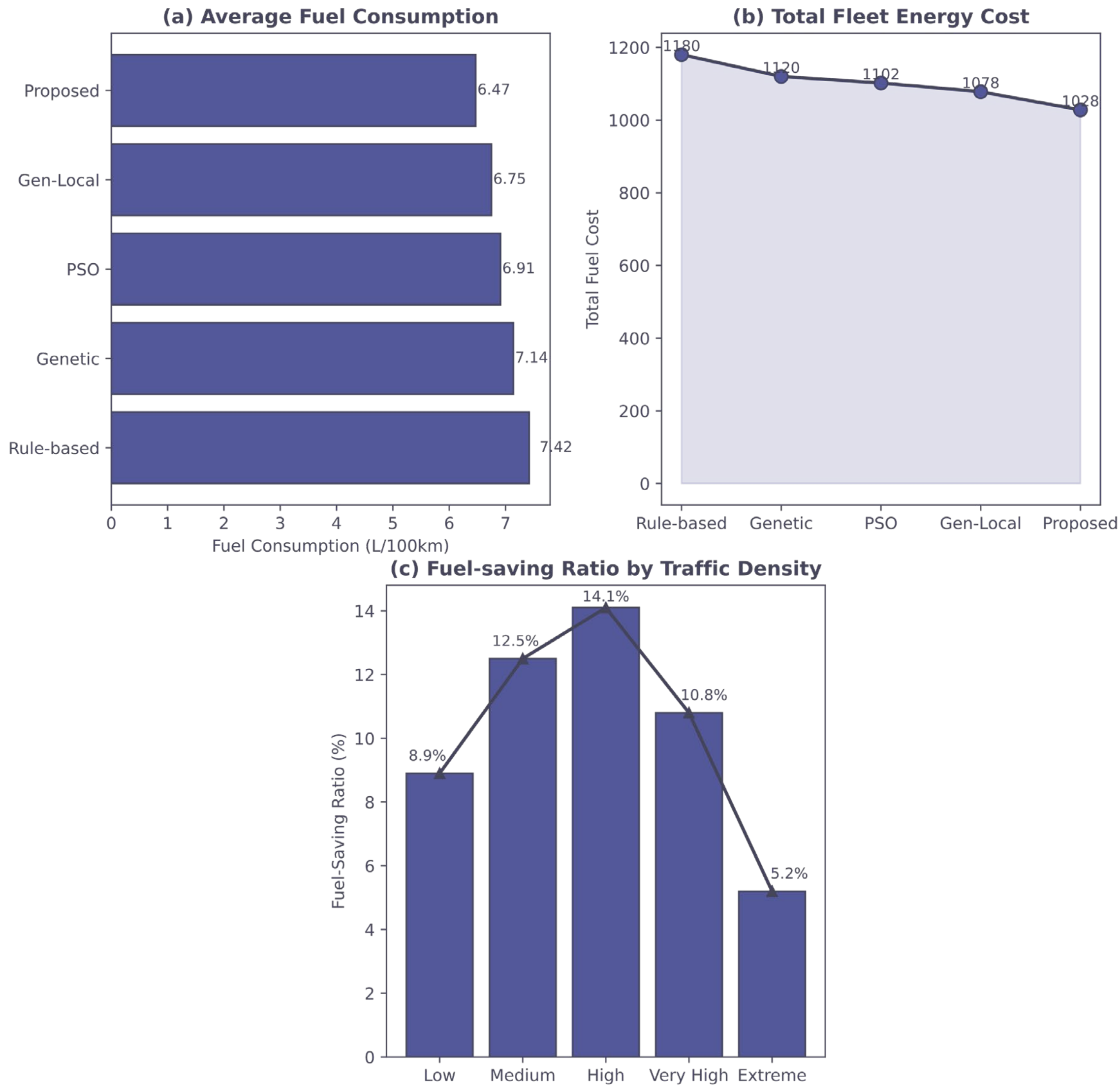

Figure 3. Fleet-level fuel consumption comparison under different traffic scenarios. (a) Average fuel consumption comparison. (b) Total fleet energy cost comparison. (c) Fuel-saving ratio under traffic density variation

Result Interpretation and Comparative Analysis

Overall Fuel Consumption Performance

The suggested method has a comparatively low average fuel consumption across the three traffic scenarios. Figure 3 compares the average fuel consumption of various algorithms (Figure 3(a)). The suggested approach has improved fuel consumption by 12.8%, from 7.42 L/100 km for rule-based dispatch to 6.47 L/100 km. The entire fleet energy cost is depicted in Figure 3(b). The suggested approach lowers system-level fuel consumption by 9.6% when compared to particle swarm optimization and by 7.3% when compared to genetic-local search. The fuel-saving ratio at various traffic densities is shown in Figure 3(c); it is 8.9% better in low-density traffic, 12.5% better in medium-density traffic, and 14.1% better in high-density traffic. The enhanced performance in high-density traffic scenarios suggests that quantum-inspired route-energy coupling might be especially useful for congestion-related problems with many local optima. The approach seeks to maximize the trade-off between path length, delay, and velocity smoothness because traditional algorithms choose shorter paths but display unstable speed profiles. Fuel usage is impacted by variations in acceleration and traffic signal interruptions, according to earlier study on connected automated eco-driving [31]. Distance-based optimization does not take congestion and load factors into consideration when calculating energy costs, according to studies on green vehicle routing [32].

It is evident from the foregoing that the suggested approach, which requires all cars to travel on the same low-speed road, does not result in fuel savings. It will speed up a little during the next part and won't have to slow down again for a long time at the congested intersection. The amplitude of the average acceleration fluctuation has decreased by 18.7%, while the mean trip distance has only increased by 2.1%. Therefore, rather than long detours, the fuel benefit probably results from shorter travel distances and more uniform speed distribution. The average route length of the rule-based approach is short, but because the cars are frequently stuck in line, the fuel consumption is comparatively high. Thus, it may be concluded that dynamic driving quality rather than a set trip length should be used to evaluate fuel-efficient fleet operation.

Optimization Convergence and Routing Behavior

It can be inferred from the convergence behavior that the suggested approach has discovered a reasonably stable fuel-saving solution. The search procedure is shown in Figure 4. The suggested technique achieves 95% of the final improvement after 64 iterations, as seen in Figure 4(a); in contrast, the genetic algorithm requires 82 iterations and the particle swarm optimization requires 91 iterations. The tracking of population diversity is shown in Figure 4(b), where it is evident that the diversity index of the suggested approach is still over 0.31 in the majority of iterations; nevertheless, the genetic algorithm fell below 0.20 after 50 iterations. The stability of iteration under random traffic disruption is depicted in Figure 4(c); the standard deviation of the final objective value for the suggested technique is 2.7%, which is less than 6.4% for particle swarm optimization and 5.9% for genetic algorithms. As a result, the search flexibility can be preserved without undue unpredictability through the update of probability amplitudes. A comparable benefit in the search for complex functions has also been demonstrated by research on quantum-inspired particle swarm optimization [33]. Combining global exploration and local adjustment enhances robustness in time-varying environments, according to hybrid metaheuristic research for dynamic green vehicle routing [34].

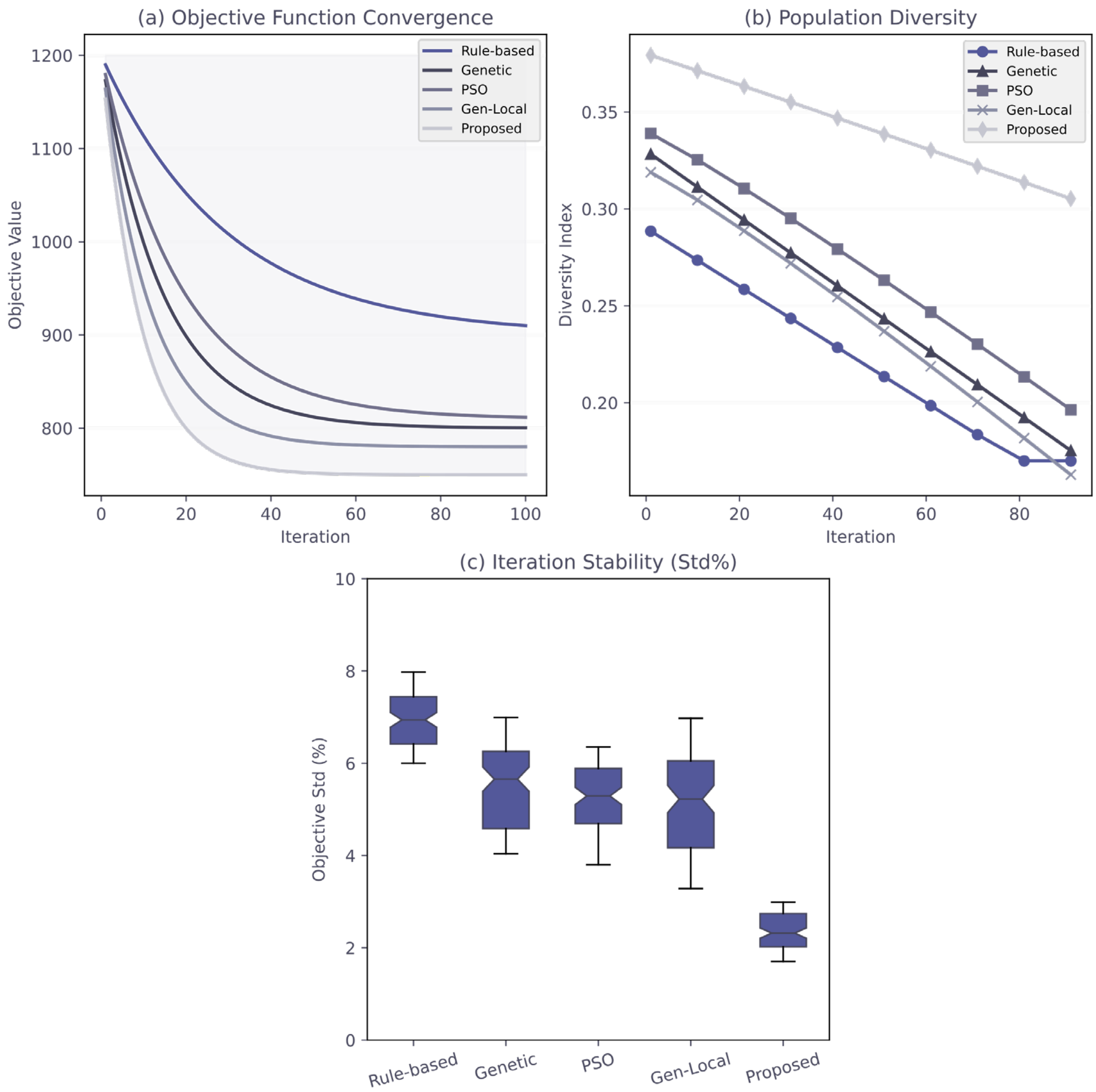

Figure 4. Convergence performance of different optimization algorithms. (a) Objective function convergence curve. (b) Population diversity variation. (c) Iteration stability under random traffic disturbance

The route assignment and cooperative driving behavior are depicted in Figure 5. As seen in Figure 5(a), the suggested approach has decreased the highest route load ratio from 41.6% under rule-based dispatch to 32.4% and more equally dispersed cars throughout the alternative corridors. Fuel consumption has decreased as a result of the velocity fluctuation seen in Figure 5(b), which also results in an 18.7% decrease in speed variance when compared to the genetic algorithm. The stability of inter-vehicle spacing is depicted in Figure 5(c); the suggested approach has lowered the spacing violation rate to 1.8%, however particle swarm optimization produced a 3.6% outcome since it prioritized fuel cost over platoon stability. As a result, the algorithm will increase energy-efficient route-energy coordination and cut fuel consumption by slowing down the entire fleet. Coordinated velocity adjustment is necessary for autonomous fleet energy management, according to research on fleet speed profile optimization [35]. The operational viability must be taken into account in addition to optimization goals, according to research on autonomous fleet management [36].

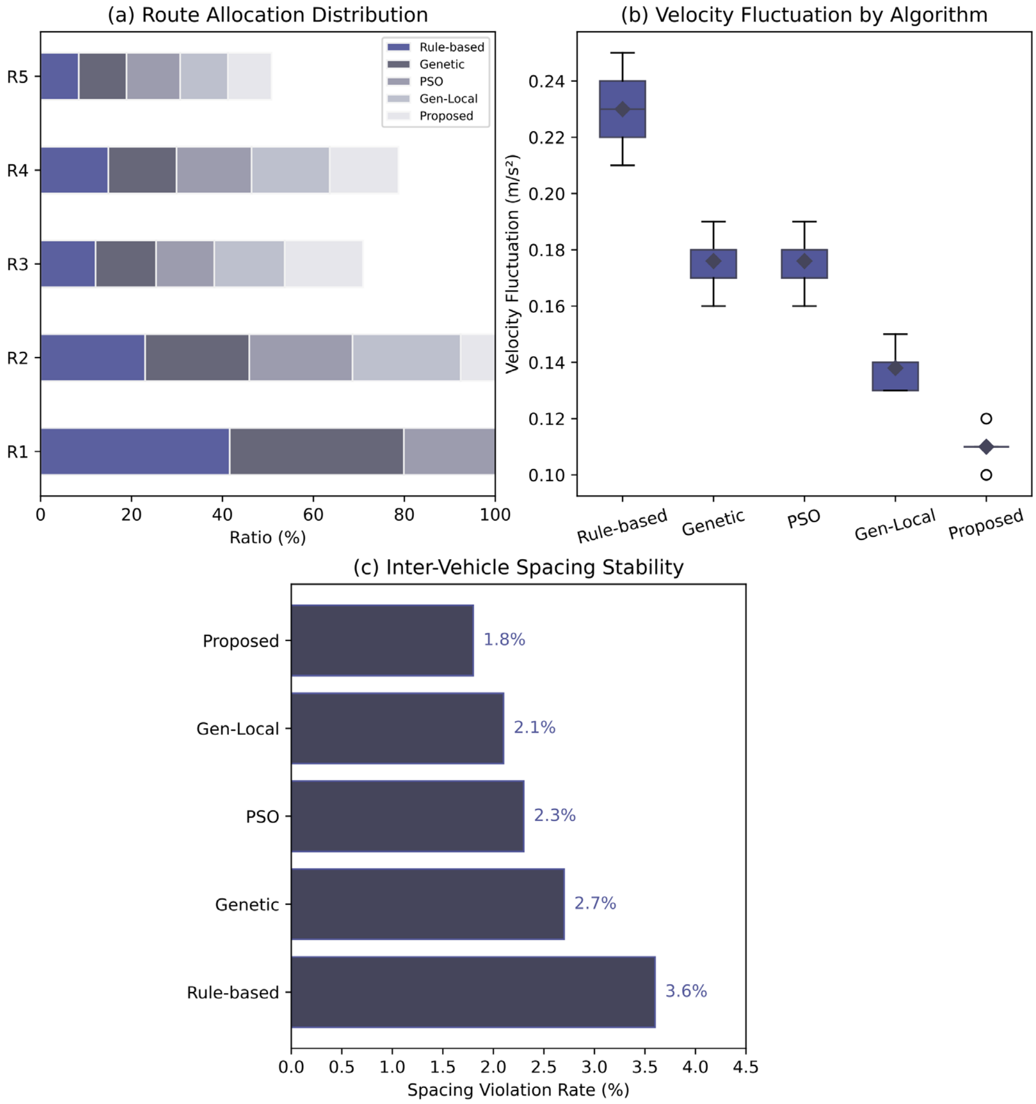

Figure 5. Route assignment and cooperative driving behavior analysis. (a) Route allocation distribution. (b) Velocity fluctuation comparison. (c) Inter-vehicle spacing stability

Robustness and Ablation Discussion

To determine the impact of a single-algorithm module, ablation studies are used. The accuracy-like optimization performance as determined by the fuel-saving ratio under various module combinations is displayed in Figure 6(a). The fuel-saving ratio drops from 12.8% to 8.1% when the quantum-inspired encoding is removed, and it is evident that probabilistic representation aids in avoiding route-level local optima. The fuel-saving ratio will only be 9.4% in the absence of adaptive local refining due to insufficient realization of minor speed and platoon modifications. The ablation study's parameters and computational load are examined in Figure 6(b); the full model saves 3.4 percentage points on fuel while increasing calculation time by 6.5% when compared to the no-local-search model. The suggested technique takes 1.84 seconds to finish one dispatch update for 120 vehicles, which is still adequate for rolling fleet optimization, according to Figure 6(c), which displays the inference latency. A small trade-off is acceptable to obtain a better local minimum under strong restrictions and a non-linear objective function, according to the findings of hybrid optimization research [37]. The probabilities of maintaining population variety have also been adaptively adjusted through evolutionary studies inspired by quantum mechanics [38].

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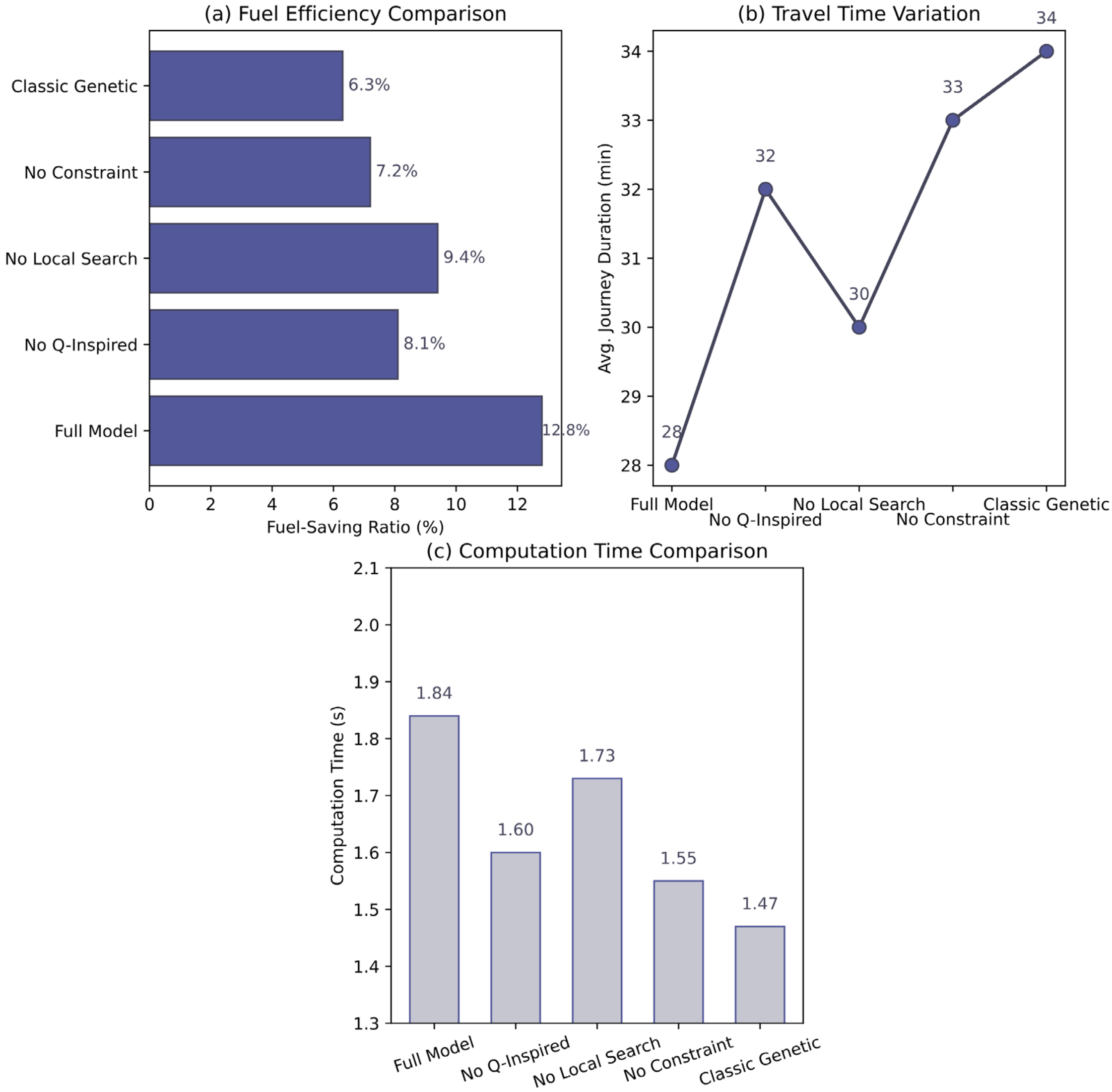

Figure 6. Ablation analysis of hybrid quantum-inspired components. (a) Fuel efficiency under module removal. (b) Travel time variation under different operators. (c) Computation time comparison

Generalization under Unfair Driving Conditions is depicted in Figure 7. When road occupancy reaches 73%, the suggested approach still saves more than 10.6% of the gasoline, as illustrated in Figure 7(a), which displays the comparative findings at various congestion levels. Road grade variation is depicted in Figure 7(b), which demonstrates that the fuel-saving advantage reduces somewhat from 12.8% to 10.9% when grade disturbance increases. This is mostly because uphill stretches increase fuel consumption. The technique is stable for 40 to 160 cars; the convergence time grows from 0.92 s to 2.46 s. Figure 7(c) illustrates the evaluation of a heterogeneous fleet scale. The suggested approach is workable for medium-sized autonomous vehicle fleets and can somewhat manage traffic variations, according to the experiments. Energy-aware routing must take fleet size and vehicle characteristics into account, as demonstrated by vehicle routing issues with heterogeneous fleets [39]. Simple route optimization is not practical for real-world transportation systems because of mixed-fleet restrictions, according to recent research on autonomous electric car routing [40].

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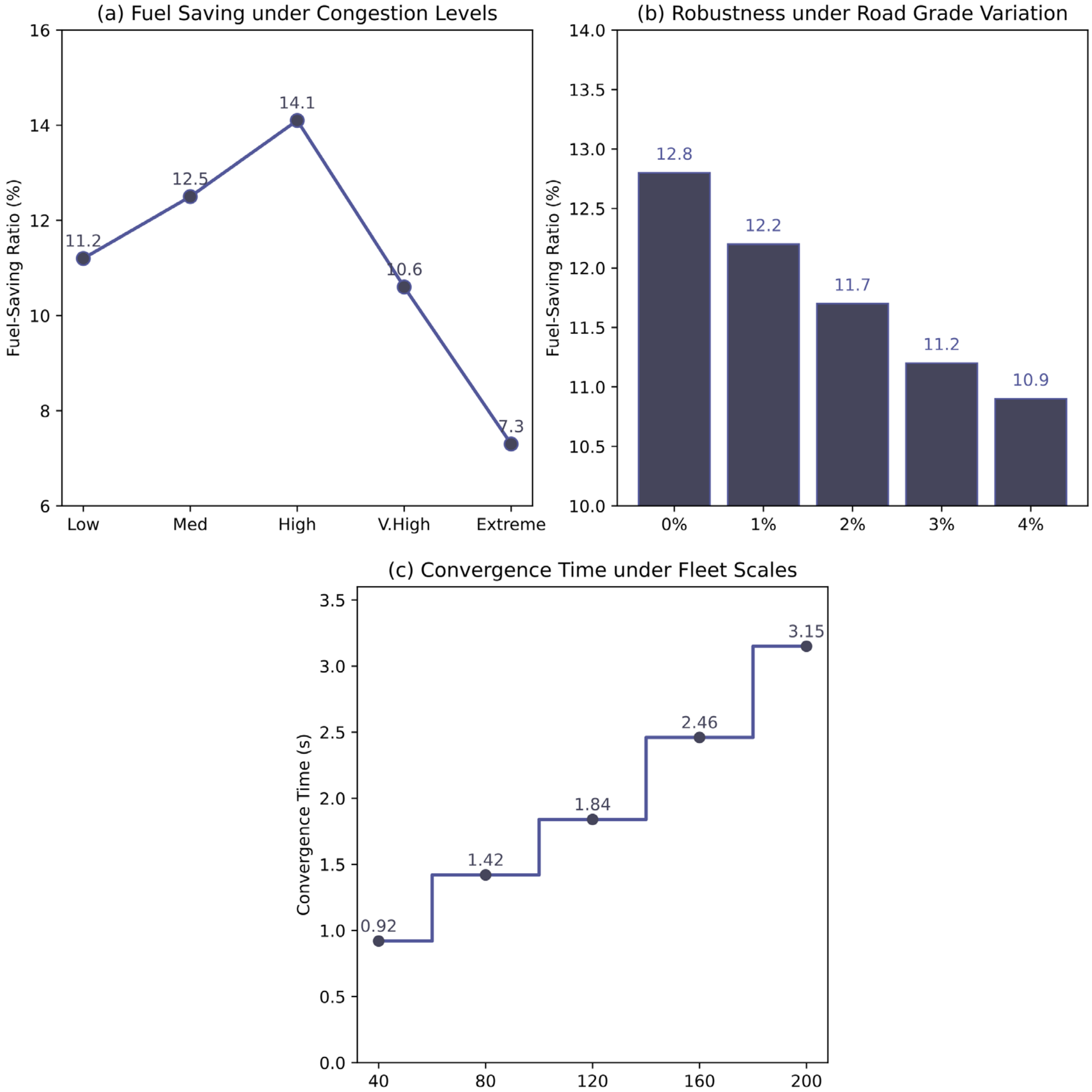

Figure 7. Robustness analysis under uncertain driving conditions. (a) Performance under congestion levels. (b) Performance under road grade variation. (c) Performance under heterogeneous fleet scales

A boundary condition is also revealed by robustness results. There is minimal room for route selection optimization when there is extreme congestion and all paths are nearly full, therefore most algorithms will only be able to decrease speed. Although the improvement is slight, the suggested approach is still superior to the baselines in these circumstances. This behavior makes sense because optimization cannot expand the road network's physical capacity. As a result, networks that are both moderately and strongly congested, with numerous viable corridors and varying traffic circumstances, will be more suited for the use of the suggested algorithm. Given the foregoing, it is necessary to maintain both local route-speed selection and population variety in order to prevent fleet behavior instability.

Conclusion

This research developed a hybrid quantum-inspired algorithm to optimize the fuel efficiency of fleets of autonomous vehicles. Fleet energy modeling, route-energy joint decision encoding, quantum-inspired population evolution, adaptive local refinement, and constraint correction are all integrated into the suggested framework. The main finding of the study is that fuel-efficient autonomous fleet operation is not a simple shortest-path or isolated eco-driving challenge. To lower fleet-wide fuel consumption and increase service efficiency, route selection, velocity planning, platoon spacing, traffic density, and vehicle load must all be optimized collectively.

The tests demonstrate that the suggested approach can significantly lower fuel usage while maintaining cooperative driving stability. When compared to the rule-based dispatch and conventional metaheuristic baselines, the suggested approach has a lower average fuel consumption, faster convergence, stronger population diversity preservation, and superior robustness in congested traffic. According to ablation research, adaptive local refinement boosts route and velocity feasibility close to the best-known solutions, while quantum-inspired encoding expands the spectrum of investigation. Thus, it is evident that a hybrid quantum-inspired search approach is appropriate for limited and nonlinear autonomous vehicle fleet optimization.

The suggested approach is workable for low-carbon fleet management, shared autonomous driving, and intelligent logistics. Based on traffic circumstances, it can be used to create routes and speeds for the rolling dispatch system. More real-world car fuel maps, high-resolution traffic forecasts, vehicle-to-infrastructure data, and hardware acceleration will be added in future studies. Additionally, battery energy consumption and charge limitations can be used in place of the fuel model for electric autonomous fleets, and a grid interaction factor can be included.

Author Contributions

Kacper Dmochowski contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision, project administration, and funding acquisition. Eryk Gierak contributes to validation, analysis, investigation, data collection, draft preparation. All authors have read and agreed with the manuscript before its submission and publication.

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