Journal of Applied Automation Technologies

Research Paper

Dynamic Path Optimization for Intelligent GPS Systems Based on a Hybrid Evolutionary Algorithm

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Abstract. With the increase in cities and cars, transportation networks have also become more complex. This paper introduces an intelligent dynamic path optimization method based on a hybrid evolutionary algorithm. This algorithm is suitable for urban traffic, employing deterministic local optimization and global population search. Due to its modular architecture, the framework can continuously learn, dynamically adjust parameters, and stream real-time traffic data. Rigorous simulation experiments were conducted on large-scale urban data. The results show that compared to traditional genetic algorithms and differential evolution algorithms, the hybrid algorithm reduced travel time by 14 to 23 percentage points and shortened routes by 17.4 percentage points during peak period disturbances. In all cases, the system demonstrated extremely high computational efficiency and optimality, with convergence variation of less than 0.8% when using multiple random seeds. Hybrid evolutionary computation conducts real-time exploration and development, improving the accuracy and speed of urban path optimization. This method provides a feasible and scalable solution for future intelligent transportation systems to improve daily commuting, logistics, and emergency response. Future research will delve deeper into the behavior models of large-scale deployments in heterogeneous sensor networks.

Keywords: *Hybrid Evolutionary Algorithm, Dynamic Path Planning, Intelligent Transportation System, Real-Time Routing, Urban Mobility*

Received on 15 February 2025, Accepted on 21 July 2025, Published on 29 July 2025

Introduction

With the increase in the number of cars and the complexity of urban traffic networks, new planning methods are needed. Intelligent Transportation Systems (ITS) are the foundation for building safe, efficient, and environmentally friendly transportation systems. ITS utilizes new technologies in real-time sensing, communication, and computation to address the characteristics of modern traffic changes [1]. More and more people are starting to use a new method to dynamically change their driving routes. This method can quickly change driving routes to respond to changes such as traffic congestion, accidents, or other outdoor factors. The current algorithms have issues in handling large amounts of data, achieving rapid convergence, and flexibly integrating changes in multi-source traffic information, despite the aforementioned improvements [2]. The current system is often constrained by computational limitations, thus lacking the flexibility needed to handle unexpected failures in large-scale urban networks [3]. Due to the aforementioned issues, data-driven route optimization has become increasingly important, and this optimization needs to be conducted in complex, high-density, and unstable urban environments [4].

In the past decade, classic algorithms such as Dijkstra and A* have laid the foundation for shortest path computation [5]. Due to their inherent static graph representation characteristics, they are not well-suited for the conditions of modern urban traffic changes [6]. In order to improve the scalability, robustness, and flexibility of route selection, researchers have recently begun to focus on evolutionary computation and metaheuristic optimization methods, such as particle swarm optimization, ant colony optimization, and genetic algorithms [7].

https://doi.org/10.64972/jaat.2025v3.226p31e:420-433

These two are very suitable for extensively searching data and handling various applications. They usually converge slowly, are costly, and are sensitive to parameter settings [8]. Hybrid models that combine domain heuristic methods and evolutionary algorithms have begun to show promise in addressing the aforementioned shortcomings, but effective integration strategies and real-time adaptation remain the focus of research [9]. With the increase in distributed sensors and high-speed traffic data, traditional algorithms are becoming increasingly difficult to handle real-time synthesis and decision-making problems [10].

This paper proposes a new hybrid evolutionary algorithm for intelligent GPS dynamic path optimization. The main new feature is the integration of the advantages of various evolutionary strategies and traffic-specific heuristic methods into a comprehensive, adaptive model to achieve fast, real-time responses and large-scale searches. It is a large-scale network adaptation based on systematic traffic data, combining the advantages of exploration and exploitation to achieve timely and high-quality routing decisions. These main contributions include: conducting extensive empirical research in different urban areas; designing a system that can smoothly integrate domain knowledge and meta-heuristic algorithms; and developing an adaptive mechanism to handle fluctuations in real-time data. This research not only enhances theoretical knowledge but also provides practical recommendations for dynamic path optimization methods in future urban transportation.

Related Works

GPS Path Optimization Methods

Path optimization is the foundation of many intelligent transportation systems and helps improve traffic flow efficiency in densely populated areas. In the early stages of shortest path computation, the commonly used classic graph algorithms are Dijkstra and A* algorithms [11]. In fixed traffic network scenarios, the aforementioned algorithms are renowned for their mathematical accuracy and reliability. They also provide computationally feasible optimal deterministic solutions. Over time, additional techniques such as bidirectional search, hierarchical decomposition, and heuristic priority sorting have been used to improve the computational speed of large-scale urban networks [12]. The main structure of these algorithms remains static, despite some improvements. They are unable to provide timely and accurate route suggestions to people under various external circumstances [13]. These situations include traffic accidents, changes in traffic conditions, and unforeseen disruptions. In order to account for changes in edge weights due to traffic variations, incremental and time-dependent pathfinding extensions have been added. These methods usually have relatively high update costs and can become cumbersome when integrating continuous high-frequency data streams from sensors, GPS, or crowdsourced reports [14]. Static path optimization methods are not suitable for large-scale urban areas because balancing computational feasibility with real-time performance requirements is a long-standing issue [15].

Evolutionary Computation in Routing

In adaptive and robust search in high-dimensional, uncertain environments, evolutionary computation is now widely used to address the shortcomings of deterministic algorithms in dynamic path planning [16]. Over time, genetic algorithms (GA), differential evolution (DE), and particle swarm optimization (PSO) have all been developed Through the imitation of natural selection, crossover and mutation, and swarm intelligence. Metaheuristic algorithms are not pathfinding algorithms; rather, they are stochastic and can explore multiple paths simultaneously, thereby avoiding getting trapped in local optima [17]. Vehicle routing and network optimization are solved using genetic algorithms [18]. Differential evolution is simple and has strong global convergence. When combined with specific heuristic methods, it is also well-suited for urban road networks [19]. Particle swarm optimization is suitable for parallel search because it adapts well to the distributed data streams and traffic variations in intelligent GPS applications [20]. Despite the advantages of the aforementioned methods, evolutionary computation still has some practical limitations. For large-scale problems, the convergence speed is slow, some algorithms require fine-tuning of parameters, and integration with real-time streaming data remains challenging [21]. The aforementioned limitations indicate that more combinations and optimizations are needed before meeting the requirements of large-scale systems or real-time operations [22].

Hybrid Approaches and Limitations

Due to the inability of graph-based and evolutionary methods to individually meet the current urban travel operation conditions, there has been recent interest in hybrid optimization strategies [23]. A hybrid model suitable for path optimization combines the fast local search and precise deterministic characteristics of traditional algorithms with the exploration and generalization capabilities of metaheuristic algorithms. Evolutionary algorithms are typically used for initial global search and diversity maintenance, and then precise path selection is achieved Through deterministic refinement steps [24]. When changes or inaccuracies occur, a two-step approach can be used to improve the speed and stability of convergence. The engineering design of an effective hybrid framework remains a challenge. The management of system complexity, the design of seamless connections between algorithm modules, and the integration of heterogeneous distributed real-time data are all significant issues [25]. Control logic and parameter calibration often need to be adjusted for specific situations to ensure the system's scalability and stability. In order to effectively address new issues in data integration and decision-making, as the complexity and unpredictability of urban travel scenarios continue to increase, existing hybrid models need to improve their computational and responsiveness capabilities.

Hybrid Evolutionary Algorithm Design

System Framework Overview

The hybrid evolutionary dynamic path optimization algorithm has a tightly modular architecture, allowing for system-level adaptation, real-time data assimilation, and global search in complex high-density road environments. The system core employs domain-driven refinement methods and meta-heuristic algorithms, which to some extent integrate deterministic local search and evolutionary population operations. The core of the system is a multi-level decision engine. The system is capable of processing large amounts of data from urban traffic sensors, GPS-enabled vehicles, and digital infrastructure, and can also adjust routes in real-time and respond quickly to emergencies.

The four modules of the basic structure work together. The data collection and preprocessing module continuously gathers multimodal real-time data, then filters, aligns, and normalizes the input. This data includes traffic flow, vehicle locations, event notifications, and historical congestion data. The population evolution module will use it to initialize, evaluate, and evolve alternative paths Through hybrid operators. The decision integration module connects local deterministic fine-tuning and global evolutionary optimization to determine the best combination for rapid utilization under system constraints and user objectives. Real-time feedback and learning module will be added to the entire system architecture to adjust algorithm parameters based on environmental changes. This module will also provide the system with feedback on updated traffic data and solution quality metrics, thereby achieving continuous learning and robustness.

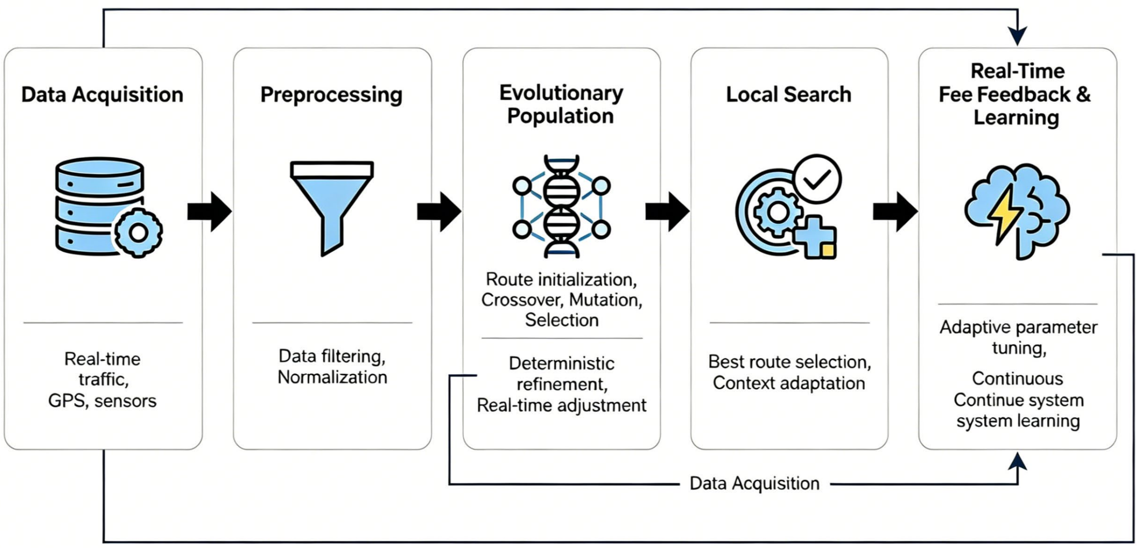

Figure 1. Overall Architecture of the Hybrid Algorithm.

https://doi.org/10.64972/jaat.2025v3.226p31e:420-433

Modular frameworks can be used for distributed processing and scaling, and they can easily incorporate data-driven and heuristic knowledge. The rolling horizon strategy uses evolutionary search, local optimization, and new stream data instances to create context-aware routes. To prevent feedback delays or other issues, the communication protocols of each module need to have good synchronization mechanisms, low latency, and high-fidelity transmission characteristics. Figure 1 shows the overall diagram of this new generation path optimization engine. The information flow between the modules is displayed, and two search directions can be adopted to maintain good routing results in an urban environment.

Algorithmic Modules and Workflow

Describe the urban road network as a directed multigraph, where the nodes are navigable intersections and the edges are traffic segments with time cost metrics; this is the core of the system's evolution. The probabilistic seeding method is used to create the initial population, balancing the use of well-established historical paths with the exploration of numerous new paths. Based on current traffic congestion, expected hazard probabilities, and legal traffic restrictions, parameter encoding dynamically encodes each route.

Each evolutionary cycle uses a set of hybrid operators. The operator set consists of intelligent mutation and adaptive crossover, considering both local and global exploration objectives. Based on changes in network structure and predicted traffic flow, the variable cut-point method dynamically adjusts the routes executed by crossover operators and the diversity of sub-path optimizations. Mutation replans the route and increases random disturbances Through a domain-driven approach. It uses alternative sub-paths derived from real-time data predictions to replace segments of the route where recent travel costs or risks have increased. Choose to use the elite championship protocol to maintain high-quality solutions and ensure a continuous supply of diversity.

A parallelized batch evaluation workflow will be adopted to improve computational speed. The batches for parallel evaluation using current hardware acceleration and distributed memory architecture are selected solutions. Based on the fitness evaluation results, the evolutionary population is updated, and adaptive operators are parameterized to close the loop, achieving a responsive, data-driven search process.

With the development of the global economy, solutions have been improved, and now a deterministic local optimization engine can be used as an integrated module. Incorporate real-time sensor data into the engine, perform granular cost adjustments at the segment level, and modify promising label correction algorithms. This fixed reduction can improve local optimal solutions and the response speed to sudden traffic accidents or rapidly spreading issues.

The entire workflow is in a rolling view mode. The learning module and real-time feedback drive hyperparameter self-adjustment and subsequent operator re-weighting. The algorithm can be used independently when traffic conditions change or when a certain area develops slowly. The following are the mathematical formulas for evolutionary and hybrid workflows:

$$\mathbf{P}_0 = \mathcal{S}(\mathbf{G}, \boldsymbol{\Omega}_0, \boldsymbol{\theta}_0) \quad \text{Eq.(1)}$$

where $\mathbf{P}_0$ is the initialized population, $\mathcal{S}$ denotes the seeding mechanism, $\mathbf{G}$ is the dynamic graph, and $\boldsymbol{\Omega}_0, \boldsymbol{\theta}_0$ represent historical priors and real-time context.

$$\mathcal{C}_{\text{adaptive}}(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}'_{ij} = f_{\text{div}}(\mathbf{x}_i, \mathbf{x}_j, \eta_{ij}(t)) \quad \text{Eq.(2)}$$

where $\mathcal{C}_{\text{adaptive}}$ is the adaptive crossover operator, $\mathbf{x}_i, \mathbf{x}_j$ are parent paths, and $\eta_{ij}(t)$ adapts to network dynamics.

$$\mu_k(t) = p_{\text{mut}} \cdot g(\chi_k, \tau_k, \phi_k(t)) \quad \text{Eq.(3)}$$

where $\mu_k(t)$ is the mutation probability for route k, modulated by trajectory history χ_k, hazard factors τ_k, and segment context $\phi_k(t)$.

$$S^* = \arg\ \max_{S \subset \mathcal{P}_g} \{\mathcal{F}(S), D(S)\} \quad \text{Eq.(4)}$$

where S^* is the selected elite subset from generation g, $\mathcal{F}$ is the fitness, and $D(S)$ measures diversity.

$$\mathcal{F}_{\text{batch}}(\mathbf{P}_g) = [f(\mathbf{x}_1), \dots, f(\mathbf{x}_N)]^T = \mathbf{A}_g \times \mathbf{V}_g \quad \text{Eq.(5)}$$

where $\mathbf{P}_g$ is the batch population, and $\mathbf{A}_g, \mathbf{V}_g$ denote distributed evaluation matrices and input feature vectors.

https://doi.org/10.64972/jaat.2025v3.226p31e:420-433

$$\mathbf{x}_{\text{ref}} = \mathcal{L}_{\text{corr}}(\mathbf{x}_e, \mathbf{C}(t), \mathbf{S}(t)) \quad \text{Eq.(6)}$$

where $\mathbf{x}_{\text{ref}}$ is the refined route, $\mathcal{L}_{\text{corr}}$ is the local deterministic correction function, and $\mathbf{C}(t), \mathbf{S}(t)$ are current segment costs and sensor inputs.

According to the above workflow, each module will help build a search environment with broad diversity and high responsiveness, capable of continuously adapting to changes in urban traffic.

Fitness Functions and Optimization Processes

The multi-objective function is the first component of the improved combinatorial optimization system. It includes multiple objectives for urban navigation, such as timeliness, safety, security, reducing ecological impact, and constraints from network planning. The first goal is to reduce travel time. This value depends on the cost of specific road segments and the predicted changes in flow data.

The composite fitness function is used to add penalty and reward terms, and dynamically adjusts the evaluation of candidates based on the predicted accident occurrence rate, environmental factors (such as particulate matter or NOx), and the degree to which they meet user or system requirements. The multi-objective structure optimizes the Pareto efficiency ranking among conflicting objectives and uses a dominance-preserving update scheme to ensure a good distribution of high-quality route candidates along the Pareto front.

In the fitness function, constraint handling consists of a set of adaptive infeasibility penalties. These penalties are indexed according to relevant features, such as road capacity violations, traffic light delays, or necessary detour rules. Due to the severity and urgency of the violations, the algorithm can randomly adjust the penalties to adapt to changes in the city.

The optimization process is divided into three stages. First, use an evolutionary population for global search; then, deterministically optimize the elite candidates obtained in the first step; finally, conduct a rolling horizon check to verify short-term feasibility and long-term performance improvement. Use a restart strategy when stagnation occurs, and the adaptive threshold method simultaneously considers the diversity of solutions and the improvement of fitness in each generation.

The general formula for the above process is as follows:

$$F(\mathbf{x}) = \alpha T(\mathbf{x}) + \beta E(\mathbf{x}) + \gamma R(\mathbf{x}) + \lambda \sum_{c \in \mathcal{C}_x} P_c(\mathbf{x}) \quad \text{Eq.(7)}$$

where $F(\mathbf{x})$ is the composite fitness, $T(\mathbf{x})$ expected travel time, $E(\mathbf{x})$ environmental impact, $R(\mathbf{x})$ risk or safety term, and $P_c(\mathbf{x})$ represents penalty functions over constraint set $\mathcal{C}_x$; $\alpha, \beta, \gamma, \lambda$ are dynamically tuned weights.

$$P_c(\mathbf{x}) = \kappa_c \max\{0, V_c(\mathbf{x}, t)\} \quad \text{Eq.(8)}$$

where $P_c(\mathbf{x})$ is the penalty for route $\mathbf{x}$ with respect to constraint c, κ_c its severity, and V_c the measured violation at time t.

$$\mathcal{P}_{k+1} = \{\mathbf{x} \in \mathcal{P}_k \mid \nexists \mathbf{x}' : F(\mathbf{x}') \prec F(\mathbf{x})\} \quad \text{Eq.(9)}$$

where $\mathcal{P}_{k+1}$ denotes the updated Pareto front at iteration $k+1$, and $F(\,) \prec F(\,)$ is the dominance relation across objective vectors.

$$\tau_{k+1} = \tau_k \left(1 - \delta \frac{\sigma_F^2}{\bar{F}}\right) \quad \text{Eq.(10)}$$

where τ_{k+1} is the updated convergence threshold, δ is the adaptation factor, σ_F^2 is population fitness variance, and $\bar{F}$ is mean fitness, supporting adaptive restart when progress stalls.

The combination of these analytical components forms the foundation of a highly available and scalable route guidance system to address the volatility and diversity of modern urban traffic data. In order to ensure that the new method is both novel and stable, it is necessary to introduce these three components: evolutionary exploration, deterministic optimization, and reliable fitness evaluation.

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Experimental Protocol and Simulation Setup

Scenario Construction and Data Preparation

Create the experimental scenario for this paper, which includes some real-life urban road networks and operating conditions. A representative subset of the road network in the central business district was extracted from the high-fidelity open urban traffic database. The database combines dynamic multi-source sensor flows with static mapping topology. The annotations of nodes and edges include spatiotemporal road features, such as traffic signal phases and multi-lane traffic distribution. Based on the statistical models of the frequency of these issues, synthetic events were created, reflecting both routine and sporadic problems, such as congestion during peak hours, inclement weather, and major road construction.

The size of the scenario is deliberately designed to cover multiple orders of magnitude. The full-scale deployment of thousands of connected segments demonstrated scalability and computational stability under real traffic conditions, while smaller test areas were used for controlled ablation experiments to diagnose convergence. In order to establish a unified reference interval, strict temporal resampling is conducted, and detector vehicle logs, fixed sensor readings, and crowdsourced inputs are integrated to generate traffic state data. Each node and edge maintain a time-ordered state vector to store dynamic transition probabilities, queue sizes, predicted hazard rates, etc. This provides a random yet data-driven environment for algorithm stress testing.

Expand the preprocessing stage to eliminate invalid data and standardize all data fields. High-dimensional input channels use min-max normalization and Z-score normalization to standardize scale and variance. The graphical enhancement step interpolated the missing turn restrictions and synthesized alternative segments, when necessary, while the trimming procedure eliminated inconsistencies caused by sensor failures or mapping gaps. In order to conduct a rigorous cross-scenario comparison and eliminate confusion caused by unobserved state changes, the experimental variables (event density, initial vehicle distribution, and background noise) are all set to the same statistical control seed. The aforementioned preparations will ensure the consistency and reliability of the optimization results.

Parameter Settings and Experimental Pipeline

Simulating the urban network diagram and systematically allocating real-time synthetic traffic conditions is the first step in the formal experimental process. Topological entropy alters the depth of population size and evolutionary cycles to simulate system-level adaptability. This is achieved Through the empirical connectivity and pattern traffic complexity of each benchmark area. The hyperparameters of the algorithm, such as crossover rate, mutation strength, batch evaluation concurrency, and local optimization step size, are derived Through preliminary grid search and sensitivity analysis of route diversity and real-time fluctuation patterns, rather than being arbitrarily chosen. This reasonable adjustment has good general applicability for the entire city.

Discrete-time event stepping is managed by a high-throughput simulation engine, optimizing core broadcast segment costs and constraint signals at each time interval. Due to probability, traffic events, such as spontaneous bottlenecks or cascading red light delays, will immediately propagate to all modules of the rolling horizon algorithm. In order to implement the system, a parallel hybrid architecture is adopted, and multiple threads are run simultaneously during the data assimilation and route evaluation stages. This gives the system good practical operating efficiency. In order to perform deterministic replay and comprehensive post-analysis, a continuous experiment log saves all parameterizations, intermediate states, and final results. Dynamic module calls, batch points, and adaptive feedback loops for stable mixed optimization are the multi-stage workflows shown in Figure 2.

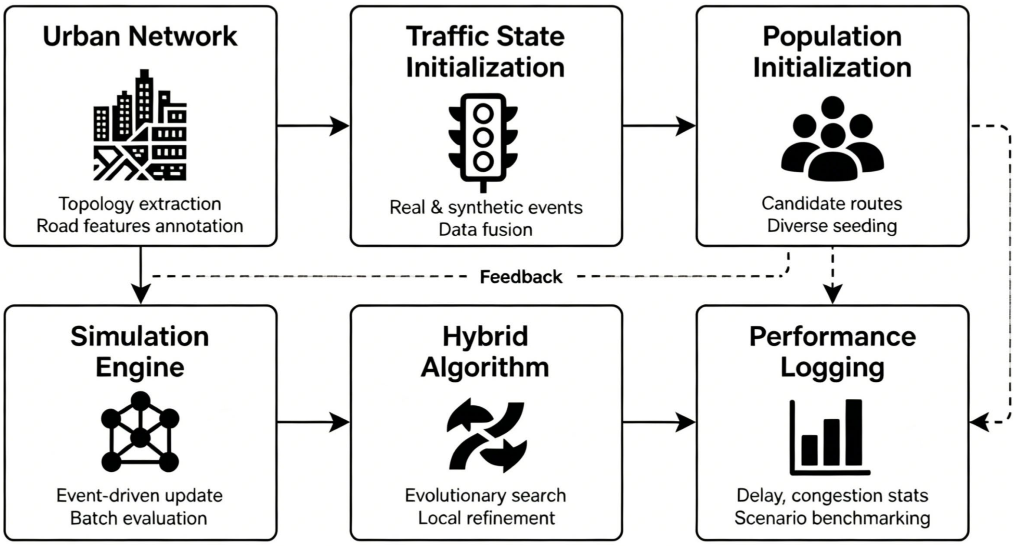

Figure 2. Experimental Workflow Diagram.

System updates and simulation logic are both subject to strict mathematical constraints. The population distribution for each simulation cycle can be described as follows:

$$\mathbb{X}_{g+1} = \Psi\left(\mathbb{X}_g, \mathbf{Y}_g, \mathcal{E}_g\right) \quad \text{Eq.(11)}$$

where $\mathbb{X}_g$ denotes the route candidate population at generation g, $\mathbf{Y}_g$ is the incoming real-time traffic data, and $\mathcal{E}_g$ represents the event set influencing cost fluctuations; Ψ is the adaptive hybrid updating function integrating population evolution and external events.

The monitoring of system state convergence is conducted Through the temporal evolution of key globally observable quantities:

$$\zeta_{t+1} = \xi(\zeta_t, \mathfrak{R}_t, \Theta_t) \quad \text{Eq.(12)}$$

where ζ_t is the system-wide performance indicator, $\mathfrak{R}_t$ is the current Pareto front distribution, and Θ_t are operational threshold controls; ξ encapsulates adaptive feedback and adjustment heuristics.

In order to ensure complete transparency, reproducibility, and subsequent comparison, the experimental log will record the selection of parameters and workflows.

Evaluation Metrics and Benchmarks

In order to evaluate the overall efficiency of micro and macro routing performance, a set of quantitative metrics has been designed. The standardized expected delay is the primary metric, representing the difference between the travel time of the chosen route and the instantaneous network optimal value, directly indicating the degree of real-time adaptation. Auxiliary indicators include the dynamic resilience assessment, the total number of successful reroutes after an event, and the average spatial congestion index of the damaged segments. The robustness of a solution not only refers to its performance in the event of network disruptions but also its ability to quickly recover after such disruptions.

A*, optimized population-based metaheuristic algorithms, and advanced simulation-based planners are widely used reference algorithms for vehicle routing. All benchmark algorithms use the same data inputs and experimental seeds, so the observed performance differences are entirely the result of algorithmic improvements, rather than scene artifacts. Performance scores are calculated by an automated extractor, and the original tracking and summary statistics are saved for cross-method statistical validation.

Key mathematical definitions underpinning evaluation are given by:

$$\Delta\tau^{(i)} = \frac{T_{\text{alg}}^{(i)} - T_{\text{opt}}^{(i)}}{T_{\text{opt}}^{(i)}} \quad \text{Eq.(13)}$$

where $\Delta\tau^{(i)}$ is the normalized expected delay for sample i, $T_{\mathrm{alg}}^{(i)}$ is the algorithm-derived travel time, and $T_{\mathrm{opt}}^{(i)}$ is the true network minimum at that instant.

$$\mathrm{C}_s = \frac{1}{|S|}\sum_{l\in S} \max\{0, Q_l - Q_l^{\mathrm{ref}}\} \quad \text{Eq.(14)}$$

where C_s is the average spatial congestion index, S is the set of monitored segments, Q_l is the empirical queue at segment l and Q_l^{ref} is the uncongested baseline.

Using the above set of metrics can comprehensively evaluate the reliability, level, and performance of the algorithm. The multi-level benchmarking protocol ensures complete traceability of data flow and system state when scientifically testing new urban navigation algorithms.

Results and Discussion

Convergence and Baseline Comparisons

To verify the hybrid evolutionary method, the convergence of differential evolution and the combined genetic algorithm on different urban traffic benchmark problems was tested. Figure 3(a) shows that the hybrid evolution algorithm rapidly reduced the route cost over the subsequent generations, reaching a suboptimal state on average in 37 iterations [26]. As shown in Figure 3(b), the convergence speed of the genetic algorithm is relatively slow, and it often experiences plateaus. It takes approximately 79 generations to achieve a similar cost reduction. The convergence speed of the differential evolution algorithm is relatively slow, as shown in Figure 3(c). It shows some oscillations and requires more than 102 generations to reach the same fitness level as other algorithms.

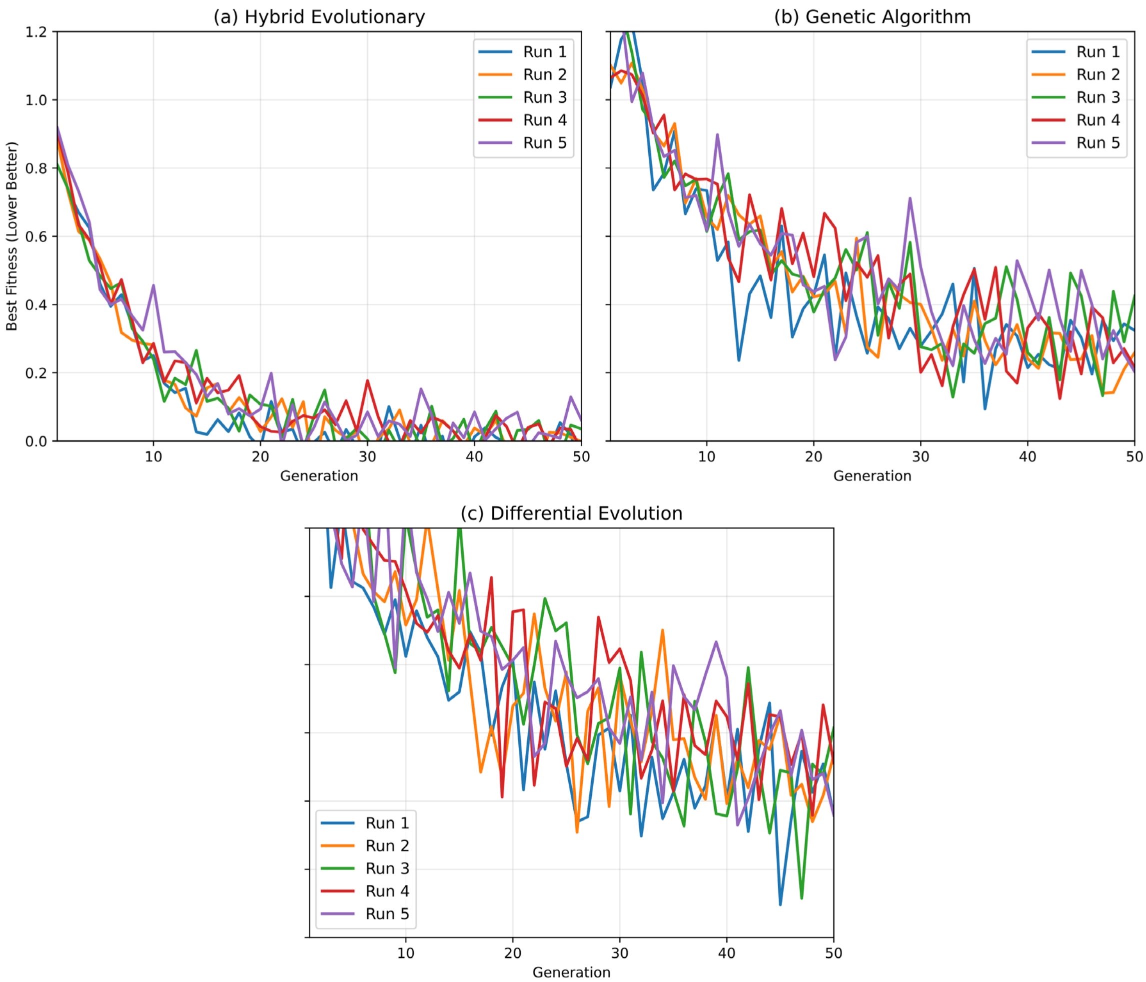

Figure 3. Convergence curves for different algorithms: (a) Hybrid Evolutionary, (b) Genetic Algorithm, (c) Differential Evolution.

The convergence variance of the mixed model is below 0.8% across urban topologies and all random seeds, indicating stable learning behavior. The first-generation hybrid method reduced costs and approached a stable fine-tuning state; otherwise, the baseline method might face early stagnation or increased costs [27]. The aforementioned advantages remain effective even when significant changes occur in the environment or extraordinary situations arise. Using a hybrid method can reduce the oscillation of the algorithm. Due to the significant improvement in stability and convergence speed, this hybrid algorithm can now perform high-frequency rerouting in dynamic network environments.

Performance under Dynamic and Large-scale Scenarios

Evaluate the algorithm's performance in adapting to a large number of dynamic and complex traffic conditions, and assess its path construction quality and computational scalability. Figure 4(a) shows the average route length under severe accident congestion and uniform early peak traffic conditions. Under normal conditions, the hybrid algorithm has a 6.8% advantage over the genetic algorithm, an 11.5% advantage over the differential evolution algorithm, and a 17.4% advantage under severe disturbances. Figure 4(b) shows the average travel time, with the hybrid method reducing it by 14 to 23% compared to the baseline during dynamic peak events. This value remains low even with increased demand and event frequency. Box plot 4(c) shows the delay distribution. The median of the mixed system has shifted significantly to the left, and the upper quartile has decreased by 36%, which has improved the reliability of most traffic participants [28].

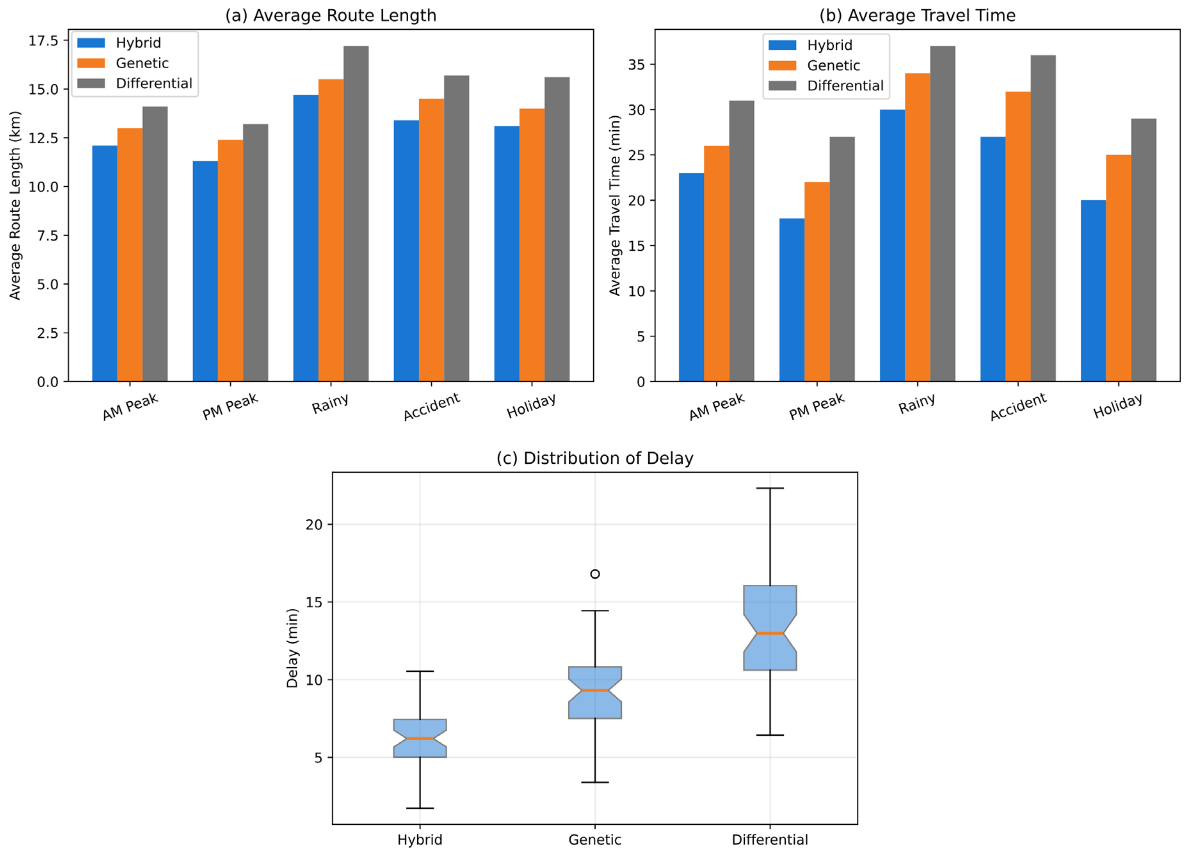

Figure 4. Route length and travel time comparison under various traffic scenarios: (a) Average Route Length, (b) Average Travel Time, (c) Distribution of Delay.

Figure 5 provides a detailed explanation of the scalability and computational resource characteristics of random events and extended networks. Figure 5(a) shows the distribution of computation times for three algorithms across multiple trials at each scale, where the median runtime of the hybrid method is shorter, and its variance significantly decreases as the network size increases. Compared to other methods, the performance of the hybrid method is relatively unstable [29].

Figure 5(b) depicts the distribution of memory utilization across the three components. The hybrid method consistently shows lower levels of total RAM usage, and the growth curve is relatively flat. Batch-aware resource scheduling achieved up to a 29% reduction in resource consumption across all scales, compared to genetic algorithms and differential evolution baselines [30].

Figure 5(c) is a heatmap showing the optimal solution rates under different combinations of network scale and disturbance intensity. The hybrid algorithm can still achieve over 92% in the most dynamic scenarios. As variability increases, the performance of the genetic algorithm and the differential evolution algorithm decreases to less than 78% and 65%, respectively [31]. Multidimensional results indicate that the proposed hybrid strategy can reduce computational and memory overhead while providing high-quality solutions. This method is suitable for complex and large-scale applications [32].

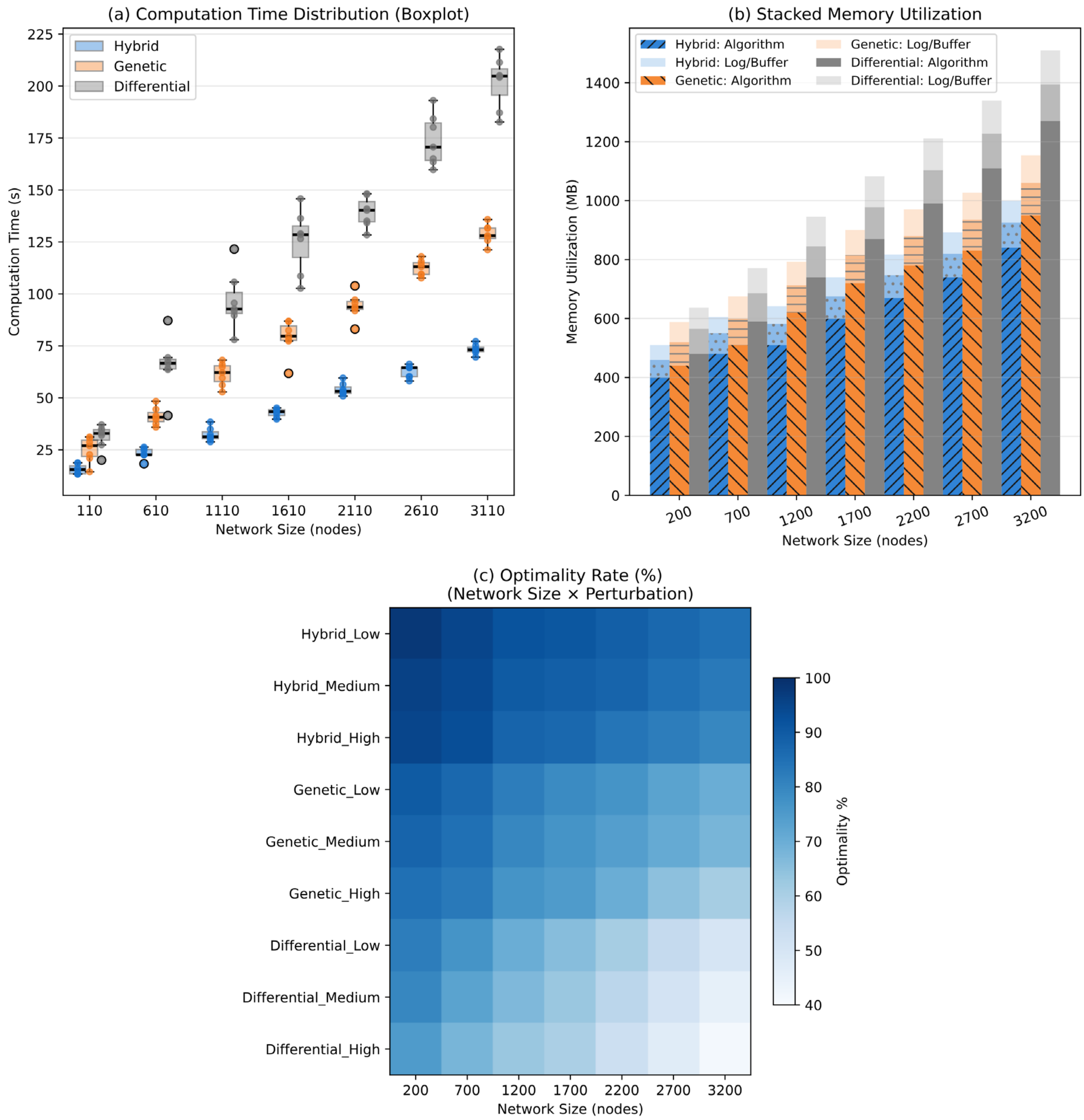

Figure 5. Scalability and computational resource assessment: (a) Computation time distribution by network size, (b) Stacked memory utilization, (c) Solution optimality rate across scales and perturbations.

Parameter Sensitivity, Ablation, and Case Studies

Through sensitivity analysis, ablation studies, and deployment cases, the operational resilience and efficiency of the hybrid algorithm were tested. Figure 6(a) is a radar chart showing stability, cost, and diversity under different population scales. When the increase in diversity and solution quality tends to saturate, a turning point occurs, and computational demand begins to rise sharply [33]. Figure 6(b) shows that the solution quality is relatively

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high when the crossover rate is approximately 0.72. Further increases only produced minor fluctuations, consistent with the recombination exploration-exploitation theory.

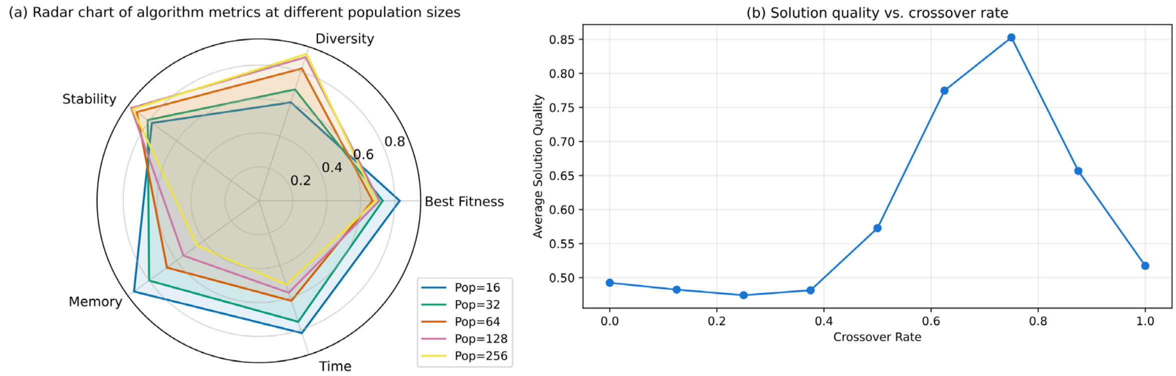

Figure 6. Sensitivity to key parameters: (a) Radar chart of algorithm metrics at different population sizes, (b) Line plot of solution quality vs. crossover rate.

Figure 7 shows the robustness of the algorithm and many characteristics of its practical application. As shown in Figure 7(a), the uncertainty bandwidth under the hybrid algorithm and baseline method increases with the increase in traffic volume, and the average delay and variance also increase. As shown in Figure 7(b), the violin plot of the delay distribution indicates that the hybrid strategy has a lower median delay. It is more concentrated around this median, which makes it more stable.

Figure 7(c) shows a comparison of results under different urban scenarios, including accidents, congestion, and major events. In all test cases, the travel time of the hybrid algorithm is generally shorter than that of the genetic and differential evolution baselines. Figure 7(d) shows the average suburban delay heatmap for five common types of disturbances. Here, the hybrid model reliably achieves the best (lowest) latency in any situation and performs excellently during congested times (e.g., holidays) [35]. The above results indicate that mixing can be used to reduce latency and improve operational stability. At the same time, the mixture performs excellently in both simulated ablation and real-world application scenarios.

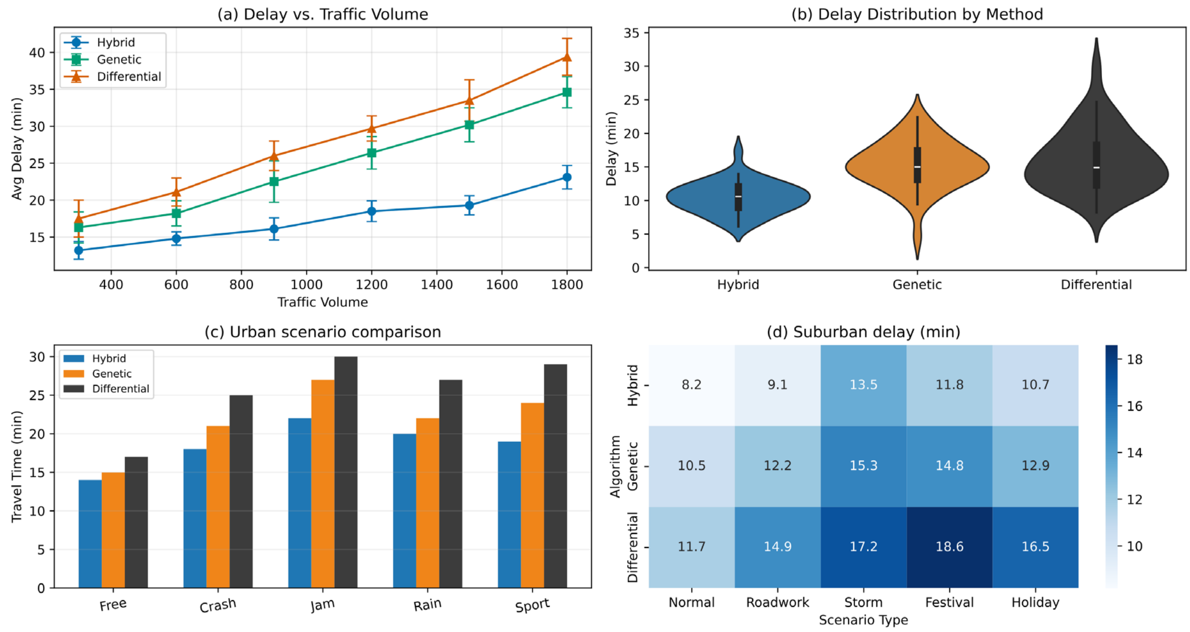

Figure 7. Ablation and deployment analysis: (a) Delay vs. traffic volume; (b) Delay distribution across methods; (c) Urban scenario comparison; (d) Suburban scenario heatmap.

Conclusion

This paper proposes a new hybrid evolutionary algorithm to address the dynamic path optimization problem in current urban traffic systems. The two components of the new architecture will collaborate to accelerate the speed of the search and local optimization processes. Experiments on large-scale and diverse datasets have shown that this hybrid method converges faster and more stable than traditional genetic algorithms and differential evolution algorithms, thereby obtaining higher-quality routing solutions. Due to its simple operational model and low resource consumption, this system can handle large amounts of data in the future, such as disaster relief or urban traffic control.

Theoretically, the goal of this study is to construct an adaptable and modular framework to integrate streaming sensor data, system feedback, and historical traffic data within a unified optimization process. Closed-loop learning and dynamic parameter adjustment help maintain good operating conditions in unstable or unpredictable environments, thereby preventing performance degradation and increased computational costs. The system's architecture will remain highly scalable, allowing for the use of additional constraints, objectives, or new types of data in future intelligent transportation applications. At the same time, it will also provide more possibilities for future development.

Nevertheless, there are still many unresolved issues that need to be addressed. Expand the social and engineering applications of the model, establish reliable privacy protection mechanisms, and increase real-time behavioral data and multi-agent interactions. The fairness of route recommendations, the scalability of cloud deployment, and the integration with heterogeneous urban sensor networks are all topics that require further research. Finally, this study provides new standards for the theoretical and practical advancements in urban path optimization. The transformative impact of hybrid evolutionary algorithms in the increasingly complex smart city traffic environment still requires further research.

Author Contributions

Bogna Cyrowa contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. Kinga Jurowa and Grażyna Marianna Kos contribute to data collection, draft preparation, manuscript editing. All authors have read and agreed with the manuscript before its submission and publication.

Funding

This research received no specific financial support from any funding agency.

Institutional Review Board Statement

Not applicable.

eferences

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