Data Engineering and Applications

Research Paper

Path Planning Optimization of Urban Traffic Systems Based on Big Data

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Abstract. The urban traffic system's route planning approach must take into account the spread of congestion, the variety of the road network, and the time-varying travel demand. This study proposes a path planning optimization paradigm for urban traffic systems based on big data. A dynamic road-network model is constructed from a variety of traffic data sources, including floating-car trajectories, road-segment speeds, signal timing, traffic-flow records, and incident information. The travel time of a link, congestion risk, route reliability, and network load will then be calculated using a spatiotemporal cost model. An adaptive route-selection method will be developed based on the model to increase individual travel efficiency and more equitably distribute system traffic. Test a large-scale metropolitan road network during periods of high demand, frequent traffic jams, and incident disruptions. The suggested approach has reduced average trip time by 13.8%, route delay variation by 18.6%, and bottleneck-link load by 16.9% when compared to the conventional static shortest-path routing, historical-average routing, and other dynamic routing techniques. The study can be used to enhance route selection stability and encourage the real-world implementation of intelligent transportation management.

Keywords: *Big Data Analytics, Path Planning Optimization, Dynamic Routing, Spatiotemporal Traffic Prediction*

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Introduction

Some of the data-intensive infrastructures seen in contemporary cities are urban traffic systems. The movement of people and cars in a road network is continuously recorded by floating-car trajectories, loop detector data, camera observations, mobile navigation trails, signal-controller logs, weather records, and traffic incident reports. As a result, path design is no longer a simple shortest-distance problem. The effectiveness of commuting, emergency response, freight delivery dependability, ride-hailing service quality, and the stability of intelligent transportation systems will all be directly impacted. A lengthier detour is required to minimize delays and distribute traffic since the direct route is blocked by traffic congestion at a major crossroads due to the high-density neighborhood. Recent research on big data for transportation and urban traffic management has shown that a lot of traffic data can detect congestion that is not visible on conventional roadmaps [1]. Route design should be based on current network conditions rather than past averages, as demonstrated by edge-assisted traffic control and big data-driven traffic-signal systems [2]. Travel decisions must take space and time variation into consideration, according to research on traffic-flow predictions [3]. Multi-modal traffic data can be utilized to detect bottlenecks earlier, as demonstrated by large-scale congestion prediction [4]. Trip-time unreliability should be taken into account in addition to the average trip time, according to route advisory studies [5]. The relationship between network load and individual routing has also been examined in studies on dynamic traffic assignment [6]. In big road systems, route planning is further supported by network-level graph prediction [7]. Additional types of traffic data are needed for urban route optimization based on the congestion analysis of several modalities [8].

The conventional method of route planning creates a road network weighted graph and chooses the path with the lowest static edge cost. Although Dijkstra, A*, and time-dependent shortest-path variations are very straightforward and easy to comprehend, they don't work well in situations when road conditions change quickly. In a few signal cycles, traffic on the main routes will move to the secondary roads during morning and evening peak hours. The distribution of travel times for a certain route may be unequal upon arrival at a downstream portion due to road construction, accidents, weather disruptions, or temporary traffic control operations ahead. Urban traffic data demonstrates substantial spatial and temporal relationships, as demonstrated by research in attention-based forecasting [9]. As a result, numerous heterogeneous data sources must be modeled in these correlations. Road-state estimation should vary depending on the time of day and the influence of neighboring links, according to spatial-temporal speed prediction [10]. According to sensor fusion research, the questionable observation should be merged with other observations rather than disregarded [11]. Although network-level state estimation has been enhanced by spatial-temporal graph neural networks, the prediction results must still be translated into route costs appropriate for real-time planning [12]. The challenge of dynamic road correlation modeling is highlighted by survey work on graph neural traffic prediction [13]. Time variation and spatial extension should not be arbitrarily combined, according to decoupled graph models [14]. Incident-condition forecasting also demonstrates that aberrant traffic situations need to be handled differently in routing decisions [15].

Path Planning Optimization of Urban Traffic Systems Based on Big Data. In order to provide a dynamic road-network state representation, evaluate spatiotemporal trip costs, and produce adaptive routes under multi-objective constraints, the suggested framework integrates multiple sources of urban traffic data. The three applications of this study are: How to present road conditions based on various sources of traffic data; How to build a route cost function that considers factors such as travel time, congestion risk, route reliability and network load; and how to avoid focusing too much on seemingly optimal roads. Boost individual travel efficiency and keep the network operating normally during periods of high demand and disruption.

Related Work

Data-Driven Urban Traffic Modeling

Multi-source data fusion has replaced single-source traffic counts in urban traffic models. Fixed detectors and manually calibrated flow-speed-density correlations were the primary tools utilized in early traffic-state estimation. Floating-car data and trajectory records have been progressively used to estimate segment speed, queue length, and turning demand as mobile sensing and connected vehicles have advanced. Based on vehicle movement, road conditions, and other external factors, multimodal big data fusion is used to forecast traffic congestion [16]. Methods of Decomposition and Attention-based Forecasting Separate Temporal Changes and Spatial Correlations to Increase the Precision of Short-Term Traffic Flow Prediction [17]. Additionally, road-speed prediction improves from selecting rating neighboring links based on dynamic correlation rather than fixed adjacency, as demonstrated by spatial-temporal attention fusion models [18]. The traffic situation can be more accurately inferred by merging uncertain observations from several sensors and vehicles, as demonstrated by multi-model Bayesian kriging and perceptual information fusion techniques [19]. An accurate judgment could not have been made without timely and geographically full road-condition information, which the research has supplied.

Deep learning models and graph learning models are currently the two primary types of devices for network-level traffic prediction. Graph convolutional networks use road topology to understand spatial relationships by representing road segments as nodes or edges. Traffic-flow forecasting in large metropolitan networks has been enhanced by gated graph wavelet recurrent networks, spatial-temporal graph neural networks, and graph filter-based models [20]. The road network is not a static graph, according to research on Graph Neural Networks for traffic prediction; correlations vary depending on factors including traffic flow direction, weather, accidents, and signal timing [21]. For route planning, where downstream congestion frequently depends on many upstream flows rather than a single nearby connection, decoupled spatial-temporal graph models and multi-head attention graph networks seek to distinguish local temporal dynamics from regional reliance [22]. To reduce prediction degradation in the case of an incident, simulation-assisted graph recurrent models can produce short-term traffic forecasts [23]. Even while these studies are connected to path planning, many of them focus just on forecast accuracy and do not specifically optimize traffic dispersion or route selection.

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Dynamic Path Planning and Intelligent Route Optimization

During travel, dynamic route planning forecasts changes in traffic costs or modifies the route in real time. Drivers may favor a route with a little longer average travel time if the arrival-time variance is smaller, according to route guidance systems that take travel-time unreliability into account [24]. In order to improve the estimation of route-choice preferences in metropolitan environments, calibration experiments utilizing automatic vehicle identification data have recently been conducted [25]. Traffic assignment models determine the equilibrium state of route selection in a network. The concept is expanded by agent-based joint route and departure-time choice models, which connect individual choices to the evolution of congestion at the network level [26]. Urban multimodal traffic assignment further suggests that the collaboration of private vehicles, public transportation, walkers, and transfers must be taken into account while building routes in densely populated areas [27]. The techniques offer theoretical support for striking a balance between user trip efficiency and system load, but they frequently call for a particular demand model and may be computationally costly for real-time routing.

The shortcomings of strict classical graph search are intended to be addressed by learning-based and data-driven route optimization techniques. Time-varying edge weights for routing can be produced by traffic-flow prediction using graph convolution and attention techniques [28]. We can anticipate bottleneck development before it manifests itself in the speed data by using multimodal fusion-based large-scale congestion prediction [29]. Early route adjustment for navigation services can be supported by deep learning and sensor fusion-based traffic-jam prediction systems [30]. Research on traffic control and edge computing has revealed that routing decisions are increasingly made on cloud-edge platforms, and that congestion feedback, data ingestion, and route search must be managed concurrently. There is still an issue: the planner should not rely the route cost solely on the anticipated speed. It should take into account the way's dependability, congestion risk, route overlap, and link-load pressure; otherwise, a path that seems ideal for one vehicle could cause serious congestion when numerous users follow the same suggestion.

Big-Data-Driven Path Planning Optimization Framework

Urban Traffic Data Fusion and Network State Representation

In the suggested framework, the urban road network is modeled as a directed graph with nodes representing intersections, ramps, or merging points and edges representing drivable road segments. Floating cars, roadside sensors, signal controllers, traffic-event reports, and historical recordings are the sources of data for a road segment. Every observation is mapped to the appropriate road segment and aligned to a five-minute interval in order to minimize the sources' unreliability. A shared road-network state representation connects traffic data fusion, dynamic cost calculation, and adaptive route selection in Figure 1's big-data-driven path planning optimization framework.

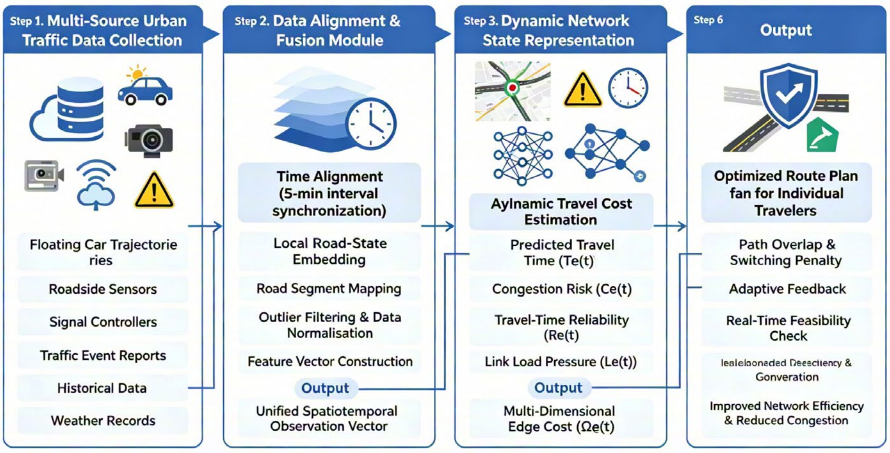

Figure 1. Big-data-driven urban traffic path planning optimization framework

Speed, flow, occupancy, signal delay, incident indication, and weather-related disturbance are all part of the fused observation vector for road segment eat time t. To lessen the effect of structural variations between expressways, arterials, and secondary roads, the vector is normalized by road class and historical baseline.

$$x_e(t) = [v_e(t), q_e(t), o_e(t), d_e(t), r_e(t)] \quad \text{Eq.(1)}$$

The local road-state embedding is obtained by combining current observations with short-term historical states. A temporal decay factor assigns higher weight to recent observations while retaining enough memory to recognize congestion trends.

$$h_e(t) = \sum_{k=0}^{K} \alpha_k W_k x_e(t-k) \quad \text{Eq.(2)}$$

Spatial dependency is introduced through neighboring road segments. Instead of treating all adjacent links equally, the model weights upstream and downstream segments according to turning probability, road class, and recent flow direction.

$$z_e(t) = h_e(t) + \sum_{j \in N(e)} \pi_{j,e}(t) U h_j(t) \quad \text{Eq.(3)}$$

The current state and the network's impact on the target section are represented by the resulting state vector. To guarantee that route-cost updates are completed within a real-time limit, K is set to 6 in the experiment, the historical window is 30 minutes, and the neighborhood depth is limited to two hops.

Dynamic Travel Cost Estimation Model

The weight of a route-search edge is determined by dynamically changing cost models. The anticipated journey time should not be the only factor considered when determining a realistic route cost. Due to the near-saturation of downstream intersections, the current high-speed route may be unreliable during peak hours. As a result, the model will be able to forecast link-load pressure, reliability penalty, congestion risk, and trip time.

$$T_e(t) = \frac{l_e}{\max(\varepsilon, \hat{v}_e(t))} \quad \text{Eq.(4)}$$

The predicted speed is obtained from the road-state vector and bounded by the physical speed range of the segment. This prevents abnormal sensor readings from producing unrealistically low or high travel time.

$$C_e(t) = \sigma(a\rho_e(t) + b\Delta v_e(t) + cI_e(t)) \quad \text{Eq.(5)}$$

The congestion-risk score increases when density, speed drop, or incident likelihood rises. It is not equivalent to current occupancy; it reflects the probability that the segment becomes unstable within the planning horizon.

$$R_e(t) = \frac{\sqrt{\mathrm{Var}(T_e \mid H_t)}}{\mathrm{mean}(T_e \mid H_t)} \quad \text{Eq.(6)}$$

The normalized dispersion of anticipated journey time is used to express route reliability. Even if the mean is tiny, the planner wishes to avoid choosing a corridor with a wide range of trip times.

The ratio of the allocated or anticipated vehicle demand to segment capacity is known as the load pressure term. To avoid too many suggested routes being concentrated on a single high-speed road, it is incorporated into the final edge-cost function.

$$\Omega_e(t) = w_1 T_e(t) + w_2 C_e(t) + w_3 R_e(t) + w_4 L_e(t) \quad \text{Eq.(7)}$$

Multi-Objective Adaptive Route Selection Strategy

The planner determines an appropriate route for the origin and destination based on the shifting edge cost. First, rather than choosing the single minimum-cost path right away, a limited number of viable paths are kept in the search process. Urban network design must take into account the possibility that different routes, even with comparable trip times, may have varying dependability and load implications. The dynamic route selection process under spatiotemporal traffic restrictions is shown in Figure 2.

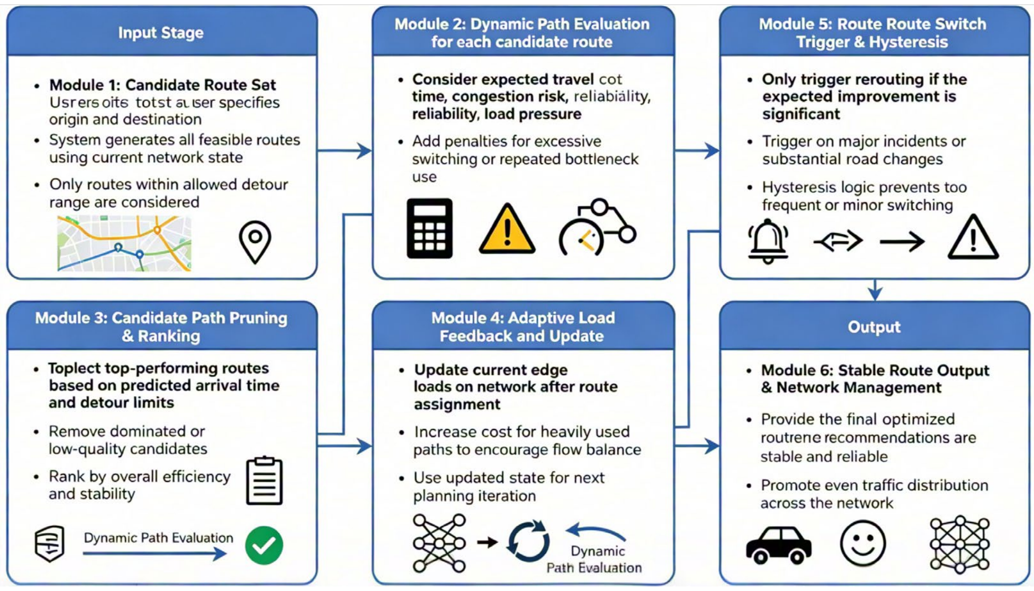

Figure 2. Dynamic route selection mechanism under spatiotemporal traffic constraints

The total of a candidate path P's edge costs, route-switching penalties, and path-overlap penalties is its cost. The overlap term lessens the possibility that numerous cars may choose the same bottleneck corridor more than once during the same time frame.

$$J(P,t) = \sum_{e \in P} \Omega_e(t_e) + \lambda_s S(P) + \lambda_o O(P) \quad \text{Eq.(8)}$$

The planner then updates edge load according to the selected route and the predicted departure interval. This feedback makes the routing process adaptive because a road segment that is repeatedly selected will gradually become less attractive.

$$n_e(t+1) = n_e(t) + \sum_{P} y_P(t) I(e \in P) - out_e(t) \quad \text{Eq.(9)}$$

The final route is selected from the feasible candidate set under travel-time and detour constraints. In the implemented setting, a path is accepted only if its length is less than 1.28 times the shortest physical path and its predicted arrival time is within the top 15% of candidates.

$$P^* = \arg\min_{P \in A} J(P,t), A = \{P \mid d_P \le 1.28 d_{\min}\} \quad \text{Eq.(10)}$$

The route is not updated at every second. A hysteresis rule is used to avoid frequent route switching. Rerouting is triggered only when the expected gain exceeds 9% or an incident changes the downstream link state.

Experimental Scheme and Evaluation Metrics

Experimental Dataset and Urban Road Network Settings

With 3,240 directed road segments, 1,086 intersections, 54 arterial corridors, and 18 significant commuter regions, the experiment is a vast urban road network. The collection includes manually indicated congestion and incident intervals, five-minute segment-speed recordings, signal phase information, and 28 days of floating-car trajectories. The model is trained for the first twenty days, validated for the next four, and tested for the last four. Morning peak, evening peak, off-peak, and incident-disturbance were the four groups into which the four types of demand throughout the test period were separated. Static shortest-distance routing, historical-average travel-time routing, traditional real-time shortest-time routing, and a graph-prediction-based routing baseline are the techniques that are compared.

$$D = \{(G_t, X_t, Y_t, R_t)\}_{t=1}^{N} \quad \text{Eq.(11)}$$

Here Gt denotes the time-varying road-network graph, Xt denotes multi-source observations, Yt denotes observed segment travel time, and Rt denotes the route request set. All methods receive the same origin-destination requests, and route results are evaluated under the same traffic propagation simulator.

Evaluation Indicators for Route Efficiency and Network Load

Mean travel time, peak-hour delay, arrival-time reliability, and rerouting reaction time are the four metrics used to assess route efficiency. Bottleneck-link load, congestion duration, and load-balance variance are the three categories of network-level performance measurements. The decrease in relative travel time when compared to the static shortest-distance baseline is the first index.

$$G_T = \frac{T_{\text{base}} - T_{\text{method}}}{T_{\text{base}}} \quad \text{Eq.(12)}$$

Route reliability is calculated from the dispersion of arrival time. A lower value means that the route provides more stable arrival prediction under changing traffic conditions.

$$B_R = \frac{\text{std}(T_{arr})}{\text{mean}(T_{arr})} \quad \text{Eq.(13)}$$

The network load-balance indicator evaluates whether the method disperses traffic away from critical bottlenecks. It uses the variance of normalized link load among selected major road segments.

$$V_L = \frac{1}{|E_c|} \sum_{e \in E_c} (L_e - \bar{L})^2 \quad \text{Eq.(14)}$$

The average time it takes to compute a route after receiving an origin-destination request and returning a feasible path is known as real-time feasibility. For typical requests, the test platform's route search time should be less than 180 ms, and for incident-triggered rerouting, it should be less than 260 ms.

Comparative Method Design

The project will isolate the impact of load-aware route selection, dynamic cost estimate, and big data fusion. The road length is the only factor taken into account by the static shortest-distance approach. The average travel time at the same time period in the past is the historical-average method. The real-time shortest-time approach disregards load feedback and reliability and modifies the segment speed based on the most recent observation. Using a spatial-temporal graph model and standard shortest-path search, the graph-prediction baseline predicts the future segment speed. Add congestion risk, reliability penalty, and link-load feedback to the previously used anticipated speed data. The organization will prioritize the issue of route optimization over the precision of traffic forecasting.

Result Interpretation and Comparative Analysis

Route Efficiency and Travel-Time Reduction Analysis

The new approach has improved the travel conditions at all times and for all loads, according to the overall route-efficiency figures. A table of travel-time performance by routing strategy is shown in Figure 3. The average travel times of the five methods under off-peak, normal peak, and severe peak conditions are displayed in Figure 3(a). The suggested method has decreased the average travel time under severe peak demand by 5.9 minutes, from 42.6 minutes to 36.7 minutes in static shortest-distance routing. The distribution of peak-hour delays is depicted in Figure 3(b). Because high-risk bottleneck links are penalized before they reach full congestion, the 90th-percentile delay drops from 18.4 minutes to 13.1 minutes. The route dependability distribution has decreased, as seen in Figure 3(c); in other words, the arrival-time reliability index decreased from 0.214 to 0.168, suggesting that the selected routes are less susceptible to variations in traffic circumstances over time [31].

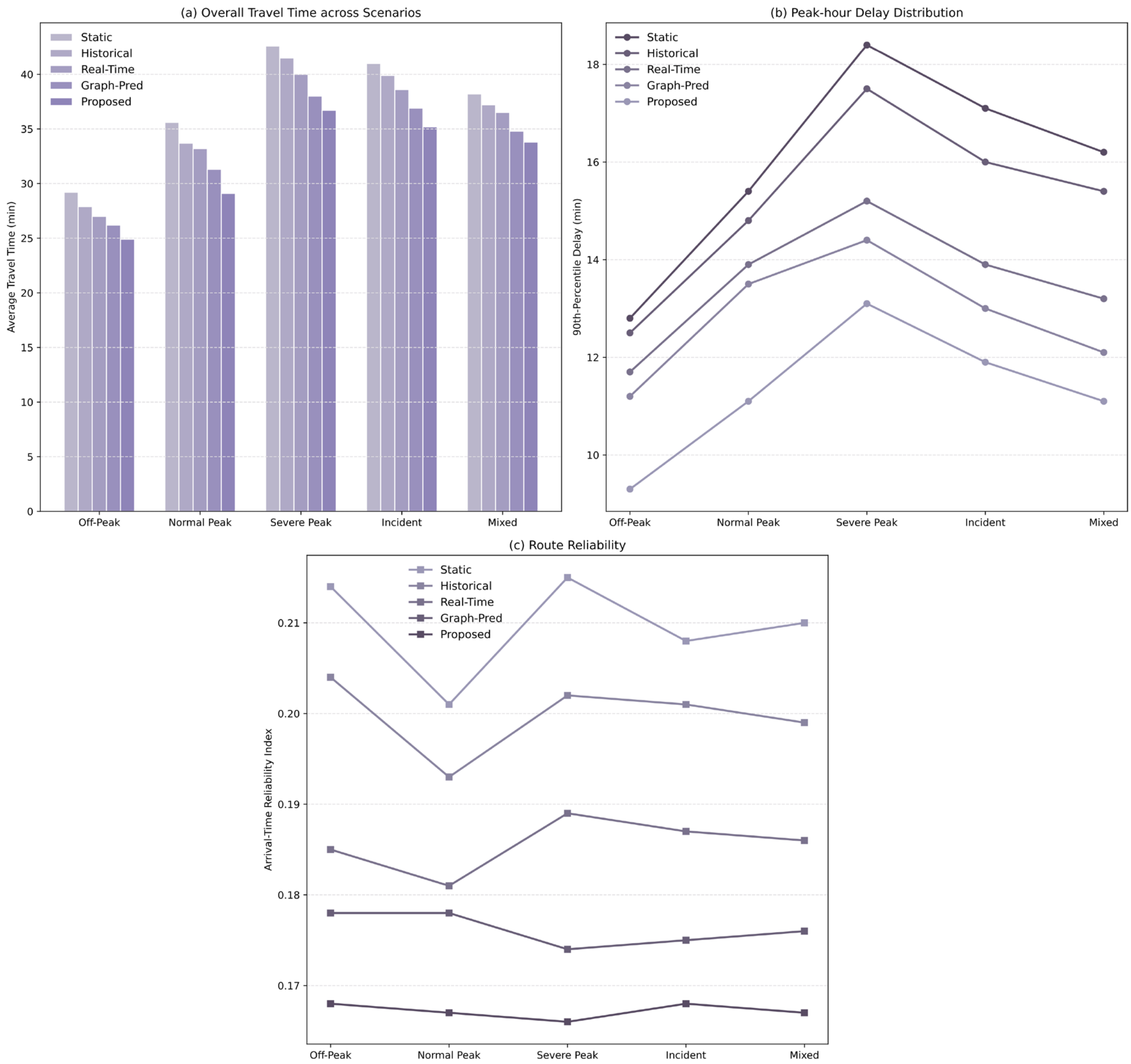

Figure 3. Travel-time performance comparison across routing strategies. (a) Overall travel time under different demand levels. (b) Peak-hour delay distribution across route groups. (c) Route reliability distribution under dynamic traffic conditions

For severe congestion, the rise in congestion is more noticeable; otherwise, the short-term queue propagation would not be taken into account by the static and historical-average routing algorithms. In the early peak hours, real-time shortest-time routing outperforms historical routing; nonetheless, it frequently directs an excessive number of vehicles onto the same briefly fast arterial road. By including a link-load term that raises the cost of routes with several selections, the suggested method circumvents this behavior. High prediction accuracy is required but insufficient for high-quality route selection, as the suggested approach reduces travel time by around 5.2% more than the graph-prediction baseline. If a predicted fast route has little residual capacity or poor reliability, it can still be inappropriate [32].

Congestion Mitigation and Road-Network Load Analysis

Congestion reduction measures will be put in place at the road network level to shorten travel times for all cars. The road network load comparison and congestion propagation are shown in Figure 4. The main corridor's congestion intensity is depicted in Figure 4(a). By using the suggested approach, the average congestion index during the evening peak was lowered from 0.71 to 0.58. Bottleneck road utilization is depicted in Figure 4(b), where the top ten important links' maximum normalized load drops from 0.93 to 0.77. The traffic distribution heatmap in Figure 4(c) shows that diverted traffic has been distributed along parallel corridors with adequate residual capacity in addition to going to the side roads [33].

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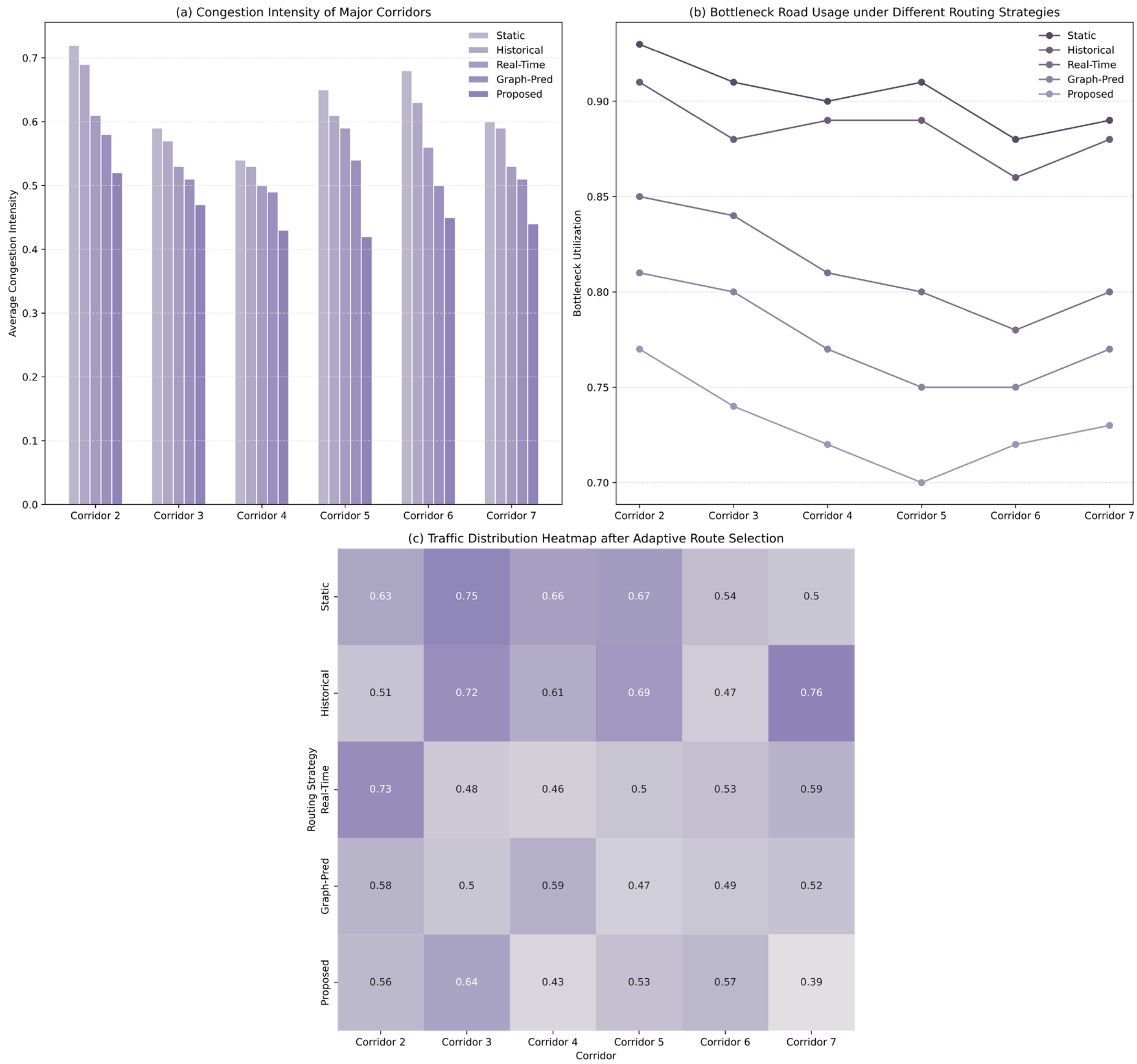

Figure 4. Congestion propagation and road-network load comparison. (a) Congestion intensity of major corridors. (b) Bottleneck road usage under different routing strategies. (c) Traffic distribution heatmap after adaptive route selection

The route's stability in the face of dynamic traffic disruption is depicted in Figure 5. The frequency of route switching is displayed in Figure 5(a). It is evident that the suggested hysteresis rule has decreased the average number of switches per trip to 1.34 as opposed to 2.07 for the conventional real-time shortest-time routing. The suggested approach restricts the delay variance to 31.6 min^2 following a simulated event on an artery link, as illustrated in Figure 5(b); concurrently, the graph-prediction baseline reaches 44.9 min^2. The event-response time is shown in Figure 5(c); the new approach satisfies the experiment's real-time requirement and lowers the average number of changed pathways to roughly 147 ms [34].

In terms of expenses, the two have different causes. Because real-time shortest-time routing reacts to speed variations quickly, its suggested routes are unreliable. When the estimated gain is low, the predicted reliability and route-switching penalty are employed to prevent needless rerouting. It will make it easier for drivers to deal with real-world driving situations; otherwise, they can become uncooperative and anxious at the crossroads. Stable responses should be employed instead of aggressive rerouting based on a single anomalous observation, according to studies on incident detection and congestion clustering [35].

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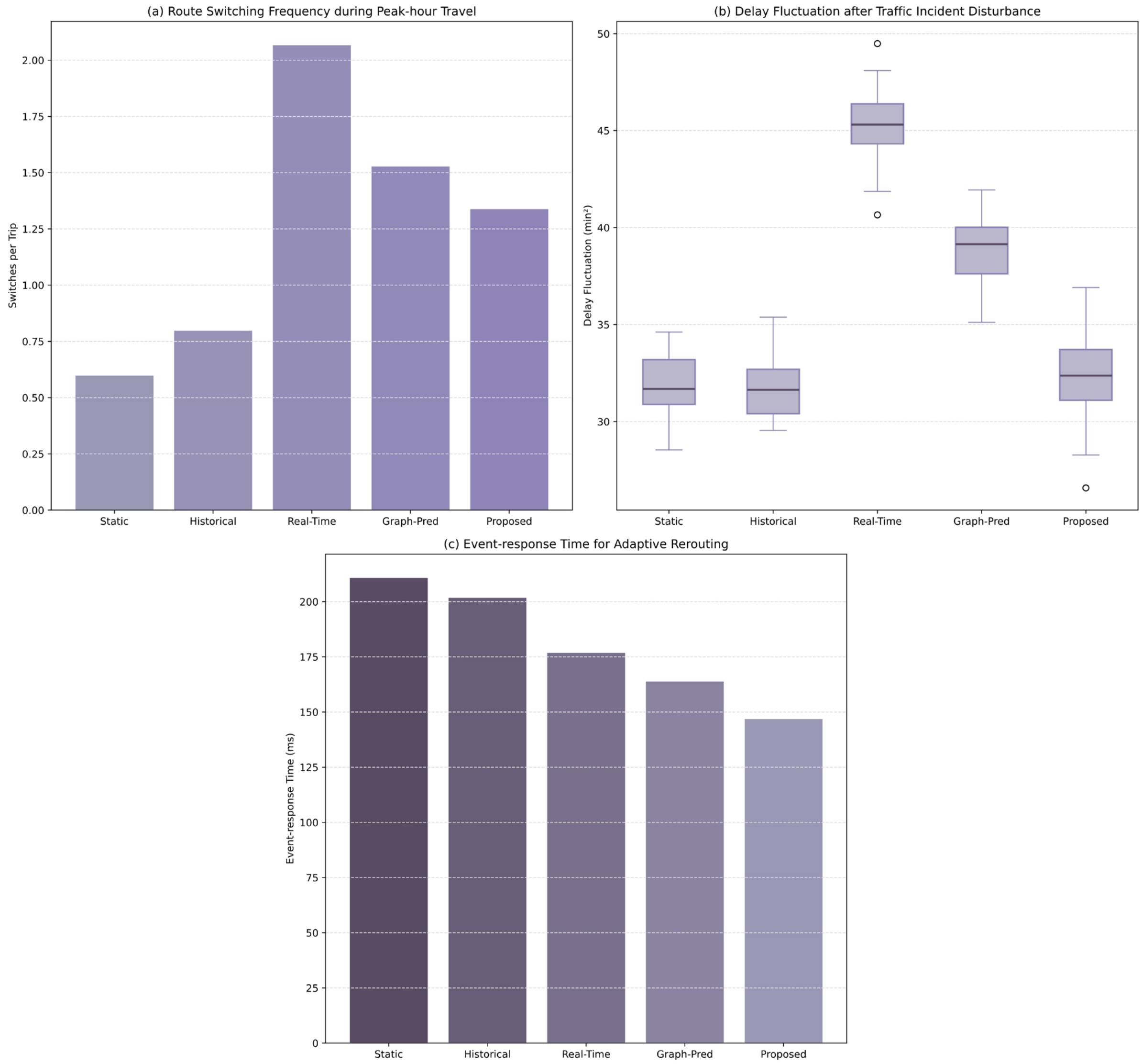

Figure 5. Route stability under dynamic traffic disturbance. (a) Route switching frequency during peak-hour travel. (b) Delay fluctuation after traffic incident disturbance. (c) Event-response time for adaptive rerouting

Ablation and Generalization Discussion

The modules needed to get the final routing outcomes are revealed via ablation studies. The contribution analysis of dynamic cost modeling and big data fusion is displayed in Figure 6. The ablation results of the modules are displayed in Figure 6(a). The model loses incident and signal-delay information when multi-source data fusion is removed, which lowers the travel-time gain from 13.8% to 8.5%. The cost sensitivity is depicted in Figure 6(b), and the arrival-time dispersion rises by 14.7% when the dependability element is removed. The full model's average computational delay is 156 ms, as seen in Figure 6(c); this is just 24 ms slower than the graph-prediction baseline because candidate-path pruning restricts the search space [36].

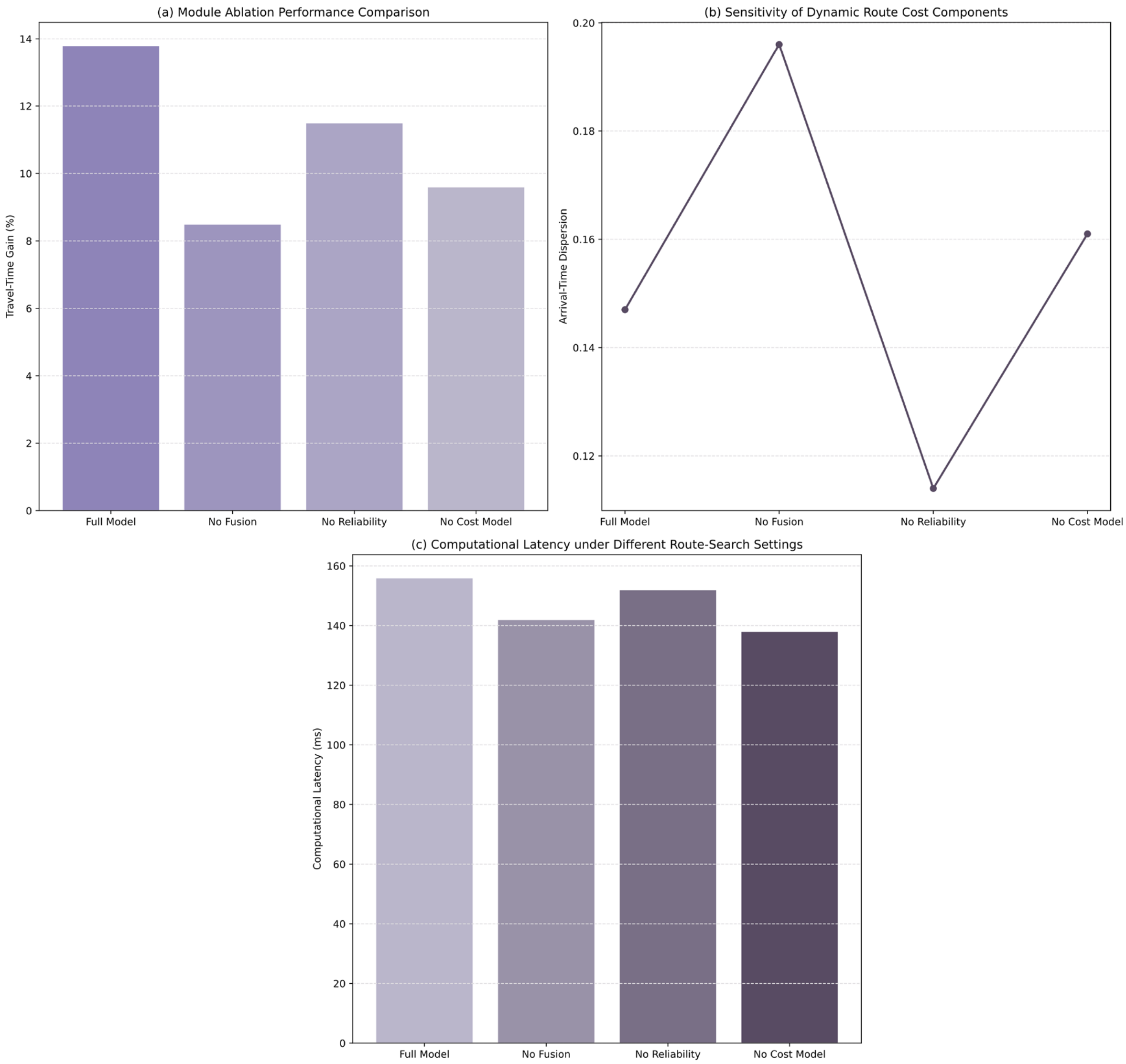

Figure 6. Contribution analysis of big-data fusion and dynamic cost modeling. (a) Module ablation performance comparison. (b) Sensitivity of dynamic route cost components. (c) Computational latency under different route-search settings

Every urban area's generalization performance is assessed. The generalization results in a cross-regional traffic scenario are displayed in Figure 7. Even after modifying simply the road-class normalization parameters, the model trained on center urban regions still reduces travel times for suburban arterial corridors by 10.6%, as Figure 7(a) illustrates. The strategy is still successful when the demand for automobiles reaches 120% of the reported peak level, as shown in Figure 7(b). However, the gain in efficiency under high saturation is quite tiny. The outcome of the incident-condition robustness evaluation is displayed in Figure 7(c). Following the implementation of the suggested route-cost feedback, the residual congestion duration for a lane-blocking event dropped from 46 minutes to 34 minutes [37].

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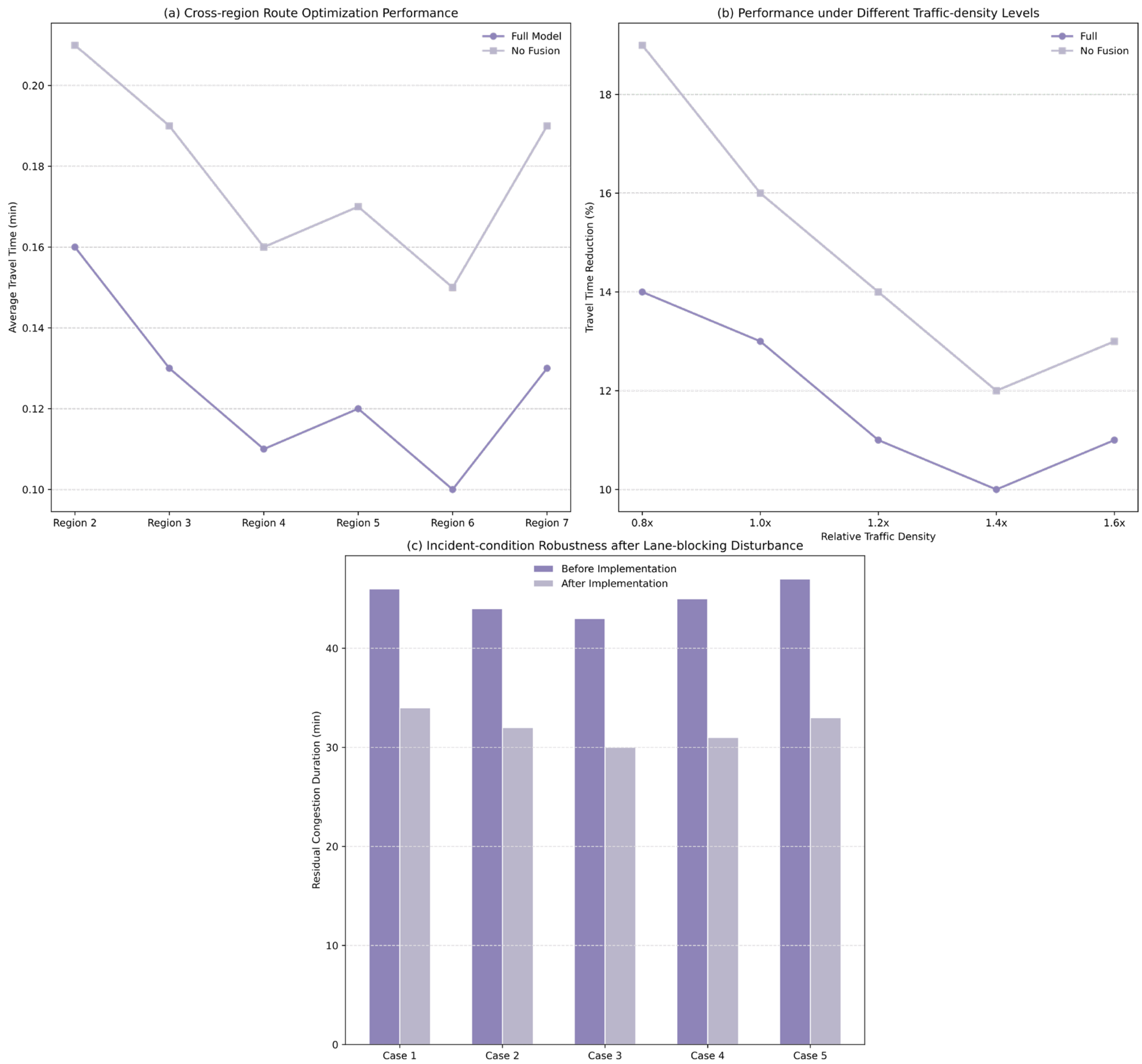

Figure 7. Generalization performance under different urban scenarios. (a) Cross-region route optimization performance. (b) Performance under different traffic-density levels. (c) Incident-condition robustness after lane-blocking disturbance

Uncertain regulations and a lack of data are further causes of the flaws. Segment-speed estimation is rather unstable when the floating-car penetration rate is less than 8%; hence, a model based on historical baselines may be employed. Although it is still longer than the previous average, the current reduction in travel time is 8.1%. Another flaw is that the current experiment does not completely represent the behavior of strategic drivers and only assumes a partial adherence to the suggested courses. It is suggested that the future route planning model will simultaneously take user approval, network equilibrium, and route recommendation into account based on traffic assignment and connected-vehicle safety research [38]. Additionally, because the route-cost weights are based on typical urban traffic, they could need to be adjusted for unique situations like heavy weather, large-scale events, or evacuations. The subsequent adaptive calibration should take this into account because research on traffic safety and incident response has demonstrated that abnormal conditions can affect both travel demand and route choice [39]. On the other hand, real-time urban navigation systems can be optimized by combining load-aware route selection, dynamic cost modeling, and traffic big data [40].

Conclusion

This research proposed a large-data path-planning optimization paradigm for urban traffic systems. The research findings indicate that the design of urban routes is no longer a static shortest-path problem; this issue cannot be disregarded due to the availability of real-time traffic data, congestion spread, and incident disruptions. The method is able to create a more comprehensive representation of the road-network state and facilitate route selection that is sensitive to changes in traffic over time and space by combining floating-car trajectories, road-segment speeds, signal delay, incident data, and historical traffic patterns.

Trip time, congestion risk, route dependability, and network load should determine the dynamic trip cost, according to the primary research findings. Even with a short present travel time, a route may still be unstable if there are too many cars assigned to the same corridor or if there is congestion later on. By reducing the load on bottleneck links and preventing needless route switching through hysteresis control, the suggested adaptive route selection technique has cut average trip time and minimized delay volatility. The optimized route can be utilized to improve individual travel speed and lessen network congestion based on the information above.

Future studies will integrate driver compliance modeling, connected-vehicle cooperative routing, weather-sensitive road capacity estimation, and policy adaptation based on reinforcement learning to further broaden the framework. To find out whether the system is long-term reliable, whether route-users are treated equitably, and how it works with traffic-signal regulation, more cross-city testing and real-navigation-platform installations will be needed. The additions have the potential to improve the stability of urban path design for intelligent transportation management and smart mobility.

Author Contributions

Themis Giannakis contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision, project administration, and funding acquisition. Panagiotis Sarris1 and Haris Triantafyllou contribute 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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Institutional Review Board Statement

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