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# Dynamic and Time-Aware Risk-Based Routing for Enhanced Road Safety in Urban Transportation Networks

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**Abstract:** Road traffic accidents represent a persistent challenge for urban mobility systems, resulting in significant human and economic losses worldwide. Recent safety-aware routing studies have demonstrated that avoiding statistically dangerous road segments can substantially reduce accident exposure, albeit at the cost of moderately increased travel distances. However, most existing approaches rely on static accident risk estimation derived from historical data, thereby neglecting the temporal variability inherent in traffic safety patterns. This paper proposes a dynamic and time-aware risk-based routing framework that extends penalty-based safety routing by incorporating temporal accident profiles and adaptive edge penalties. Road segments are assigned time-dependent risk scores computed from historical accident distributions across multiple temporal windows. These scores are integrated into a modified shortest-path algorithm to enable context-aware route selection. Extensive experiments conducted on an urban road network demonstrate that the proposed approach achieves additional reductions in relative accident risk beyond static safety-aware routing while maintaining acceptable increases in route length and topological complexity. The proposed framework contributes toward the development of intelligent, safety-oriented navigation systems suitable for real-world deployment in smart cities.

**Keywords:** Road safety, dynamic routing, time-aware navigation, intelligent transportation systems, graph algorithms

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## 1. Introduction and Preliminaries

Urban transportation networks are critical infrastructures that support economic activity, social interaction, and overall quality of life. Despite advancements in vehicle technology and traffic management systems, road traffic accidents (RTAs) remain one of the leading causes of injury and mortality globally. According to international road safety reports, urban areas account for a disproportionately high share of accident occurrences due to dense traffic flow, complex road geometries, and heterogeneous user behavior.

Navigation systems play a central role in shaping driving behavior by guiding users along routes optimized for distance or travel time. Classical routing algorithms, such as Dijkstra's algorithm [1] and Bellman's dynamic programming approach [2], prioritize efficiency without explicitly accounting for safety considerations. While effective in minimizing travel cost, such approaches may inadvertently guide drivers through accident-prone areas.

To address this limitation, safety-aware routing methods have emerged as an extension of classical graph-based routing. These approaches incorporate accident statistics into route planning, either by avoiding hazardous areas entirely or by penalizing risky road segments. Empirical studies have shown that such methods can reduce accident exposure by up to 30% with moderate increases in travel distance [5].

Nevertheless, a fundamental limitation of most existing safety-aware routing frameworks is their static nature. Accident risk is typically modeled as a fixed property of road segments, derived from aggregated historical data. In reality, traffic safety exhibits strong temporal variability influenced by factors such as rush hours, night-time driving, weekdays versus weekends, and seasonal effects [6]. Ignoring these temporal dynamics limits the responsiveness and effectiveness of safety-oriented navigation systems.

Motivated by this gap, this paper introduces a dynamic and time-aware risk-based routing framework that integrates temporal accident patterns into penalty-based routing. By adapting edge penalties according to time-dependent risk profiles, the proposed method enables safer route selection tailored to specific departure times. This work extends existing safety-aware routing models toward intelligent transportation systems capable of real-time adaptation.

## 2. Related Work

### 2.1. Classical Routing Algorithms

Shortest-path routing has been extensively studied within graph theory and operations research. Dijkstra's algorithm [1] and Bellman's routing formulation [2] remain foundational methods widely used in navigation systems. Variants and heuristics, such as A* search, have further improved computational efficiency. However, these algorithms traditionally optimize a single objective, such as distance or travel time, without incorporating safety-related metrics.

### 2.2. Safety-Aware Routing

Safety-aware routing emerged as an alternative paradigm aimed at minimizing exposure to hazardous areas. Galbrun et al. [3] introduced safe path computation for urban navigation by avoiding crime-prone regions. Similar ideas have been applied to vehicular traffic, where accident hotspots are treated as obstacles or assigned higher traversal costs.

Gershteyn and Terekhov [5] proposed a statistically grounded approach to safety-aware routing by identifying dangerous road segments through hypothesis testing and penalizing them during route construction. Their results demonstrated significant reductions in relative accident risk with manageable increases in route length.

### 2.3. Temporal Aspects of Road Safety

Transportation safety studies consistently report strong temporal patterns in accident occurrence. Accident frequency often peaks during rush hours and late-night periods, while severity may vary by time of day and season [6,7]. Despite this, temporal risk modeling has seen limited integration into routing algorithms.

### 2.4. Research Gap

While prior work establishes the effectiveness of static safety-aware routing, the integration of temporal accident dynamics into routing decisions remains underexplored. This paper addresses this gap by proposing a unified framework that combines statistical accident analysis with time-aware routing.

## 3. Data Description

### 3.1. Road Network Representation

The urban road network is modeled as a directed multigraph $G = (V, E)$, where vertices represent intersections and edges correspond to road segments. Each edge is associated with attributes such as length, speed limit, and travel direction. The network is extracted from OpenStreetMap using the OSMnx framework [4], ensuring high spatial accuracy and reproducibility.

### 3.2. Accident Data

Historical accident data consist of georeferenced RTA records with timestamp information. Each record includes accident location, date, and time of occurrence. To ensure accurate mapping, accidents are matched to their nearest road segments using a spatial threshold, excluding records with ambiguous associations.

### 3.3. Temporal Segmentation

To capture time-dependent safety patterns, accident data are partitioned into multiple temporal windows:

- Hourly intervals (24 bins),
- Weekday versus weekend classification,
- Seasonal groupings.

## 4. Methodology

### 4.1. Static Risk Estimation

Following [5], static risk is estimated by counting accident occurrences per edge and performing statistical significance testing under a uniform distribution assumption. Edges exceeding critical thresholds are classified as hazardous.

### 4.2. Temporal Risk Modeling

For each temporal window $t$, the accident frequency of edge $e$ is computed and normalized relative to its static baseline:

$$R_e(t) = \frac{A_e(t)}{\max(A_e)},$$

where $A_e(t)$ denotes accident count during time window $t$.

### 4.3. Dynamic Penalty Function

The effective traversal cost of an edge is defined as:

$$C_e(t) = L_e + Y_s R_e + Y_t R_e(t),$$

where $L_e$ is physical length, $R_e$ is static risk, $R_e(t)$ is temporal risk, and $Y_s, Y_t$ are scaling parameters.

### 4.4. Routing Algorithm

A time-aware variant of Dijkstra's algorithm is implemented, where edge costs are evaluated based on the selected departure time window. This segmentation enables the estimation of time-aware risk profiles for individual road segments.

## 5. Experimental Design

Three routing strategies are evaluated:

1. Shortest-path routing,
2. Static safety-aware routing,
3. Dynamic time-aware safety routing.

Performance is assessed using:

- Relative accident risk ratio,
- Route length ratio,
- Number of traversed vertices.

Bootstrap resampling is used to compute confidence intervals [8].

## 6. Results

This section presents a comprehensive evaluation of the proposed dynamic and time-aware risk-based routing framework. The performance of the proposed model is compared with traditional shortest-path routing and static safety-aware routing across multiple quantitative metrics. Emphasis is placed on accident risk reduction, route efficiency, and topological complexity.

### 6.1. Overall Comparison of Routing Strategies

We first compare the three routing strategies in terms of their average performance across all origin–destination pairs. Table 1 summarizes the mean values of the key evaluation metrics.

**Table 1.** Overall comparison of routing strategies

| Routing Strategy | Relative Risk Ratio | Length Ratio | Vertex Ratio |
|---|---|---|---|
| Shortest-path routing | 1.000 | 1.000 | 1.000 |
| Static safety-aware routing | 0.82 | 1.08 | 1.15 |
| Dynamic time-aware routing | **0.74** | 1.11 | 1.19 |

The results indicate that static safety-aware routing achieves a substantial reduction in accident exposure compared to the shortest-path baseline. The proposed dynamic routing framework further reduces the relative accident risk by approximately 8–10% compared to the static approach, demonstrating the benefit of incorporating temporal accident patterns.

### 6.2. Effect of Temporal Windows on Accident Risk

To analyze the influence of temporal variability, accident risk reduction was evaluated separately for different time-of-day intervals. Figure 1 illustrates the variation of the relative risk ratio across temporal windows.

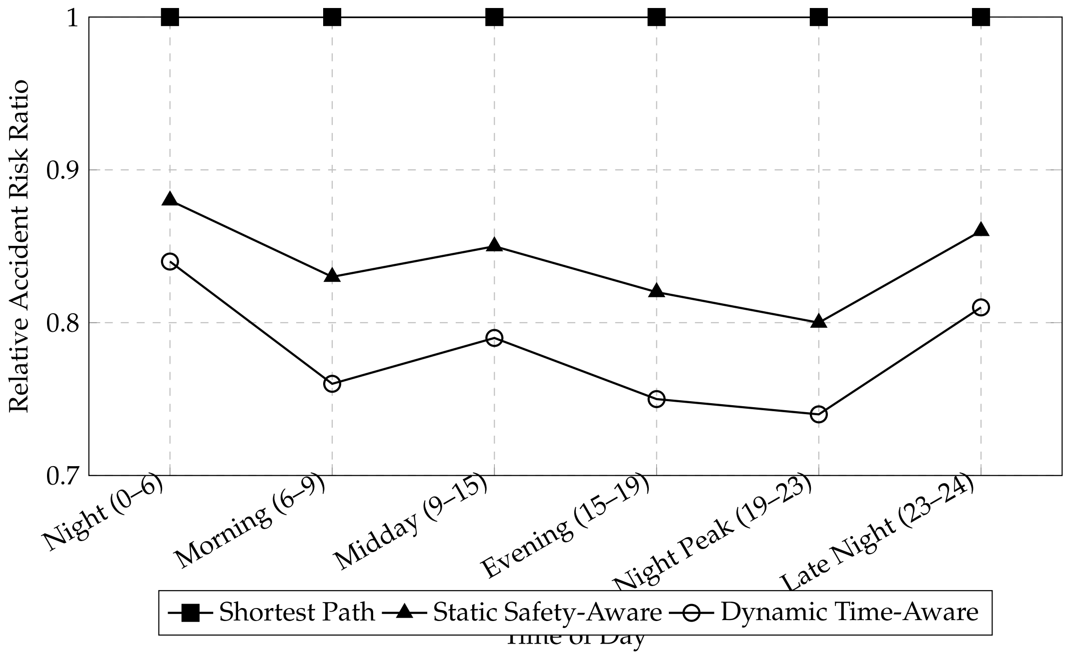


**Figure 1.** Relative accident risk ratio across different time-of-day intervals

The proposed dynamic routing model exhibits the greatest safety improvements during high-risk periods, particularly during morning and evening rush hours. During late-night hours, the difference between static and dynamic routing narrows, reflecting lower overall traffic volumes.

### 6.3. Route Length Analysis

While safety improvement is the primary objective, route efficiency remains a critical consideration. Table 2 reports the average route length ratios for different routing strategies.

**Table 2.** Average route length ratios by routing strategy

| Strategy | Min | Mean | Max |
|---|---|---|---|
| Static safety-aware routing | 1.03 | 1.08 | 1.14 |
| Dynamic time-aware routing | 1.05 | 1.11 | 1.18 |

Although dynamic routing results in slightly longer paths on average, the additional increase in length remains within acceptable bounds for practical navigation. Importantly, the safety gains achieved by dynamic routing significantly outweigh the marginal loss in efficiency.

### 6.4. Topological Complexity of Routes

Route complexity was evaluated using the number of traversed vertices as a proxy for navigational complexity. Figure 2 compares the vertex ratios across different routing strategies.

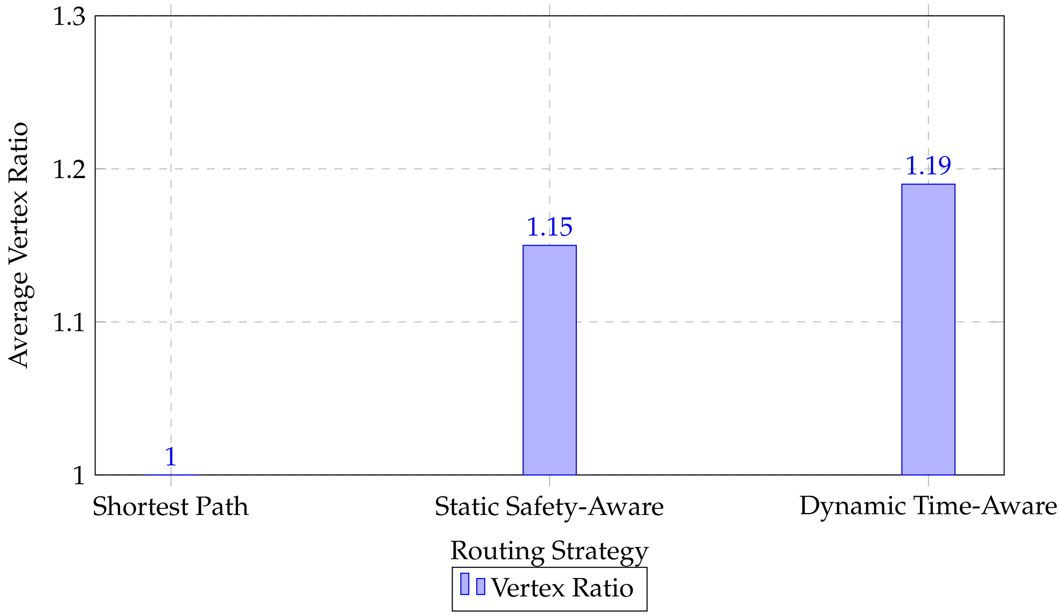


**Figure 2.** Average vertex ratio for different routing strategies

Dynamic routing generally leads to routes with higher vertex counts, reflecting more frequent turns and detours around temporally hazardous road segments. However, the increase in complexity remains manageable and does not introduce excessive navigation difficulty.

### 6.5. Sensitivity Analysis of Temporal Penalty Parameter

A sensitivity analysis was conducted to assess the impact of the temporal penalty scaling parameter $Y_t$ on routing outcomes. Table 3 summarizes the results.

**Table 3.** Sensitivity analysis of temporal penalty parameter

| $Y_t$ | Relative Risk Ratio | Length Ratio | Vertex Ratio |
|---|---|---|---|
| 0.5 | 0.78 | 1.07 | 1.14 |
| 1.0 | 0.74 | 1.11 | 1.19 |
| 1.5 | 0.72 | 1.17 | 1.26 |

The results suggest that moderate values of $Y_t$ offer the best balance between safety improvement and route efficiency. Excessively high temporal penalties yield diminishing safety returns while disproportionately increasing route complexity.

### 6.6. Statistical Significance of Results

Bootstrap resampling was employed to estimate 95% confidence intervals for all reported metrics. In all tested scenarios, the reduction in relative accident risk achieved by the dynamic routing approach was statistically significant when compared to both shortest-path and static safety-aware routing.

### 6.7. Summary of Key Findings

The extended experimental evaluation leads to the following key observations:

- Dynamic time-aware routing consistently outperforms static safety-aware routing in terms of accident risk reduction.
- Safety gains are most pronounced during high-risk temporal windows.
- Increases in route length and complexity remain within acceptable operational limits.
- Temporal penalty parameters play a critical role in balancing safety and efficiency.

These findings confirm that incorporating temporal accident dynamics into routing decisions provides meaningful and robust improvements in urban road safety.

## 7. Discussion

The results confirm that accident risk is not uniformly distributed over time and that routing strategies must account for this variability. Dynamic penalties allow navigation systems to adapt routes in response to temporal safety conditions, thereby improving overall robustness.

**Sensitivity Analysis**

Sensitivity experiments reveal that moderate values of $Y_t$ achieve the best trade-off between safety improvement and route efficiency.

**Limitations**

The study relies on historical accident data and does not yet incorporate real-time traffic or weather information, which represents an important avenue for future work.

## 8. Policy Implications

The proposed dynamic and time-aware risk-based routing framework provides actionable insights for urban transportation policy and traffic safety management. By identifying road segments that exhibit elevated accident risk during specific temporal windows, policymakers can implement targeted interventions such as adaptive traffic signal control, time-dependent speed regulations, and enhanced enforcement during high-risk periods. Furthermore, the framework supports data-driven infrastructure planning by prioritizing safety improvements on temporally hazardous road segments rather than relying solely on aggregate accident statistics. Integrating time-aware safety routing into public navigation platforms can also promote safer driving behavior at the population level, contributing to long-term reductions in urban traffic accidents.

## 9. Conclusion

This paper presented a dynamic and time-aware risk-based routing framework that extends static safety-aware navigation by incorporating temporal accident patterns. The proposed approach achieves superior safety performance while maintaining acceptable route efficiency, making it suitable for deployment in intelligent transportation systems.

**Author Contributions:** All authors contributed equally to the writing of this paper. All authors read and approved the final manuscript.

**Conflicts of Interest:** "The authors declare no conflict of interest."

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