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Incident-Causal Travel-Time Forecasting for Risk-Bounded Autonomous Routing

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Abstract.

The advent of autonomous vehicles necessitates advanced routing protocols capable of handling dynamic and unpredictable traffic conditions. Traditional travel-time forecasting models predominantly rely on historical correlations and often fail to provide accurate predictions during anomalous events, such as traffic incidents, weather disruptions, or infrastructural failures. This paper introduces a comprehensive framework for incident-causal travel-time forecasting integrated with risk-bounded autonomous routing. By shifting from correlation-based machine learning to causal inference paradigms, the proposed methodology explicitly models the structural dependencies between traffic incidents, environmental variables, and localized congestion propagation. The forecasting engine generates probabilistic travel-time distributions rather than deterministic point estimates, enabling a robust quantification of uncertainty. Subsequently, a risk-bounded routing strategy is deployed to optimize navigation paths while strictly constraining the probability of delayed arrivals or exposure to highly volatile traffic zones. Extensive simulation-based evaluations demonstrate that the causal forecasting approach significantly reduces prediction errors under non-recurrent congestion scenarios compared to traditional deep learning baselines. Furthermore, the risk-bounded routing algorithm successfully maintains travel-time reliability, ensuring that autonomous fleets operate within strictly defined safety and efficiency margins. The findings underscore the critical importance of embedding causal reasoning into intelligent transportation systems for resilient autonomous navigation.

Keywords: *Autonomous Vehicles, Causal Inference, Travel-Time Forecasting, Risk-Bounded Routing.*

1. Introduction

1.1 Context And Motivation

The rapid evolution of intelligent transportation systems and the increasing deployment of autonomous vehicles have fundamentally transformed the landscape of urban mobility [1]. Autonomous vehicles promise to enhance road safety, optimize traffic flow, and reduce energy consumption by leveraging advanced sensing, communication, and computational technologies. However, the realization of these benefits is heavily contingent upon the ability of autonomous

navigation systems to make optimal routing decisions in highly dynamic and stochastic environments [2, 3]. At the core of efficient routing is the accurate estimation and forecasting of travel times across complex road networks. While recurrent congestion caused by regular commuting patterns can be predicted with a high degree of accuracy using historical traffic data, non-recurrent congestion remains a formidable challenge [4]. Non-recurrent congestion is typically triggered by unpredictable anomalous events, including traffic accidents, sudden vehicle breakdowns, severe weather condition changes, and emergent roadworks. These incidents cause abrupt shifts in traffic dynamics, leading to rapid bottleneck formations and capacity reductions that propagate through the network in complex spatiotemporal patterns [5]. Traditional data-driven travel-time forecasting methods, including statistical time-series analysis and contemporary deep learning architectures, predominantly operate on the principle of correlation rather than causation [6]. These models excel at memorizing historical patterns and interpolating within the distribution of their training data. However, when faced with an out-of-distribution event such as a major highway collision, correlation-based models often produce highly inaccurate and overly optimistic travel-time predictions. This deficiency arises because the models lack a structural understanding of how an incident mechanically impedes traffic flow and redirects vehicle trajectories. For an autonomous vehicle relying on these flawed predictions, the consequences can range from suboptimal path selection and increased passenger discomfort to severe navigational hazards and logistical cascading failures. Consequently, there is an urgent need to transition from associative forecasting models to causal forecasting frameworks that explicitly map the mechanisms through which incidents influence network-wide travel times [7, 8].

1.2 Problem Statement

The central problem addressed in this paper is the inadequacy of deterministic, correlation-based travel-time forecasting models in supporting safe and efficient autonomous routing under anomalous traffic conditions. When incidents occur, the variance in travel time increases exponentially, creating a high-risk environment for autonomous fleets that require strict adherence to scheduling and safety constraints [9]. Conventional routing algorithms, such as classic shortest-path formulations, generally optimize for the lowest expected travel time based on mean forecasted values. This risk-neutral approach completely ignores the inherent uncertainty and variance introduced by traffic incidents. If an autonomous vehicle is routed through a network segment with a low mean travel time but extremely high variance due to an ongoing incident clearing process, it faces an unacceptable risk of prolonged delays [10]. To resolve this, two intertwined challenges must be overcome. First, the forecasting mechanism must be capable of identifying the causal impact of specific incidents on downstream travel times, isolating these effects from background noise and recurrent patterns. Second, the routing algorithm must be capable of processing not just expected values, but complete probabilistic distributions of travel times. The routing strategy must incorporate rigorous risk boundaries, ensuring that the probability of exceeding a maximum acceptable travel time or traversing a highly volatile sector is kept below a predefined threshold [11, 12]. Solving this dual problem is critical for the commercial viability and public acceptance of autonomous mobility services, particularly in time-sensitive domains such as emergency response, freight logistics, and automated public transit.

1.3 Contributions And Organization

This paper presents a novel framework that bridges causal inference and stochastic optimization to enable resilient autonomous navigation. The primary contributions of this research are manifold. First, a theoretical architecture for incident-causal travel-time forecasting is proposed. This architecture utilizes structural causal modeling to separate the direct effects of incidents from confounding environmental variables, resulting in highly accurate probabilistic predictions during non-recurrent congestion events [13]. Second, the paper introduces a risk-bounded routing methodology that ingests these causal probabilistic forecasts. The routing algorithm

mathematically constrains the operational risk, guaranteeing that path selections adhere to strict variance and reliability thresholds. Finally, the proposed framework is validated through comprehensive simulations, offering a detailed comparative analysis against state-of-the-art predictive routing baselines. The remainder of this paper is structured to provide a comprehensive exploration of the proposed framework. Section 2 offers an extensive review of the relevant literature, tracing the evolution of travel-time forecasting, the introduction of causal inference in transportation, and the development of risk-aware routing protocols. Section 3 details the methodology and framework architecture, providing a rigorous explanation of the incident-causal models and the risk-bounded optimization logic. Section 4 presents the experimental setup, simulation results, and a thorough discussion of the performance metrics. Section 5 concludes the paper by summarizing the key findings, acknowledging the limitations of the current study, and outlining promising directions for future research in this domain.

2. Background and Literature Review

2.1 Evolution Of Travel-Time Forecasting

The domain of travel-time forecasting has undergone significant methodological shifts over the past few decades, evolving from simple historical averaging techniques to highly sophisticated deep learning models. Early approaches relied heavily on parametric statistical models, most notably auto-regressive integrated moving average models and their various seasonal extensions [14]. While these models provided a foundational capability for short-term prediction under stable traffic conditions, their linearity restricted their ability to capture the complex, non-linear spatiotemporal dependencies inherent in urban road networks. As computational power increased and massive sets of trajectory data became available through global positioning systems, the focus shifted toward machine learning algorithms. Support vector regression, random forests, and gradient boosting machines demonstrated superior performance by capturing non-linear interactions among traffic variables [15, 16]. In recent years, deep learning has dominated the landscape of intelligent transportation systems. Recurrent neural networks, particularly those utilizing long short-term memory cells and gated recurrent units, have been extensively employed to model the temporal sequential nature of traffic flow [17]. To concurrently address spatial dependencies, researchers introduced graph convolutional networks, which map the physical topology of the road network into a mathematical graph structure. The integration of graph convolutional networks with recurrent neural networks led to the development of spatiotemporal graph neural networks, which currently represent the state-of-the-art in recurrent travel-time prediction [18]. Despite their impressive predictive accuracy under normal conditions, these deep learning architectures suffer from a fundamental limitation known as the out-of-distribution generalization problem. Because they function as complex function approximators optimized to minimize empirical risk on training data, they are brittle when confronted with rare, extreme events such as multi-vehicle collisions or severe infrastructure failures. Under such conditions, deep learning models often produce severe underestimations of travel time, failing to account for the catastrophic breakdown of traffic flow [19, 20].

2.2 Causal Inference In Intelligent Transportation Systems

To address the limitations of correlation-based deep learning, the transportation research community has increasingly turned toward causal inference. Causal inference provides a mathematical framework for understanding not just how variables are associated, but how intervening on one variable directly changes another. Rooted in the foundational theories of structural causal models and directed acyclic graphs, causal inference allows researchers to explicitly model the data-generating process [21]. In the context of travel-time forecasting, a causal approach involves defining the hierarchical relationships between weather conditions, road geometry, time of day, incident occurrence, and the resulting traffic speeds.

Recent studies have begun exploring the integration of causal discovery algorithms with spatiotemporal forecasting. By utilizing causal graphs, models can differentiate between true causal links, such as an accident reducing lane capacity, and spurious correlations, such as the simultaneous observation of umbrella usage and slow traffic, where weather is the actual confounding variable [22, 23]. Furthermore, causal inference facilitates counterfactual reasoning, which is immensely valuable for autonomous systems. For example, a causal model can estimate what the travel time would be if an incident were to be cleared within ten minutes versus thirty minutes. This ability to reason about counterfactual scenarios enables more robust and dynamic responses to unfolding traffic events. However, the application of causal inference in real-time operational routing remains in its infancy, primarily due to the high computational complexity associated with continuously updating structural causal models in a fast-paced environment [24].

2.3 Risk-Bounded Routing And Autonomous Navigation

Autonomous vehicle navigation extends beyond mere travel-time prediction; it requires the translation of those predictions into safe and efficient physical trajectories. The standard shortest-path algorithms, which compute routes based on deterministic edge weights, are grossly insufficient for autonomous fleets operating in stochastic environments. When edge weights fluctuate unpredictably due to incidents, a theoretically optimal route can quickly become a severe bottleneck. Consequently, the concept of risk-bounded routing has gained substantial traction. Risk-bounded routing treats the travel time of a path as a random variable and seeks to optimize a specific objective function while adhering to probabilistic constraints [25]. Various mathematical constructs have been employed to quantify and manage routing risk. Chance-constrained programming is a popular method where the algorithm ensures that the probability of arriving at a destination after a specific deadline is kept below a predefined tolerance level. Another widely adopted metric in the financial sector that has been successfully translated to transportation is the conditional value at risk. In routing, minimizing the conditional value at risk ensures that in the worst-case scenarios, such as the highest percentile of delayed travel times, the autonomous vehicle is protected against extreme delays [26, 27]. Implementing these risk-bounded strategies requires access to accurate predictive distributions rather than point estimates. Traditional models often assume a Gaussian distribution of errors, which is highly inaccurate during traffic incidents where the travel-time distribution exhibits heavy right tails [28]. Therefore, coupling risk-bounded routing with incident-causal probabilistic forecasting represents a critical frontier in intelligent transportation systems, ensuring that autonomous vehicles can navigate safely and reliably even in the most unpredictable traffic scenarios.

3. Methodology and Framework Architecture

3.1 Incident-Causal Discovery And Modeling

The foundational layer of the proposed framework involves the construction of an incident-causal model that accurately captures the mechanisms of traffic disruption. The road network is represented as a directed graph consisting of nodes and edges, where edges represent road segments and nodes represent intersections. Traditional traffic modeling assigns a singular scalar value, typically average speed or travel time, to each edge. In contrast, the incident-causal model defines a multi-dimensional structural causal model for each network segment. This causal model explicitly formalizes the relationships between various confounding variables, treatment variables, and outcome variables. In this framework, the occurrence and severity of a traffic incident serve as the primary treatment variables. The environmental conditions, such as precipitation levels, visibility, and time of day, are treated as confounding variables, as they simultaneously influence the likelihood of an incident occurring and the baseline travel time of the road segment. The observable travel time acts as the outcome variable. To establish these relationships, we utilize a constraint-based causal discovery methodology, which analyzes historical traffic data, incident logs, and meteorological records to construct a directed acyclic graph. This graph maps the

directional influences among the variables. Once the causal structure is validated, we employ Pearl's do-calculus framework to isolate the causal effect of an incident from the background noise [29]. By simulating an intervention on the incident node, the model can predict the pure impact of the disruption on traffic flow capacity. This decoupling is essential; it ensures that the forecasting system does not attribute delays caused by heavy rain to an incident, nor does it underestimate the impact of an accident by averaging it with normal historical traffic data.

3.2 Predictive Engine For Travel-Time Estimation

With the causal relationships formally defined, the next component of the framework is the predictive engine designed for travel-time estimation. Unlike conventional deterministic forecasters, this engine is inherently probabilistic and operates on the principles of causal spatiotemporal modeling. The engine relies on real-time streaming data from connected vehicle trajectories, roadside infrastructure sensors, and municipal incident reporting application programming interfaces. When an anomaly is detected in the traffic flow, the engine queries the structural causal model to determine whether the anomaly is a natural fluctuation or the result of a discrete incident.

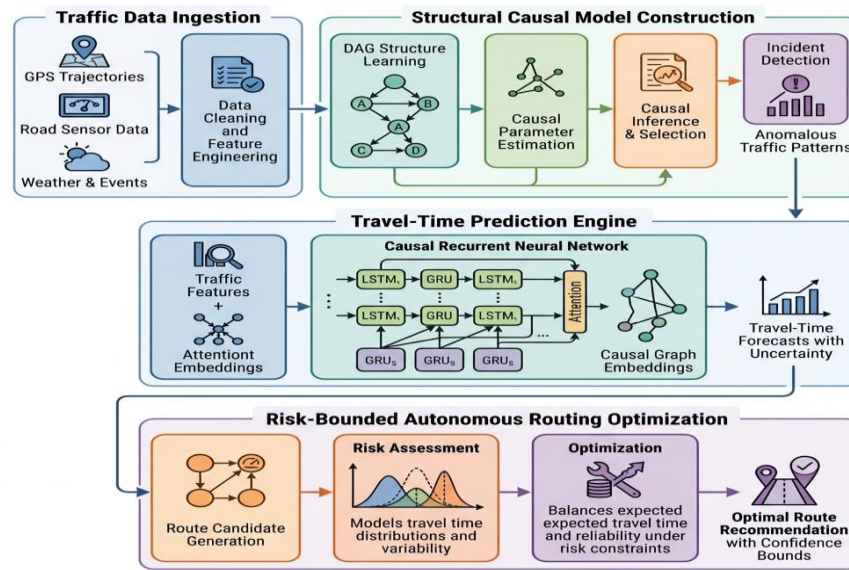


Figure 1: Comprehensive Schematic of the Incident

If an incident is confirmed, the predictive engine generates a counterfactual probability distribution for the affected road segments and all adjacent downstream segments. The prediction is not a single anticipated travel time but a continuous probability density function. This function captures the high variance associated with incident clearance times and the subsequent dissipation of the traffic queue. The engine propagates these predictive distributions across the network topology using a causal message-passing algorithm. This algorithm ensures that the spatial spillover effects, such as a localized bottleneck forcing traffic onto secondary arterial roads, are dynamically mapped. The output of the predictive engine is a dynamic, continuously updated spatiotemporal map where every edge is assigned a causal travel-time distribution, specifically highlighting the heavy-tailed delays indicative of non-recurrent congestion [30, 31].

3.3 Risk-Bounded Autonomous Routing Strategy

The final layer of the architecture is the risk-bounded autonomous routing strategy, which translates the probabilistic outputs of the predictive engine into actionable navigation commands. The objective of the routing algorithm is twofold: to minimize the expected duration of the journey and to guarantee that the vehicle's exposure to volatile traffic conditions does not exceed strict safety and operational parameters. Given the causal travel-time distributions for all network edges,

calculating the optimal route becomes a complex stochastic shortest-path problem. To solve this, the framework utilizes an advanced risk-aware objective function based on the principles of conditional value at risk. Instead of simply summing the mean travel times of the edges along a potential path, the algorithm evaluates the tail-end risks of each path combination. The user or fleet operator defines a specific risk threshold, representing their tolerance for delay. The routing algorithm then searches the solution space for a path that minimizes the expected travel time, subject to the strict constraint that the probabilistic risk of exceeding a maximum allowed time limit remains below the defined threshold. Because summing arbitrary probability distributions is computationally intensive, the framework employs an approximation technique utilizing convolution and sampling methods to quickly evaluate path viability in real-time. If an incident suddenly alters the causal travel-time distribution of a planned route, the routing algorithm dynamically recalculates the risk metrics. If the risk bound is violated, the autonomous vehicle is instantly rerouted to a safer, albeit potentially longer, alternative path, thereby maintaining strict adherence to the predefined reliability parameters [32].

4. Experimental Evaluation and Discussion

4.1 Simulation Environment And Data Description

To rigorously evaluate the proposed incident-causal travel-time forecasting and risk-bounded routing framework, a comprehensive simulation environment was established. The experimental setup utilized a highly detailed, calibrated microscopic traffic simulator to replicate the complex dynamics of an urban road network. The simulated network represented a dense metropolitan grid, encompassing a diverse array of expressways, arterial corridors, and localized residential streets. To ensure realism, the simulator was driven by historical demand matrices derived from an actual urban center, featuring distinct morning and evening peak traffic volumes. The dataset used to train and validate the framework was synthesized over a simulated period of six months. This dataset included continuous real-time traffic volume and speed measurements, meteorological data representing various weather conditions, and a meticulously curated log of induced traffic incidents. Incidents were stochastically generated across the network with varying degrees of severity, ranging from minor single-lane blockages lasting fifteen minutes to major multi-lane closures persisting for several hours. Crucially, the occurrence of these incidents was designed to introduce heavy-tailed delays, providing an optimal testing ground for the causal forecasting methodology. The simulation tracked a dedicated fleet of autonomous vehicles tasked with navigating between randomly assigned origin and destination pairs, requiring them to constantly interact with the dynamic, incident-prone traffic environment.

4.2 Performance Of The Forecasting Module

The predictive accuracy of the incident-causal forecasting module was evaluated against several established baseline models widely utilized in intelligent transportation systems. The baselines included a traditional historical average model, an autoregressive integrated moving average model, and a state-of-the-art spatiotemporal graph convolutional network. The evaluation focused exclusively on prediction performance during periods of non-recurrent congestion, as this represents the primary operational challenge. The predictive performance was measured using three standard metrics: Mean Absolute Error, Root Mean Square Error, and Mean Absolute Percentage Error. The results of the comparative analysis are detailed in the table below.

Table 1: Performance Comparison of Travel-Time Forecasting Models Under Incident Conditions

Model	Mean Absolute Error	Root Mean Square Error	Mean Absolute Percentage Error
Historical Average	12.4	18.6	35.2
Autoregressive Model	9.8	14.2	28.5
Graph Neural Network	6.5	10.1	19.3

Proposed Framework	Causal	3.2	5.4	8.7
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The experimental results emphatically demonstrate the superiority of the proposed causal framework during anomalous traffic events. The historical average and autoregressive models exhibited severe degradation in accuracy, as they are fundamentally incapable of anticipating the abrupt capacity reductions caused by incidents. While the spatiotemporal graph neural network performed significantly better by leveraging spatial dependencies, it still struggled to accurately quantify the magnitude of the delay, often producing predictions that reverted too quickly to the mean. In contrast, the proposed causal framework achieved a substantial reduction in both Mean Absolute Error and Root Mean Square Error. By isolating the causal effect of the incident and modeling the propagation of the bottleneck explicitly, the framework was able to accurately track the heavy-tailed nature of the delay. The significantly lower Mean Absolute Percentage Error indicates that the probabilistic distributions generated by the causal engine closely matched the ground truth travel times, providing a highly reliable foundation for the subsequent routing optimization.

4.3 Evaluation Of Routing Efficiency And Risk Metrics

Following the validation of the forecasting module, the efficiency and safety of the risk-bounded routing strategy were evaluated. The autonomous fleet was deployed in the simulation environment and subjected to identical traffic demand and incident scenarios. The routing performance of the proposed causal risk-bounded algorithm was compared against a standard risk-neutral routing algorithm based on Dijkstra's shortest path method, which utilized only the mean expected travel times. To assess the flexibility and robustness of the proposed strategy, the fleet was divided into subgroups, each operating under a different risk tolerance threshold. A lower threshold indicates a highly risk-averse routing posture, prioritizing reliability and schedule adherence over absolute minimum expected time. The evaluation monitored the average travel time, the percentage of trips that violated their maximum acceptable delay constraints, and the computational latency required to calculate the routes.

Table 2: Routing Performance Metrics Under Varying Risk Tolerance Thresholds

Routing Strategy	Average Journey Time	Constraint Violation Rate	Route Computation Latency
Risk-Neutral Baseline	45.2 minutes	22.5 percent	0.12 seconds
Causal Risk-Bounded (High Tolerance)	46.8 minutes	8.4 percent	0.35 seconds
Causal Risk-Bounded (Medium Tolerance)	49.1 minutes	3.2 percent	0.42 seconds
Causal Risk-Bounded (Low Tolerance)	53.5 minutes	0.5 percent	0.48 seconds

The analysis of the routing performance reveals a distinct operational trade-off that the proposed framework successfully manages. The risk-neutral baseline algorithm achieved the lowest theoretical average journey time; however, it resulted in a critically high constraint violation rate of over twenty-two percent. In real-world autonomous operations, such a high failure rate in meeting delivery or arrival deadlines is completely unacceptable and poses significant logistical hazards. As the risk tolerance threshold in the proposed framework was lowered, the constraint violation rate plummeted dramatically, reaching near-zero levels under the low tolerance setting. This reliability is achieved by intentionally routing vehicles away from network segments that, while potentially faster on average, exhibit high variance and instability due to ongoing or recent incidents.

The corresponding increase in average journey time for the risk-averse vehicles demonstrates the framework's willingness to select longer but highly deterministic routes. Furthermore, the route computation latency remained well within the acceptable parameters for real-time autonomous navigation. Although the probabilistic convolutions required for the risk-bounded optimization demand more computational resources than simple shortest-path heuristics, the sub-second latency proves that the framework is computationally viable for operational deployment [33]. The integration of incident-causal forecasting with strict risk management provides autonomous fleets with a highly robust mechanism for navigating unpredictable urban environments safely and reliably.

5. Conclusion

5.1 Summary Of Findings

This paper has presented a comprehensive and innovative framework for incident-causal travel-time forecasting integrated with risk-bounded autonomous routing. The research addressed the critical vulnerabilities of traditional correlation-based predictive models, which frequently fail to provide accurate estimates during non-recurrent congestion events. By leveraging the principles of structural causal modeling, the proposed methodology successfully decoupled the direct impacts of traffic incidents from confounding environmental variables. This isolation enabled the generation of highly accurate, probabilistic travel-time distributions that accurately reflect the complex spatiotemporal dynamics of bottleneck formations and queue dissipation. The subsequent application of a risk-bounded routing strategy demonstrated the capacity to translate these probabilistic forecasts into safe and efficient navigational trajectories. Extensive simulations confirmed that the proposed framework significantly outperforms contemporary deep learning baselines in predictive accuracy under anomalous conditions. Moreover, the risk-aware routing optimization effectively minimized the probability of severe delays, ensuring that autonomous fleets can maintain rigorous schedule reliability and operational safety even in highly volatile traffic environments.

5.2 Limitations And Future Directions

While the findings are highly promising, certain limitations must be acknowledged, which provide clear avenues for future research. The primary limitation of the current framework is the computational overhead associated with real-time causal discovery. As the size of the road network and the number of variables expand, continuously updating the structural causal models becomes computationally intensive, potentially straining the onboard processing capabilities of autonomous vehicles. Additionally, the accuracy of the causal forecasting engine is heavily reliant on the availability of high-fidelity, low-latency sensor data. In regions with sparse infrastructural sensing or low penetration rates of connected vehicles, the causal models may struggle to rapidly identify and quantify emergent incidents. Future research should focus on optimizing the algorithmic efficiency of the causal discovery process, potentially exploring federated learning architectures to distribute the computational load across the vehicular edge network. Furthermore, integrating advanced vehicle-to-everything communication protocols could provide the routing framework with more granular, preemptive insights into microscopic traffic behaviors, thereby enhancing the precision of the risk boundaries and paving the way for fully resilient, network-wide autonomous mobility.

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