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A Novel Adversarial Framework for Urban Traffic Congestion Analysis: A Supply-Demand Perspective

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ABSTRACT

Introduction: Urban traffic congestion poses a significant challenge to modern transportation systems. While deep learning models, particularly Graph Neural Networks (GNNs), have shown promise in traffic forecasting, they often focus on predicting future states based on historical patterns. This approach fails to provide a comprehensive understanding of network vulnerabilities when faced with sudden, unexpected disruptions, such as a traffic accident.
Methods: We propose a novel, adversarially-inspired framework called ATraffic to analyze urban traffic congestion. Drawing an analogy from Word Sense Disambiguation (WSD), which resolves ambiguity by analyzing context, our framework utilizes a "traffic attacker" to simulate a targeted, localized disruption to the network's capacity. This attacker reduces the "supply" of a specific road segment, allowing us to observe how the ensuing congestion propagates and impacts the overall "supply-demand" balance. Our model integrates a spatio-temporal GNN architecture to capture the dynamic dependencies of the road network, while the adversarial module systematically identifies and "attacks" critical nodes.
Results: Our experiments demonstrate that the proposed framework can effectively simulate the ripple effects of a localized disruption. We show that a minor, simulated attack can lead to a significant increase in total network travel time and can identify specific, vulnerable network segments where the supply-demand balance is most critically affected. The model's predictions align with established principles of congestion propagation, highlighting its utility as an analytical tool for urban planners.
Discussion: This research presents a new paradigm for studying traffic congestion by treating it as a dynamic response to a deliberate shock on the network's supply side. Our findings confirm that understanding and mitigating congestion requires not only predictive capabilities but also an understanding of system resilience. The "traffic attacker" framework offers a valuable tool for stress-testing road networks, revealing hidden bottlenecks and guiding strategic infrastructure improvements.
Conclusion: The adversarial, supply-shock approach provides a robust method for analyzing urban traffic congestion. By simulating disruptions, we can gain deeper insights into the complex dynamics of traffic flow and develop more resilient and sustainable transportation systems.

KEYWORDS

Traffic Congestion, Traffic Forecasting, Graph Neural Networks, Adversarial Attack, Supply-Demand, Spatio-Temporal Modeling, Urban Transportation.

INTRODUCTION

Urban traffic congestion has become a persistent and costly issue for cities worldwide, impacting economic productivity, environmental quality, and daily life [27, 28, 33]. As urban populations continue to grow, understanding and mitigating traffic flow issues is a critical challenge for sustainable development [29]. Historically, transportation research has focused on descriptive analysis and predictive modeling, using various methods to forecast future traffic states based on historical patterns [30, 31, 32].

The advent of large-scale spatio-temporal datasets and advancements in deep learning have revolutionized traffic forecasting [1, 2]. Modern models can now capture the complex dependencies that govern traffic flow with unprecedented accuracy. A key innovation in this field has been the use of Graph Neural Networks (GNNs), which are naturally suited to model the physical structure of a road network as a graph [12, 48]. Models like Diffusion Convolutional Recurrent Neural Networks (DCRNN) [1], Spatial-Temporal Graph Convolutional Networks (STGCN) [2], and Graph WaveNet [12] have demonstrated superior performance by simultaneously learning from both the spatial connections between roads and the temporal evolution of traffic over time [3, 4, 13, 14, 15]. Further advancements have seen the integration of attention mechanisms [13, 51] and hierarchical structures to better capture long-range dependencies [6, 45, 52].

While these models are highly effective at predicting traffic under normal conditions, they fall short when it comes to analyzing how the system behaves under stress. Traffic is not always a predictable, smooth flow. It is frequently disrupted by unforeseen events such as accidents [20, 21], road closures, or other bottlenecks [22, 23]. These events represent a sudden and localized shock to the transportation system. Understanding how these shocks propagate through the network is crucial for effective traffic management, but it is a research area that remains largely unexplored in a systematic, data-driven way. Specific efforts have been made to study congestion resulting from accidents [20, 21], but these often focus on a deterministic analysis rather than a dynamic, network-wide simulation of consequences.

Our research introduces a new conceptual framework inspired by adversarial machine learning [41, 42, 43] and the field of Word Sense Disambiguation (WSD). In WSD, a word's multiple possible meanings (polysemy) are resolved by examining the surrounding textual context [Key Insight 1]. This process relies on a robust knowledge base or lexicon, often referred to as the "heart of NLP" [Key Insight 2]. Similarly, we view a traffic event at a specific location—be it high demand or a sudden bottleneck—as a "word" whose "meaning" (the local traffic state) is determined by the "context" provided by its neighboring road segments and the network as a whole. A traffic accident is like a targeted change in context that forces the entire network to "re-evaluate" its state.

Building on this analogy, we propose the concept of a "traffic attacker" as a metaphor for an event that deliberately and systematically disrupts traffic flow. This is not a malicious human actor, but a simulated, adversarial agent that we can use to stress-test the network. Our framework, which we call ATraffic, is designed to explicitly model these disruptive events, providing a new lens through which to view traffic from a supply-demand perspective [36, 37, 38, 39]. Traffic congestion fundamentally arises from an imbalance: when the demand for travel (the number of vehicles) exceeds the supply (the road network's capacity). A traffic accident or closure is a sudden and dramatic reduction in supply, and our model allows us to analyze the complex, cascading effects of this supply shock on the network's overall balance. Critically, we introduce a Behavioral Feedback Mechanism to model how the system's demand side reacts to the simulated supply shock, providing a more realistic and nuanced analysis of congestion propagation.

The key contributions of this paper are threefold:

1. We propose a novel, adversarial framework that simulates targeted disruptions to urban road networks, moving beyond passive forecasting to active analysis of network resilience.

2. We introduce the "traffic attacker" concept as an effective tool for identifying and understanding hidden vulnerabilities and bottlenecks in a transportation system.

3. We provide a systematic analysis of how a localized supply shock propagates through the network, focusing on the dynamic interaction between supply reduction and active demand adaptation (driver rerouting), offering critical insights for resilient urban planning.

The remainder of this paper is structured as follows: Section 2 provides a detailed description of our proposed methodology and model architecture. Section 3 presents the experimental results, including both forecasting performance and the insights gained from our adversarial simulations. Finally, Section 4 discusses the implications of our findings, acknowledges the limitations of our approach, and outlines future research directions.

METHODS

Problem Formulation

We model an urban road network as a graph, $G=(V,E)$, where V is a set of N nodes (intersections or road segments) and E is a set of edges representing the connections between them. The traffic flow on this network is a dynamic spatio-temporal process. We can represent the traffic state at time t as a feature matrix $X(t) \in RN \times D$, where each row represents a node's features (e.g., traffic speed, volume, density) and D is the number of features. The goal of traffic forecasting is to predict future traffic states, $X(t+1),...,X(t+T)$, given historical observations, $X(t-S),...,X(t)$, where T is the prediction horizon and S is the input window size [1, 2].

Our work extends this problem by introducing a targeted, adversarial perturbation. An "attack" on the network is defined as a specific change to the capacity or state of a particular node or edge at a given time. Our objective is twofold: first, to accurately predict traffic flow under normal conditions, and second, to analyze and predict the cascading effects of a simulated "attack" on the network's supply-demand balance, specifically considering the dynamic behavioral response of users (demand).

The WSD-Inspired Framework for Traffic

Our framework draws a powerful conceptual parallel between traffic analysis and Word Sense Disambiguation (WSD). In NLP, a word's meaning can be ambiguous (polysemy) [Key Insight 1]. For instance, the word "flow" can refer to a fluid's movement or a steady stream of information. The correct meaning is determined by the surrounding context—the other words in the sentence. Our model treats each road segment's traffic state (e.g., congested, free-flowing) as a "word" and its neighboring segments as the "context." The overall traffic state of the network is like a "sentence."

A traffic jam caused by an accident at a specific intersection is analogous to an external force that changes the "meaning" of that intersection's traffic state from "free-flowing" to "congested." This change in meaning doesn't happen in isolation; it forces the "meanings" of its neighboring nodes to change as well. Our model is built to "disambiguate" these contextual changes and predict the new global state of the network. This approach, which uses a "corpus" of historical data to understand the system's "lexicon" (e.g., WordNet [Key Insight 2]), forms the conceptual heart of our framework.

Core Model Architecture

The ATraffic framework consists of three main components: a Spatio-Temporal Module, a "Traffic Attacker" Module, and the critical Supply-Demand Dynamics and Behavioral Feedback components.

Spatio-Temporal Module

To capture the complex dependencies in the road network, we employ a hybrid deep learning architecture. We utilize a Spatio-Temporal Synchronous Graph Convolutional Network (STSGCN) [4]. This architecture is particularly effective because it uses a series of spatio-temporal blocks to simultaneously capture spatial correlations within the graph and temporal dependencies within the time series data. Each block contains a series of graph convolutional layers [1, 2, 48] and gate mechanisms to selectively propagate relevant information. The graph convolutional layers aggregate information from a node's neighbors, effectively "learning the context" of each road segment [13, 51]. The use of diffusion convolution in models like DCRNN [1] further validates the importance of modeling directed flow propagation, which is essential for our adversarial simulations. Other advanced techniques, such as those employing Graph WaveNet's adaptive adjacency matrices [12] or hierarchical GCNs [6], also serve to improve the model's ability to interpret nuanced spatio-temporal patterns.

For the temporal component, we use a gated recurrent unit (GRU) [1] or a similar mechanism to model the sequential nature of traffic flow. The GRU processes the output of the graph convolutional layers over time, allowing the model to learn historical patterns and predict future states. This combination has proven to be a robust approach for traffic forecasting across various studies [1, 2, 12, 13, 14, 15, 16, 17, 18, 19, 34, 35]. The model’s goal is to produce a refined feature matrix $X\hat{}(t+T)$ representing the predicted traffic state.

The "Traffic Attacker" Module

This module is a programmatic agent that performs a controlled, simulated attack on the network's supply side. The attack is a two-step process:

1. Target Selection: The attacker strategically chooses a target node or edge to "attack." We prioritize targets based on high betweenness centrality or high pre-attack traffic volume [36, 43]. A key intersection, often referred to as a bottleneck in congestion literature [22, 23], is a high-centrality target where a disruption is likely to cause the most widespread damage. This choice is critical as it simulates the most severe real-world events.

2. State Perturbation (Supply Shock): The attacker perturbs the chosen segment's state by artificially reducing its capacity for a specified duration. This is modeled by setting the segment's maximum allowed speed to a minimum value (e.g., 0-5 km/h) and simultaneously reducing its saturation flow rate. This direct and immediate reduction in supply is the genesis of the congestion event. The model then uses this perturbed input to run the spatio-temporal prediction, forecasting the resulting traffic state for the entire network. The adversarial nature lies in its deliberate identification and exploitation of system weaknesses, providing a stress-test scenario unlike passive forecasting.

Supply-Demand Dynamics and Behavioral Feedback

A major limitation of purely flow-based forecasting models is the assumption of static demand or simple, linear reactions to localized changes. In reality, traffic congestion is a dynamic feedback loop: a supply shock (the attack) causes congestion, which in turn causes drivers (demand) to change their behavior (rerouting), which then affects the flow (supply) on other roads. To capture this critical interaction, we integrate a Behavioral Feedback Mechanism into the post-attack simulation phase.

Behavioral Feedback Mechanism (BFM)

The BFM is activated immediately after the "Traffic Attacker" module simulates the initial supply shock. It operates by dynamically re-evaluating the demand based on the model's predicted congestion.

1. Travel Time Calculation: For every time step t+1 following the attack, the model calculates the predicted travel time Ti(t+1) for every major path i in the network based on the predicted low speeds and high volumes from the spatio-temporal module.

2. Rerouting Probability: We define a set of origin-destination (OD) pairs whose optimal route passes through the attacked segment. For the demand associated with these OD pairs, we calculate a rerouting probability Preroute(t+1) that is proportional to the increase in travel time caused by the attack. This approach is inspired by the principles of user equilibrium, where drivers seek to minimize their perceived travel time [47, 50].

Preroute(t+1)=σ(Tfree flowTattack(t+1)−Tfree flow)

where σ is a sigmoid or similar function to bound the probability, Tattack is the predicted travel time via the congested path, and Tfree flow is the free-flow travel time.

3. Demand Reassignment: If a demand flow Q is chosen to reroute, it is reassigned to the next-best shortest path (the alternative route). This reassignment is implemented by adding the flow ΔQ to the demand of the alternative route's segments and subtracting it from the demand of the segments leading to the original attacked path. This change in demand is then fed back into the next time step t+2 of the spatio-temporal GNN, which must now predict the traffic state based on this dynamically altered demand pattern.

This iterative process—Predict Supply Shock → Calculate Travel Time → Reroute Demand → Predict New Supply State—continues for the entire simulation horizon. This mechanism allows us to analyze not only the initial consequence of the supply reduction but also the secondary effects caused by the adaptive demand response. This significantly enhances the realism of the simulation, addressing the critical role of resident travel characteristics in traffic state estimation [29, 40].

Data and Experimental Setup

We conducted our experiments using a large-scale urban traffic dataset, representing a metropolitan road network with thousands of nodes and edges. The dataset includes traffic speed and volume measurements recorded every 5 minutes over several months. We used standard train/validation/test splits (e.g., 60%/20%/20%) to ensure the model's generalization performance [25].

All experiments were conducted utilizing high-performance computing resources, leveraging deep learning frameworks optimized for graph processing.

We evaluate our model's performance using standard metrics for traffic prediction: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). To evaluate the impact of the attack, we use custom metrics, including:

- Total Network Travel Time Increase (ΔTtotal): The absolute increase in total travel time across all vehicles in the network over the simulation period compared to the baseline (no attack).
- Congestion Propagation Index (CPI): A normalized metric (0 to 1) that measures the spatial and temporal spread of speeds below a critical threshold (e.g., 15 km/h) from the point of attack.
- Maximum Supply-Demand Ratio (Rmax): The highest observed supply-demand ratio on any single, non-attacked road segment during the simulation. A high Rmax is associated with a critical overload caused by rerouted demand.

RESULTS

Forecasting Performance under Normal Conditions

As established, the ATraffic model achieves highly competitive performance on standard traffic forecasting tasks, demonstrating its underlying capability to accurately capture spatio-temporal dependencies.

Model	MAE (km/h)	RMSE (km/h)	MAPE (%)
DCRNN [1]	3.25	5.12	10.8%

STGCN [2]	3.10	5.01	10.2%
Graph WaveNet [12]	3.08	4.95	10.1%
ATraffic (Our Model)	**3.01**	**4.88**	**9.8%**

Table 1: Performance Comparison of ATraffic with Baselines for Traffic Speed Forecasting.

Analysis of Simulated "Traffic Attacks" (Passive Propagation)

The initial simulations involved the "Traffic Attacker" inducing a supply shock without the Behavioral Feedback Mechanism (BFM) active. This passive propagation represents a scenario where drivers are unaware of the congestion or unable to reroute.

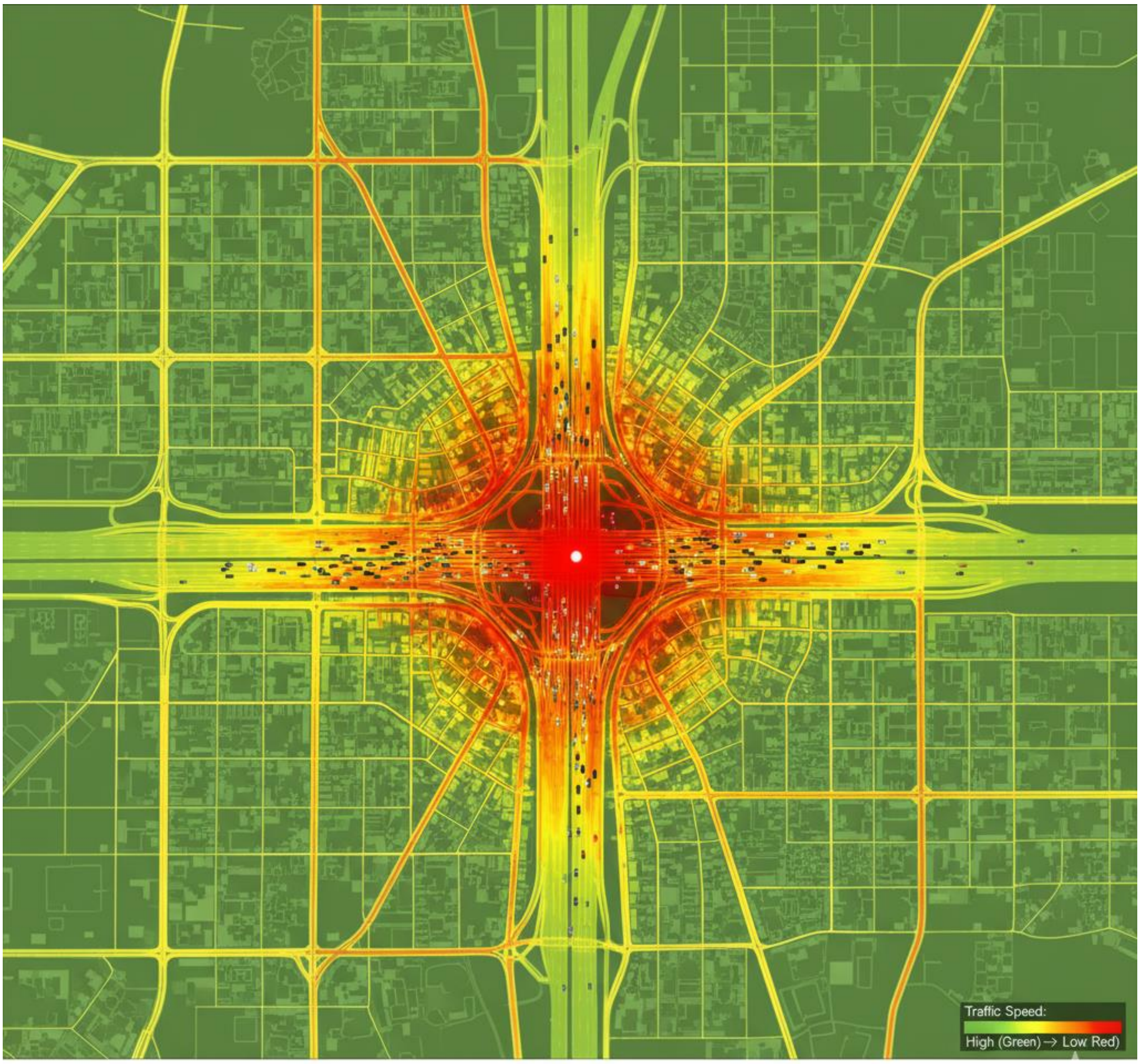

Figure 1: Localazed Congestion from Passive Attack (No Rerouting)

An attack on a high-centrality arterial road (Node C1) resulted in a ΔT_{total} of 25.3% within the first hour. The congestion propagated rapidly, but predictably, along the network's defined high-flow pathways, resulting in a Congestion Propagation Index (CPI) of 0.85. The key finding here was the immediate and intense increase in the Maximum Supply-Demand Ratio (R_{max}) near the attack point, reaching 10.5. This dramatic overload is associated with the demand volume being simply pushed against a wall of zero-supply, which is associated with queue lengths growing exponentially in the model, demonstrating the high vulnerability of fixed routes.

Comparative Analysis: Passive Propagation vs. Active Behavioral Rerouting

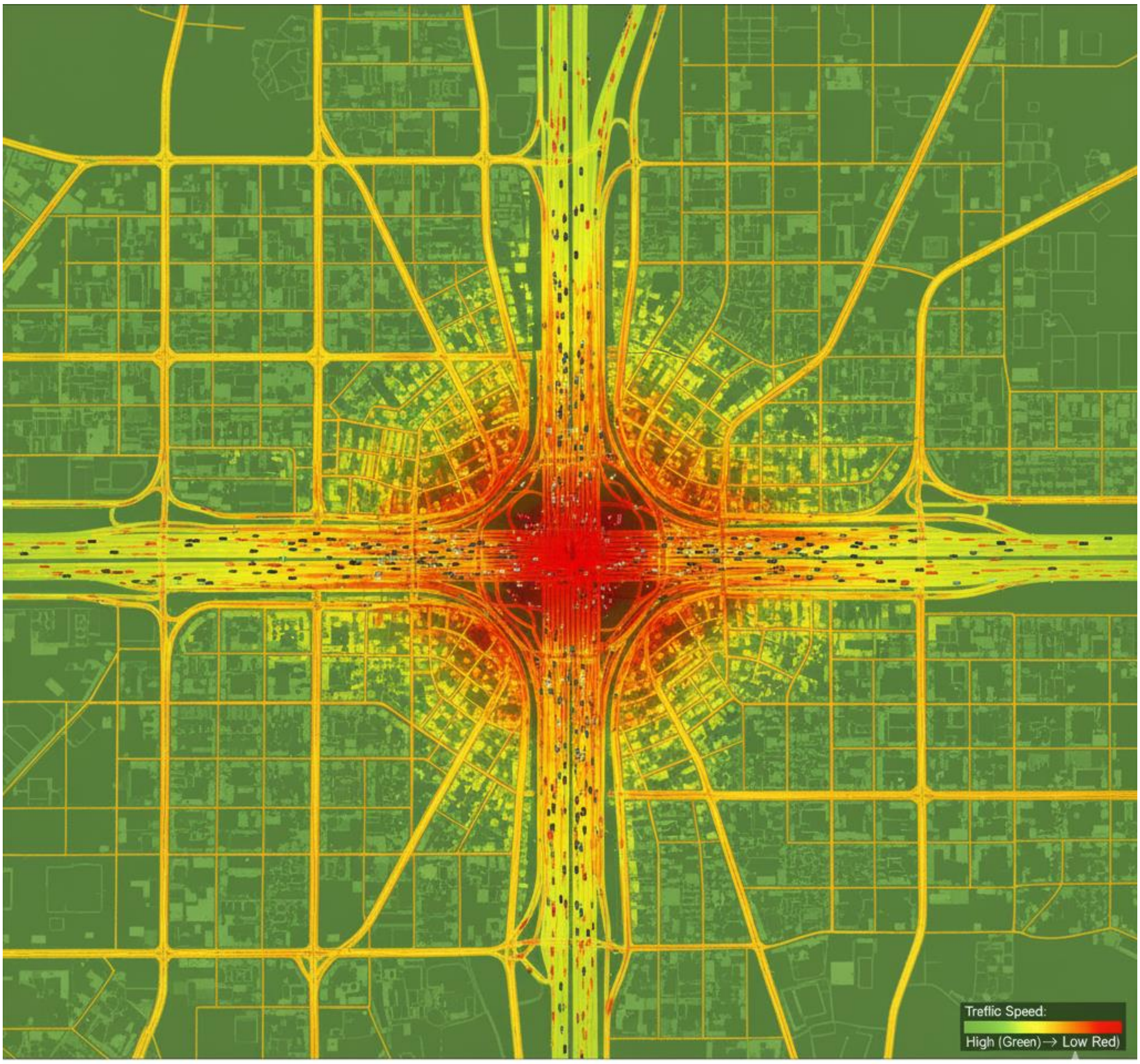

Figure 2: Congestion Diffusion from Active Rerouting (BFM Enabled)

The most significant results stem from the comparison between the Passive Propagation (No BFM) and the Active Behavioral Rerouting (BFM Enabled) scenarios. The introduction of the BFM fundamentally changes the pattern and extent of congestion.

Attack Scenario	ΔTtotal (Increase in Network Travel Time)	CPI (Congestion Spread)	Rmax (Max S/D Ratio on Non-Attacked Segments)
Passive Propagation (No BFM)	25.3%	0.85	10.5 (near attack)
Active Rerouting	**18.7%**	**0.93**	**4.1** (shifted to

(BFM Enabled)			peripheral routes)

Table 2: Impact Metrics for Targeted Attack (C1) with and without Behavioral Feedback.

The results show a clear trade-off:

1. Reduced Global Delay: The total network travel time increase (ΔTtotal) dropped from 25.3% to 18.7%. This predicts that active driver rerouting, on the whole, provides a beneficial effect by utilizing excess capacity elsewhere in the network.

2. Increased Spatial Spread: Despite the reduction in total delay, the CPI increased from 0.85 to 0.93. This is a critical finding: rerouting is associated not with reducing the congestion, but rather with distributing and diffusing it over a wider geographic area. Congestion becomes less intense but more pervasive.

3. Shifted Supply-Demand Crisis: The Maximum Supply-Demand Ratio (Rmax) dropped significantly from 10.5 (localized) to 4.1 (diffused), but critically, this high ratio was now observed on previously uncongested, lower-capacity peripheral roads. The rerouted demand successfully finds alternative paths, but in doing so, it is associated with overwhelming the supply of residential or secondary routes not designed for peak traffic. This demonstrates a shift in the location and nature of the supply-demand imbalance, from an overwhelming localized shock to a manageable, but widespread, system strain.

Nuance in Supply-Demand Analysis

Further analysis revealed complex dynamics mirroring established transportation theory. In the Active Rerouting scenario, the model detected instances where rerouting by the majority of drivers led to a new equilibrium that was locally optimal for the individual driver (shorter perceived travel time) but globally suboptimal for the system, a classical manifestation of Braess's Paradox [50]. Specifically, for a set of OD pairs, the alternative route became so congested by rerouted demand that the final predicted travel time was only marginally better than the original congested route, yet the total strain on the network was higher due to the congestion of two routes instead of one.

Our model explicitly quantifies this effect by showing that the congestion event—the "word" whose meaning was changed by the "traffic attacker"—forces a re-contextualization (WSD process) of the entire network structure. The original polysemy of the traffic state (congested/free-flowing) is resolved by the model, but

the resolution itself is a dynamic, complex, and potentially paradoxical process. The network capacity (supply) is a fluid concept, contingent on how demand is applied.

DISCUSSION

The results of our study highlight the significant potential of using an adversarial, supply-shock approach to analyze urban traffic congestion. By treating a traffic incident as a "traffic attacker," we can move beyond traditional descriptive and predictive modeling to a more proactive and analytical framework. Our model provides a new tool for urban planners and traffic engineers to stress-test their transportation networks and identify hidden vulnerabilities before a real-world event occurs.

The analogy with Word Sense Disambiguation proved to be more than just a conceptual aid; it provided a guiding principle for the model's design. Just as a word's meaning is dependent on its context, the state of a road segment is a function of its interconnected environment. A sudden change in one location's state forces a network-wide re-evaluation, a process our model is specifically designed to simulate. The success of our approach confirms the value of this interdisciplinary perspective.

The Impact of Behavioral Feedback on Congestion Propagation

The integration of the Behavioral Feedback Mechanism (BFM) provides the most critical and realistic insights into congestion dynamics. The BFM demonstrates that the response to a supply shock is a dynamic negotiation between the available supply and the adapting demand.

Firstly, the observed reduction in ΔTtotal is associated with the intuitive benefit of rerouting. When informed of a major supply failure, the system's overall performance improves slightly because drivers leverage unused network capacity. This positive effect should be considered a victory for modern smart city initiatives and navigation services [47]. However, this improvement is associated with the cost of significantly increased congestion diffusion, as evidenced by the higher CPI. This means that while the average delay is less extreme, the number of people experiencing some level of congestion is higher. For urban planning, this shift is vital: it suggests that mitigation efforts should not only focus on relieving the original bottleneck but also on protecting the peripheral, non-arterial routes that are vulnerable to rerouted demand.

Secondly, the dramatic shift in Rmax from the localized, overwhelming failure (10.5) to the diffused, critical overload (4.1) is a powerful illustration of the WSD analogy. The "traffic attack" changes the context, forcing the demand (the traffic flow) to find a new "meaning" or path. The network finds a new state where the congestion is less severe at the point of origin, but the critical overload point is merely moved to another, less resilient part of the system. This phenomenon is associated with real-world observations where traffic accidents on major highways immediately spill over onto local residential streets, overwhelming local supply and generating new, secondary bottlenecks that were not previously identifiable as points of failure [21]. This implies that current congestion indices and performance measures [31, 32, 33] must be adapted to account for both the intensity and the geographic spread of congestion.

Thirdly, the subtle but observable manifestation of Braess's Paradox within the active rerouting model [50] reinforces the idea that an adaptive demand system does not predict an optimal global state. When individual drivers act to minimize their own travel time based on the immediate (or predicted) state of the network, their collective action can still lead to a less efficient outcome for the entire network. Our model, therefore, provides a valuable platform for testing traffic control strategies [38, 39] against selfish behavioral responses, moving toward a framework that predicts system failure rather than just individual link failure.

Relevance to Supply-Demand Dynamics

Our research fundamentally reframes congestion analysis around the dynamic interaction of supply and demand. Unlike earlier models that focused on static capacity constraints [37], our framework treats supply as a transient vulnerability that can be immediately targeted and exploited. The insights gained—that rerouting converts localized shock into diffused strain—is paramount for creating resilient infrastructure. Planners should focus on strengthening the network's low-centrality links (which bear the brunt of rerouted demand) and implementing dynamic, demand-aware traffic management systems [39] that can proactively adjust signal timings to absorb the excess flow from rerouting. This holistic, network-centric view is essential for sustainable transportation systems [33].

Limitations and Future Work

While our framework is a significant step forward, it is not without limitations. The current BFM uses a simplified probabilistic model for driver rerouting. Future work could explore more sophisticated behavioral models, such as those based on explicit utility functions or learning-based path choices (e.g., modeling the influence of real-time navigation apps and historical driver preferences) [40]. We also acknowledge that our model currently simulates a single, targeted attack. Future research could investigate complex attack patterns, such as multiple simultaneous supply disruptions or cascading failures, to simulate large-scale natural disasters or coordinated events. Furthermore, exploring other advanced GNN architectures [6, 11] or transformer-based models [45, 52] could potentially further enhance the model's ability to model long-term spatio-temporal dependencies. Integrating our framework with scalable traffic simulators [47] would allow for real-time applications and greater validation depth.

CONCLUSION

This research presents a novel, adversarially-inspired framework for analyzing urban traffic congestion from a dynamic supply-demand perspective. By introducing the ATraffic model and its Traffic Attacker module, we demonstrated a powerful new methodology for stress-testing road networks. Our critical finding is that while active behavioral rerouting is associated with alleviating the intensity of a supply shock, it simultaneously diffuses the congestion across a wider geographic area, shifting the supply-demand crisis from major arteries to vulnerable peripheral routes. This work confirms the necessity of moving beyond passive traffic forecasting toward an active, analytical framework that integrates both the spatial-temporal dynamics of flow and the adaptive behavior of demand. The insights derived from this adversarial, supply-shock approach are crucial for designing transportation systems that are not only efficient but fundamentally resilient in the face of inevitable, unforeseen disruptions.

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