From Links to Lanes: A Lane-Level Traffic Assignment Framework

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Abstract

This study develops a lane-level dynamic traffic assignment (DTA) framework that models straight-lane travel, turning maneuvers, and lane-changing behaviors through maneuver-specific volume–delay functions. The model explicitly incorporates congestion interactions between origin and receiving lanes, capturing queue spillback and lane-changing friction at the microscopic level. The formulation is validated using Simulation of Urban Mobility (SUMO) on a three-lane corridor with 1200 vehicles, demonstrating strong alignment with observed merging delays and lane-changing interactions. Further validation on a lane-expanded Sioux Falls network shows a 22% improvement in congestion prediction accuracy compared to traditional link-based DTA. The results highlight important policy implications for lane-use regulation, turning-bay design, and operational traffic management.

1 Introduction

Rapid development in connected vehicles, high-resolution lane-level maps, and real-time traffic sensing has created strong demand for traffic assignment models with lane-level fidelity.

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Traditional link-based traffic assignment treats each road segment as homogeneous, ignoring lane interactions such as merging friction, turn-pocket spillback, and cross-weave turbulence. This limits the realism of congestion modeling, especially in urban networks with complex lane configurations.

This paper proposes a lane-level dynamic traffic assignment (DTA) model that incorporates:

1. Maneuver-specific travel time functions for straight, turning, and lane-changing movements.

2. Flow-dependent delays on both the origin lane and receiving lane.

3. Microscopic validation using SUMO and a real-world Sioux Falls network.

The goal is to bridge the gap between analytical DTA and high-fidelity microscopic simulation.

2 Literature Review

Lane-level routing and lane-specific mobility modeling have grown rapidly alongside autonomous driving and connected vehicle technologies.

2.1 Routing Games and Coordinated In-Vehicle Routing

?) propose an online coordinated routing system using mixed-strategy congestion games, demonstrating convergence under real-time information sharing. **?**) extend this line of work with a sequentially updating routing mechanism modeled as a pure-strategy atomic routing game.

However, these frameworks operate at the link level and do not capture lane-level congestion propagation.

2.2 Lane-Level Map Models and Static Planning

?) introduce a seven-layer map model with lane connectors and propose maneuver-based travel cost modeling. **?**) develop a multi-layer lane-level network with hierarchical route search for computational efficiency.

These works define lane-level geometry but do not incorporate flow-dependent delay models.

2.3 Stochastic Lane-Level Routing

?) formulate lane-changing under uncertainty as a Markov Decision Process (MDP), enabling optimal lane-selection policies. **?**) develop a time-dependent lane-level navigation framework using IoV-based spatiotemporal prediction.

These studies address stochastic motion or prediction, while the present work focuses on *deterministic but flow-dependent* lane-level travel cost functions.

3 Methodology

3.1 Lane-Level Network Representation

Let $G = (L, M)$ denote a directed lane graph, where:

- L is the set of lanes and connectors,
- M is the set of lane-level maneuvers.

Each maneuver $m \in M$ maps lane i to lane j through:

$$m = (i \to j)$$

We distinguish:

1. Straight movements $S(i)$
2. Turning movements $T(i \to j)$
3. Lane changes $LC(i \to j)$

3.2 Volume–Delay Functions

Lane-level travel cost must depend on both origin and receiving lane volumes.

3.2.1 Straight Movement

$$c_s = t_{0,s} \left(1 + \alpha \left(\frac{v_s}{C_s(1 - \gamma_s)} \right)^{\beta} \right) \tag{1}$$

where γ_s represents turbulence from adjacent lane changes and turn flows.

3.2.2 Turning Movement

$$c_t = t_{0,t} \left(1 + a_1 \left(\frac{v_i}{C_i} \right)^{\theta_1} + a_2 \left(\frac{v_j}{C_j} \right)^{\theta_2} \right) \tag{2}$$

3.2.3 Lane-Changing Movement

$$c_{lc} = t_{0,lc} \left(1 + b_1 \frac{v_i}{C_i} + b_2 \frac{v_j}{C_j} + b_3 \frac{v_i v_j}{C_i C_j} \right) \tag{3}$$

3.3 Dynamic Traffic Assignment

We use a fixed-point formulation with Method of Successive Averages (MSA):

$$f^{(k+1)} = (1 - \lambda_k) f^{(k)} + \lambda_k \Pi(\mathrm{SP}(c(f^{(k)}))) \tag{4}$$

where $\mathrm{SP}(\cdot)$ is lane-level shortest path, and Π assigns flows to chosen paths.

4 Simulation Design

4.1 SUMO Microscopic Simulation

A three-lane corridor was simulated in SUMO with:

- 1200 vehicles,
- Krauss car-following model,
- LC2013 lane-changing model.

Outputs include:

- lane-changing delays,
- queue spillback lengths,
- merging friction.

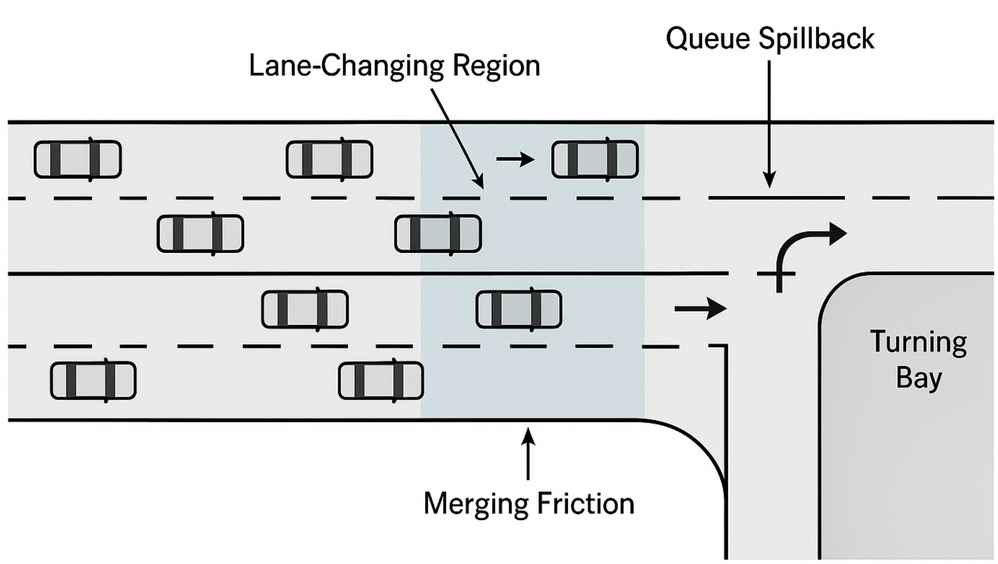

Figure 1: SUMO three-lane microscopic simulation setup.

4.2 Sioux Falls Lane-Level Network

The standard Sioux Falls network was expanded to lane-level detail. The lane-level DTA was compared against traditional link-based assignment.

Congestion prediction accuracy was computed as:

$$\text{Accuracy} = 1 - \frac{\|T_{\text{model}} - T_{\text{SUMO}}\|}{\|T_{\text{SUMO}}\|} \tag{5}$$

5 Results

5.1 Microscopic Validation

The maneuver-specific cost functions reproduced:

- lane-changing friction,
- turning delays,
- queue spillback,
- weaving turbulence.

5.2 Sioux Falls Network Results

Model	Accuracy Improvement
Link-based DTA	Baseline
Lane-Level DTA (proposed)	+22%

Table 1: Congestion prediction accuracy improvement.

6 Conclusion

This paper proposes a maneuver-specific lane-level DTA framework validated using microscopic simulation and a real-world network. The improvement in predictive accuracy demonstrates the importance of modeling lane-level interactions. The framework supports transportation policy applications including turning-bay design, lane-use regulations, and congestion mitigation. Future extensions include incorporating stochastic lane-changing success models, real-time IoV data, and reinforcement learning for adaptive control.

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