

Macroscopic Dynamic Lane Allocation for Ride-Sharing Vehicles: Incorporating Local Correction Factor

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SHORT SUMMARY

Modern transportation systems are increasingly challenged by rising diversity and density in urban traffic, driven by technological advancements and increased travel demands. Dynamic lane allocation provides a pivotal solution by adapting lane usage based on real-time traffic conditions to enhance urban mobility and mitigate congestion. This research introduces a novel dynamic lane allocation strategy that allows ride-sharing vehicles access to dedicated bus lanes during select periods and locations to alleviate urban congestion. We use the MnMS (Multimodal Network Modeling and Simulation) framework, which employs a trip-based Macroscopic Fundamental Diagram (MFD) to support diverse travel options and accelerate computation. Additionally, this study integrates a Local Correction Factor (LCF) that refines speed estimations on individual links for more accurate and realistic route choices. In this study, a Large Neighborhood Search (LNS) optimization solver is employed to efficiently solve complex problems by exploring extensive solution neighborhoods iteratively. Experiments on a 6x6 Manhattan grid network show that optimized dynamic lane allocation significantly outperforms static lane usage, particularly under high demand, reducing total travel time by approximately 15.3%. The proposed approach is identified as crucial for urban traffic management, offering substantial potential to reduce congestion and enhance mobility in densely populated cities.

Keywords: Dynamic lane allocation, Ride sharing, Macroscopic Fundamental Diagram Local correction factor, Large Neighborhood Search

1 INTRODUCTION

Modern transportation systems are currently undergoing transformative changes driven by technological advancements. These innovations have expanded transportation options and significantly boosted urban travel demand (Severino et al., 2021; Menouar et al., 2017). With a growing number of vehicles and diverse transportation modes occupying limited urban spaces, managing congestion has become a critical challenge (Gonzales et al., 2010). This increased density and diversity necessitate solutions to optimize road usage efficiently and effectively.

Dynamic lane allocation emerges as a crucial strategy in managing this complexity, aiming to adapt lane usage dynamically based on current traffic conditions to alleviate congestion and improve urban mobility (Valença et al., 2021). Studies such as Zyryanov & Mironchuk (2012) use microscopic traffic simulation to evaluate Intermittent Bus Lane (IBL) operations, exploring both the benefits and limitations under various traffic volumes and bus priority scenarios. Xie et al. (2012) demonstrate how bus lanes with intermittent priority can improve bus transit based on microsimulation. Additionally, Anderson & Geroliminis (2020) propose a novel dynamic bus lane policy that adjusts the car-to-bus ratio within a lane, rather than enforcing complete vehicle separation. The results suggest that this policy can improve outflow during peak periods and expedite system recovery, with advantages for both vehicles and buses. Fayed et al. (2023) propose an occupancy-dependent space allocation strategy in multi-modal networks, by allowing pooled ride-hailing vehicles to use bus lanes. These studies collectively highlight the potential of dynamic lane allocation to improve urban transportation dynamics significantly.

This paper introduces a novel dynamic lane allocation strategy that permits ride-sharing vehicles access to dedicated bus lanes at selected time periods and locations to reduce private car

usage and alleviate urban congestion. We employ an agent-based simulation framework MnMS (Multimodal Network Modeling and Simulation) developed by the LICIT-ECO7 research laboratory, which utilizes a trip-based Macroscopic Fundamental Diagram (MFD) to support diverse travel options and expedites computation (Paipuri & Leclercq, 2020). To overcome the limitations of MFD-based simulators that can't reflect local diversity in the individual link, we incorporate a Local Correction Factor (LCF) that precisely estimates individual link speeds based on network configurations, ensuring realistic and effective route choices. The LCF estimates the speed of individual links with high precision by incorporating the network mean speed from the MFD and detailed network configurations, including spatial attributes of each link and the network's topology. To optimize dynamic lane allocation, we use a Large Neighborhood Search (LNS) solver, known for its ability to efficiently solve complex problems by iteratively exploring extensive solution neighborhoods. This approach aims to enhance urban transport efficiency by optimizing dynamic lane allocation.

2 METHODOLOGY

2.1 Local Correction Factor (LCF)

The Local Correction Factor (LCF) is designed to address the critical challenge of estimating individual link speed accurately at time t , which is essential for effective route choices especially when different road configurations can affect the speed. The LCF is a function that utilizes Graph Attention Networks (GATs) and Gated Recurrent Units (GRUs) to estimate the individual link speed based on the comprehensive road network configuration G and network mean speed at time t , V_{mean}^t . The network configuration includes topology and spatial attributes such as the length of the road link L_i , the total number of lanes N_{total} and the number of dedicated bus lanes N_{DBL} . Additionally, we introduce a network partitioning technique, enhancing model performance by segmenting the urban network into more homogeneous regions. The process of speed estimation is expressed in Eq. (1) and (2),

$$[V_1^t, V_2^t, \dots, V_N^t] = f_{\text{LCF}}(G; V_{\text{mean}}^t) \quad (1)$$

$$f_{\text{LCF}}(G; V_{\text{mean}}^t) = \text{Combine}(\text{GAT}(\text{Partition}(G)), \text{GRU}(V_{\text{mean}}^t)) \quad (2)$$

where f_{LCF} represents the LCF; GAT extracts information from the network configuration; GRU models the temporal dynamics of the network; and Partitioning refers to the method of network partitioning, employing K-Means clustering. In addition, V_i^t represents the speed of the i^{th} road link at time t and N signifies the total number of road links. In this experiment, the proposed method is used to estimate the speed of the normal vehicle layer. For bus layer, we utilize a speed MFD function, which calculates the speed based on the accumulation of ride-sharing vehicles.

2.2 Optimization of Dynamic Lane Allocation

To effectively address the dynamic lane allocation problem, we employ the Large Neighborhood Search (LNS) optimization solver. LNS is a powerful heuristic method that systematically explores large segments of the solution space through a cyclical process of "destruction" and "repair." This exploration is pivotal for escaping local optima and discovering more globally optimal solutions.

The LNS operates on a binary vector with a length of 576, representing possible lane configurations across different time periods and locations within the network. Each simulation cycle within the LNS involves ten repair operations, enabling substantial variations to be tested within the framework of the current best solution. The destruction rate starts at 0.5, meaning half of the vector's elements can be altered initially, and it gradually reduces to 0.05 as the solution converges optimally. This reduction is critical as it allows the algorithm to fine-tune the solutions when it progresses, shifting from broad explorations to more detailed refinements.

Our primary objective is to maximize system performance through the strategic allocation of dynamic lanes. This can be considered as minimizing the total travel time total of all users traveling in the network — Private Vehicles (PV), Ride-sharing Vehicles (RS), and Buses. This is quantified by the following equations:

$$\min T_{\text{total}} = \sum_{i \in \text{pv}} t_i^{\text{pv}} + \sum_{j \in \text{bus}} t_j^{\text{bus}} + \sum_{k \in \text{rs}} t_k^{\text{rs}} \quad (3)$$

where

$$t_i^{\text{pv}} = \sum_{l \in L^i} \frac{d_l^i}{LCF_{\text{pv}}(v_{\text{pv}}^t)}, \quad (\text{individual travel time for private vehicles}) \quad (4)$$

$$t_j^{\text{bus}} = \sum_{l \in L^j} \frac{d_l^j}{LCF_{\text{bus}}(v_{\text{bus}}^t)}, \quad (\text{individual travel time for buses}) \quad (5)$$

$$t_k^{\text{rs}} = \sum_{l \in L^k} \frac{d_l^k}{[LCF_{\text{pv}}, LCF_{\text{bus}}](v_{\text{pv}}^t, v_{\text{bus}}^t)}, \quad (\text{individual travel time for ride-sharing vehicles}) \quad (6)$$

where d_l^i represents the distance in link l traveled by mode i ; L^i is the link sets of one route of mode i , v_i^t denotes the network mean speed of mode i at time t ; and t_j^i signifies the travel time of user j using transportation mode i . The LCF_{mode} represents the local correction factors of the mode's layer.

3 RESULTS AND DISCUSSION

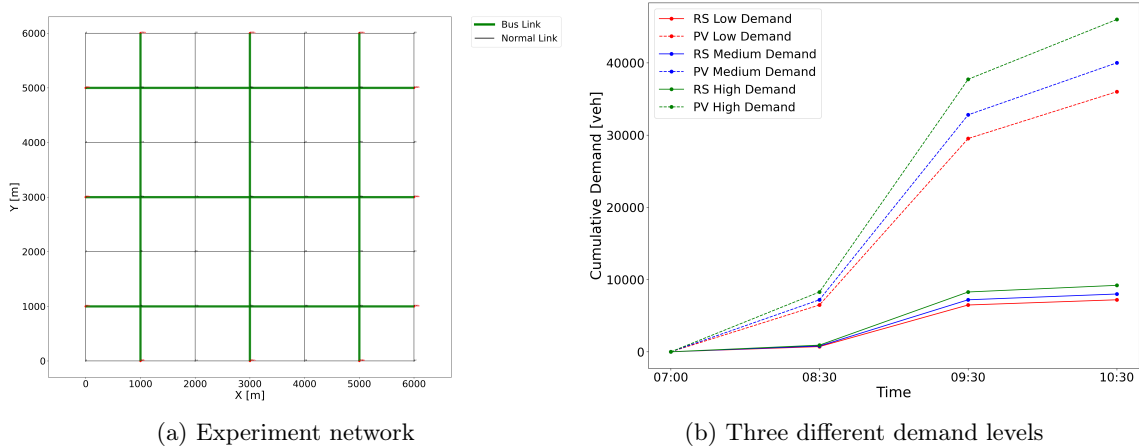


Figure 1: The experiment network with three different demand levels

Our experiment is conducted on a 6x6 Manhattan network grid with each segment measuring 1000 meters and featuring two lanes, illustrated in Figure 1(a). This network includes 72 bus links, marked in green, designated as candidates for dynamic lane allocation, with a set maximum speed of 50 km/h. The simulation period extends from 7:00 AM to 11:00 AM, with adjustments to lane allocations occurring every 30 minutes

The optimization utilizes a binary matrix of 8x72 cells to represent possible changes in lane allocations over time and across different links. Vehicle occupancy is assumed to be one person per private vehicle, two per ride-sharing vehicle, and twenty per bus, to simulate realistic vehicle loadings. We evaluate three demand patterns—low, medium, and high—for Private Vehicles (PVs) and Ride-Sharing (RS) vehicles, as illustrated in Figure 1(b). Bus demand remains constant, except during the peak hour from 8:30 to 9:30 AM when buses run at a one-minute frequency, switching to every three minutes outside this peak period.

We explore three traffic management scenarios: prohibiting ride-sharing vehicles in all bus lanes, allowing them access to all bus lanes, and applying an optimized dynamic lane allocation. The outcomes of these scenarios are comprehensively analyzed and presented in Table 1.

The results clearly demonstrate the superiority of optimized dynamic lane allocation, which outperforms scenarios where bus lanes are either completely banned or fully permitted to ride-sharing vehicles across various traffic demands. Notably, the benefits of optimized approach is

Table 1: Results of total travel time of the network with different scenarios [s]

Demand	Type	PV	RS	BUS	TOTAL
Low	All banning	17,623,700	17,623,700	12,225,600	40,571,660
	All opening	16,565,540	9,727,440	15,110,400	41,403,380
	Solution	17,075,180	9,742,520	13,084,800	39,902,500
Medium	All banning	20,809,420	12,686,320	12,225,600	45,721,340
	All opening	19,097,380	11,175,960	15,729,600	46,002,940
	Solution	19,685,960	11,149,800	13,329,600	44,165,360
High	All banning	30,821,640	19,173,480	12,225,600	62,220,720
	All opening	23,693,860	14,008,280	16,833,600	54,535,740
	Solution	24,370,280	13,716,000	14,620,800	52,707,080

obvious in high-demand conditions where effective traffic management is crucial, reducing total travel time by approximately 15.3% compared to the all-banning scenario. The advantages of using the optimized solution are significant across all scenarios but most pronounced under high demand. In low-demand scenarios, the impact on ride-sharing vehicles is less significant, as the optimization process primarily focuses on minimizing bus travel time. However, as demand increases, the sensitivity of bus travel time decreases, making the benefits of the optimized solution more apparent. This diminishing sensitivity, coupled with increased operational efficiency for other modes, particularly ride-sharing vehicles, is significant. When compared to scenarios that allow unrestricted access to bus lanes, the optimized solution consistently reduces the total travel time for ride-sharing vehicles across all demand levels. This suggests that dynamic lane allocation optimizes traffic flow and resource utilization more effectively than static lane assignments. The strategic advantages make dynamic lane allocation as an essential tool for urban traffic management, particularly valuable in cities facing challenges with heavy congestion.

4 CONCLUSIONS

In this study, we introduce a novel dynamic lane allocation strategy that utilizes a macroscopic fundamental diagram-based simulator, enhanced with a Local Correction Factor (LCF). The results from our simulations conclusively demonstrate the efficiency of our proposed strategy. By dynamically adapting lane usage, this method significantly reduces the total travel time across various traffic demand scenarios. The promising outcomes highlight the potential for implementing this strategy to improve the network efficiency.

For future research, it will be essential to test this approach in more extensive urban settings to evaluate its scalability and further refine the effectiveness of the dynamic lane allocation. Potential improvements could focus on enhancing the accuracy of the LCF across different transportation modes, ensuring that the system can reliably perform under varying traffic conditions. Additionally, exploring more efficient optimization techniques could help reduce the computational costs of the solution space, potentially enabling real-time applications. This could lead to more adaptive and responsive urban traffic systems, capable of addressing congestion in real time and improving overall traffic efficiency.

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