*hEART 2019 - 8th Symposium of the European Association for Research in Transportation*

*September 4-6, 2019, Budapest*

# Modeling and Optimization of Dedicated Bus Lane network design under dynamic traffic congestion

Dimitrios Tsitsokas [1] Anastasios Kouvelas [2] Nikolas Geroliminis [1]

[1]Urban Transport Systems Laboratory, School of Architecture, Civil & Environmental Engineering
École Polytechnique Fédérale de Lausanne (EPFL), Switzerland
{dimitrios.tsitsokas,nikolas.geroliminis}@epfl.ch

[2]Institute for Transport Planning & Systems, Department of Civil, Environmental & Geomatic Engineering
ETH Zurich, Switzerland
anastasios.kouvelas@ivt.baug.ethz.ch

## ABSTRACT

Collective transport has been seen for long as a proper solution to fight congestion. While collectivity has been successful with respect to subways, it is not the norm in road traffic. Dedicated Bus Lanes (DBL) have been proposed as a measure to reduce the impact of traffic congestion in the travel time and accuracy of buses, by providing them with exclusive road space. However, DBL presence decreases road capacity, which may induce local congestion. Balancing this inherent trade-off of a DBL network, by carefully selecting the location of DBLs while considering the dynamics of congestion propagation is challenging. This work aims at finding a reliable modeling and optimization methodology to address this problem. An adjusted version of Store-and-Forward queuing model and microscopic simulation are used to simulate the traffic dynamics in presence of DBLs and assess the global network performance, while a local search algorithm is used to improve some state-of-practice solutions.

**Keywords:** *Dedicated Bus Lanes; Network Modeling; Queueing model; Local Search; Optimization.*

## INTRODUCTION

As traffic congestion increases in large cities, designing and maintaining a high-quality mass transit service becomes crucial in achieving lower congestion and acceptable travel times in areas of high demand. Rail or light-rail systems (e.g. metro) can usually guarantee low travel time and high accuracy in departure and arrival times since vehicles do not interact with regular traffic as they travel in exclusive space. The element of dedicated space can be transferred to regular bus systems by introducing Dedicated Bus Lanes (DBL) in certain roads and arterials. In this way, travel time is reduced for public transit without the extreme cost of a rail system construction that many cities, especially in developing countries, cannot afford. Shorter travel time for buses means that more commuters are likely to take the bus for their daily commute, therefore decreasing the number of circulating vehicles in areas of high demand.

Creating the DBL plan for a specific urban network, i.e. deciding in which roads and for what distances DBLs will be introduced, as also the days and time intervals during which they will be active, is not trivial. Many different factors influence the performance of the network in presence of DBLs; among others, the prevailing demand pattern inside the network during the day, the number, frequency and occupancy of all buses travelling in the candidate roads, the available physical space and the correlation of queue lengths over time between connected roads. Although DBLs offer an advantage to transit vehicles, they reduce the space that is available to regular cars, which may lead to faster queue growing. In congested traffic states, where the system is unstable, several roads may become gridlocked and cause neighbouring roads to reach the same state due to spillback effect. Therefore, poorly allocated DBLs may aggravate congestion and create long vehicle queues in several neighbourhoods. Moreover, in presence of DBLs that alter travel time both for buses and cars, passengers and drivers are likely to adapt their travel behaviour, by switching mode (from cars to buses and vice versa) or by changing their regular routes. Even though a shift from cars to buses is highly desired in this case, how to quantify and control this shift in relation to the DBL network configuration is difficult to define.

While numerous studies have addressed this problem (see [*1*], [*2*], [*3*] and others) in most cases static conditions are assumed, which fail to capture the effects of backwards propagation of congestion and the forming of queues; the latter can significantly affect the system performance in cases of congested networks. Microsimulation is often used for scenario evaluations in what-if studies (e.g. [*4*]) but cannot be used in an optimization framework due to very high computational cost. A dynamic macroscopic approach on this problem can be found in [*5*], but the exact locations of DBLs are not determined. The objective of this work is to propose a reliable methodology to find the optimal DBL allocation in a given network by considering the dynamic characteristics and the physics of traffic congestion. In this work, a mesoscopic traffic model based on queueing theory principles is used as a computationally low-cost simulation model that can quantify the queue forming and estimate the total travel time for a specific network geometry and DBL allocation. The DBL allocation problem is formulated in an optimization framework and a local search algorithm is applied to provide improved solutions based on initial state-of-practice solutions. An aggregated mode choice model is used to capture the changes in mode choice that are expected from commuters, due to DBL presence.

## PROBLEM DEFINITION

The traffic network of a specific city center is given. The geometry, topology and traffic signal settings are considered known and fixed. Two modes of transport are present in this network: buses and private cars. Without loss of generality, the operational characteristics of the existing bus system (routes and frequencies) as well as the average passenger occupancy in buses during their trips in the various links of the network are considered known for the period of interest (e.g. the morning peak). A time-dependent Origin-Destination demand matrix feeds the network with private car flow while buses run based on their fixed schedule. Assuming that, for the purpose of improving mobility in the network, a specific fraction of road space - considered known from separate study -is to be given to DBLs, our goal is to identify the best set of roads (out of a broader set of candidate roads) where one DBL should be introduced, in order to achieve a system optimum traffic performance.

The DBL plan that we seek to identify is assumed to be active during the whole period of interest of this study. It is also assumed that in every selected road, one DBL will be placed on the rightmost lane, so that buses can easily stop at bus stops to board and alight passengers. The introduction of a DBL on the road means that the available space for regular vehicles is decreased.

## METHODOLOGY

In this study, we use a modified form of a queueing-based mesoscopic traffic model called "Store-and-Forward" in order to simulate the flow of vehicles in the network. As the interest is focused on the global performance of the bi-modal network from a passenger perspective, a suitable objective function is constructed based on the system state provided by the simulation model and as a function of the location of the DBLs. Then an optimization method is used to provide improved solutions based on initial state-of-practice solutions.

### The adjusted Store-and-Forward model

The Store-and-Forward (SaF) modeling paradigm (see [*6*]), is composed of a mathematical structure which simulates the evolution of queues inside the network, given the demand generation rates and the split ratios at the intersections. In its initial form, SaF simulates the evolution of queues based on a discrete-time form of a flow conservation equation. It allows to replicate the spill-back effect by dictating that the outflow of an upstream to a downstream link at every time step is zero if the downstream link is full (the queue has reached the link's capacity). A drawback of the simple version of this model is that vehicles move from one queue (intersection) to the next one in one time step. This does not allow for an accurate calculation of the total travel time -that is necessary for decision making- in cases of low congestion. This is because links have different lengths which may be much larger than the distance travelled by car in one time step. To address this issue, a more detailed form of this model is proposed, following the structure of a similar model as seen in [*7*].

$$x_z(k) = m_z(k) + w_z(k) \tag{1}$$

$$m_z(k+1) = m_z(k) + T\left(u_{VQ_z}(k) + \sum_{\forall i \in I_{S_z}} \left(1 - t_z^{end}(k)\right) u_{iz}(k) - a_z(k)\right) \tag{2}$$

$$w_z(k+1) = w_z(k) + T\left(a_z(k) - \sum_{\forall i \in O_{E_z}} u_{zi}(k)\right) \tag{3}$$

$$x_{VQz}(k+1) = x_{VQz}(k) + T\left(d_z(k) - u_{VQz}(k)\right) \tag{4}$$

$$l_{\mathrm{ff,z}}(k) = \frac{(c_z - w_z(k))l_{\mathrm{veh}}}{(l_z - y_z)} \tag{5}$$

$$\rho_z(k) = k - \mathrm{ceil}\left(\frac{\mathrm{l_{ff,z}(k)}}{\mathrm{v_{ff}T}}\right) \tag{6}$$

$$C_{a_z}(k) = \sum_{\rho=1:\rho_z(k)} \sum_{\forall i \in I_{S_z}} \left(1 - t_z^{end}(\rho)\right) u_{iz}(\rho) \tag{7}$$

$$a_z(k) = C_{a_z}(k) - C_{a_z}(k-1) \tag{8}$$

$$S_{z,w} = \min(l_z, l_w)1800 \tag{9}$$

$$u_{zw}(k) = \eta_{zw}(k) \begin{cases} 0 & \text{if } x_w(k) \geq c_w \\ \min\left\{S_{z,w} t_{zw}(k), \frac{w_z(k) t_{zw}(k)}{T}\right\} & \text{else} \end{cases} \quad (10)$$

$$\eta_{zw}(k) = \begin{cases} 1 & \text{if z-w has ROW at time step k} \\ 0 & \text{else} \end{cases} \quad (11)$$

The mathematical structure of the model is given by Eq. 1 to 11. In this work the number of vehicles inside a link is composed by a number of moving and a number of queueing vehicles (Eq. 1). Each batch of vehicles that is considered to move in the interval between two time steps from an upstream to a downstream link firstly joins the *moving* part of the link. At every time step, the position of the end of the queue that is formed by all *waiting* vehicles is calculated. Then the flow of vehicles that is transferred from the moving group to the waiting group is found based on the current distance between the entrance of the link (starting point) and the end of the queue. The number of time steps $\rho_z(k)$ needed for a vehicle to cover this distance is calculated. Then, all vehicles that have entered the link $\rho_z(k)$ time steps before the current time are considered that have already moved to the waiting group. In this part of the road, cars are supposed to travel with a pre-specified flow speed. Building on this principle, the traffic state of the network is depicted in terms of the total number of vehicles inside each link (the sum of moving and waiting) at every time step of the simulation. Detailed explanation of the notations is omitted due to space constraints.

## Optimization problem

Our objective is to identify the optimal road set, in terms of total passenger delay, for the installation of DBLs in the network. In order to mathematically formulate the optimization problem, we define a set of binary decision variables $Y = \{y_z | \forall z \in Z\}$, where $y_z$ indicates the setting or not of an EBL in link $z$, as follows:

$$y_z = \begin{cases} 1, & \text{EBL in link } z \\ 0, & \text{else} \end{cases}, \qquad \forall z \in Z \quad (12)$$

The dedication of space to buses leads to a decrease in the storage capacity and the saturation flow of the link. This change is modelled by representing the number of lanes available for the regular traffic as $l_z - y_z$, where $l_z$ is the total number of lanes of link $z$. In order to estimate the total passenger hours travelled based on the model presented in the previous subsection, we use the following equation to estimate the total Passenger Hours Travelled (PHT) during the simulation time:

$$PHT = \sum_z \sum_k x_z(k) \xi T + \sum_z \sum_k \sum_l \left[(1 - y_z) P_l(z,k) \left(1 + \frac{x_z(k)}{c_z} D\right) + y_z P_l(z,k)\right] T \quad (13)$$

In Eq. 13, the first term refers to the total travel time of passengers in private cars. The second term refers to the total travel time of passengers travelling by bus. This bus passenger flow rate is calculated based on the historical transport demand provided by the bus company on the assumption that buses travel in free flow conditions (as inside DBLs). In order to capture the influence of congestion over the travel time of the buses, the term $\left(1 + \frac{x_z(k)}{c_z} D\right)$ serves as a scaling factor that linearly "increases" the bus time that the model will consider in link $z$ as a function of the link occupancy at the specific time step. This means that in a gridlocked link $z$, i.e. $x_z(k) = c_z$, the model will count that buses in mixed traffic lanes will spend $(1 + D)$ times the time that they would spend if they were travelling in DBLs inside link $z$. The value of parameter $D$ can be user-defined after trial-and-error simulation experiments and depends on the value of $T$.

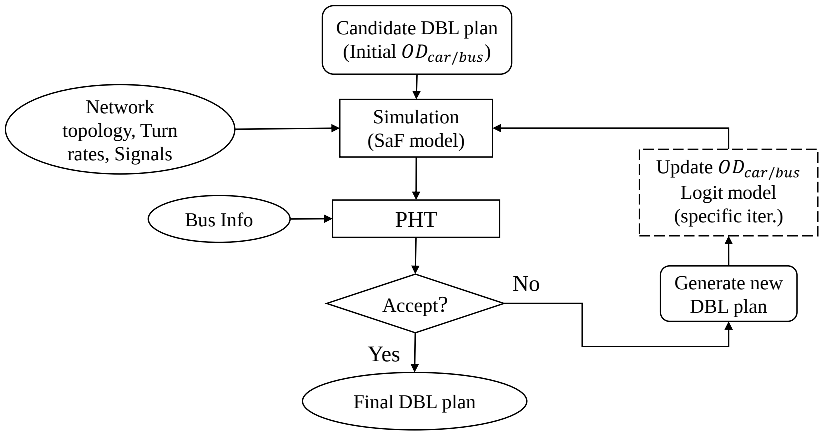


**FIGURE 1 Flow chart of the iterative optimization process. The generation of new solution can be done via various techniques.**

### Solution Process

The optimization problem that we formulated is non-linear in its current form. Although our ultimate objective is to transform it to a Mixed-Integer Linear Programming problem (MILP), in this preliminary stage we perform scenario evaluation and utilize a local search algorithm to identify better solutions by starting form initial ones. The process that we followed can be seen in Fig. 1.The necessary inputs in order to perform one simulation test based on the SaF model are the network topology and dimensions, the fixed traffic signal plan, the dynamic O-D demand matrix and the turning ratios of every link towards all downstream links over time. In order to have realistic values of these ratios, we perform an initial microscopic simulation by using an appropriate software (Aimsun) where the initial case (no DBL) is considered.

In the context of this work, a set of practice-oriented DBL allocation scenarios, based on civil engineering principles are defined, evaluated and improved by a local search algorithm. The algorithm improves an initial solution based on the following idea: for every road which is assigned with a DBL in the initial scenario, we evaluate the case where the DBL is removed by running a simulation experiment. Then the removed DBL is added back to the solution and another one is removed. The same process is repeated for every link with a DBL in the initial solution. By evaluating all the possible scenarios where one DBL is removed, we locate the most efficient removal, i.e. the one that leads to minimum PHT. We follow the same process for all roads of the initial solution where no DBL exist, by adding one to each of them. In this way we identify the location of the most efficient DBL addition. Then the initial solution is updated by moving one DBL from the position found for ”most efficient removal” to the one found for ”most efficient addition”. We repeat the whole process for every update of the initial solution until no further improvement is achieved.

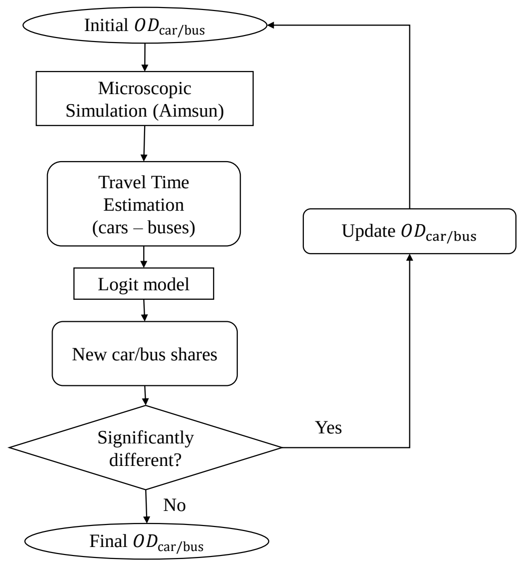


**FIGURE 2 Adjustment process of OD demand matrix for a specific DBL allocation plan**

Regarding the mode selection (car or bus), it is assumed that the initial passenger share of cars and buses (case of no DBL) represents an equilibrium state. Based on this assumption, an aggregated simplified logit model is used to re-define the mode selection by taking into account the specific DBL plan that is being evaluated. Given the average travel time per passenger for each mode, which is computed based on total travel time per mode that a microscopic simulation provides for a specific DBL allocation scenario, the logit model calculates the respective share of bus and car passengers. If the newly calculated demand is significantly different from the one that the microsimulator used in order to provide the values of the total travel time, the bus and car demands are adjusted and a new microscopic simulation is performed. This process is repeated several times until the initial and final demand for car and bus trips converge. As this process is computationally expensive, it is not performed for every different DBL scenario (solutiuon update) that is tested during the optimization process, but only for a fraction of them. A schematic representation of this process can be found in Fig. 2.

## PRELIMINARY RESULTS

The case study where the proposed methodology is applied is a part of Downtown San Francisco, in California, USA. The network is composed of 426 links with lengths varying between 40 and 400 metres and 156 intersections, out of which 92 are signalized. There is a bus service in this area consisting of 29 bus lines running in regular frequencies (e.g. every 10 minutes). A well-calibrated microsimulation model in Aimsun software is used to extract turning ratios and detailed performance indicators for comparison reasons.

A set of scenarios are evaluated by simulation tests. We present here the results of the best scenario among them. In Fig. 3 the step-by-step improvement of the initial solution by the local

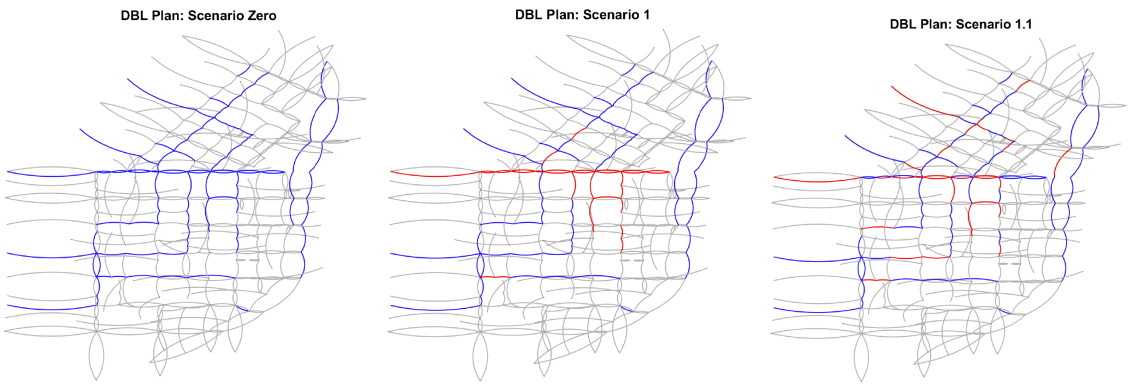


**FIGURE 4 DBL plans: (a) No DBL (b) Initial DBL plan (c) Final DBL plan. In blue: links without DBL. In red: links with DBL. In grey: links non-candidate for DBL.**

search algorithm is shown. It is noted that mode choice adjustment is performed for the initial and final scenarios only. During the local search process, the mode shares in the network remain constant. In Fig. 4 we can see: i) the DBL plan for the current state (no DBL), ii) an initial scenario that assigns DBLs in 33 out of 95 candidate roads (roads with high bus frequencies are selected), and the final DBL plan that is the output of the local search algorithm after 15 iterations, starting from the initial scenario. In Fig 4, non-candidate links for DBLs are in grey, candidate links that are not selected for DBL are in blue and links with DBL are in red. Due to space restrictions, analytical results will be provided in a later publication.

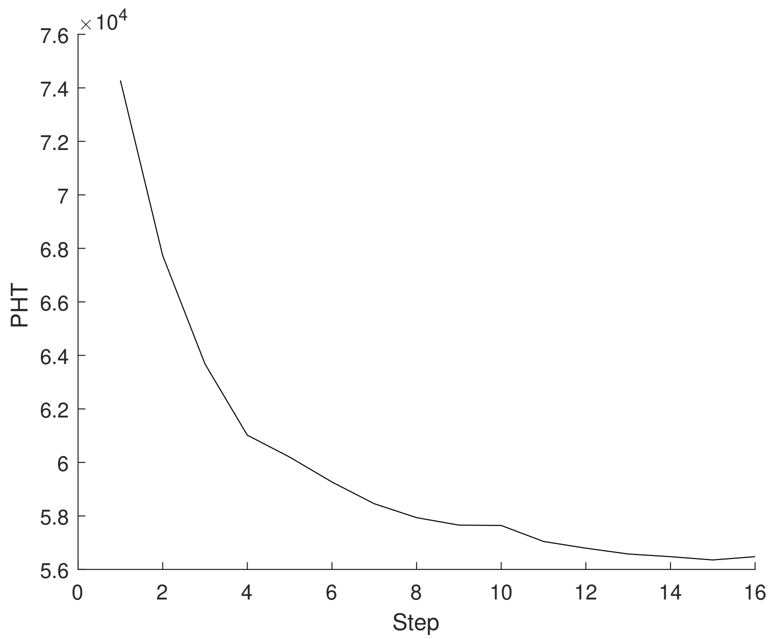


**FIGURE 3 Improvement of initial solution by local search algorithm**

**REFERENCES**

1. Yu, B., Kong, L., Sun, Y., Yao, B., and Gao, Z. A bi-level programming for bus lane network design. *Transportation Research Part C: Emerging Technologies*, Vol. 55, 2015, pp. 310–327.
2. Yao, J., Shi, F., Zhou, Z., and Qin, J. Combinatorial optimization of exclusive bus lanes and bus frequencies in multi-modal transportation network. *Journal of Transportation Engineering*, Vol. 138, No. 12, 2012, pp. 1422–1429.
3. Bingfeng, S., Ming, Z., Xiaobao, Y., and Ziyou, G. Bi-level programming model for exclusive bus lanes configuration in multimodal traffic network. *Transportation research procedia*, Vol. 25, 2017, pp. 652–663.
4. Arasan V. Thamizh, and Vedagiri P. Microsimulation Study of the Effect of Exclusive Bus Lanes on Heterogeneous Traffic Flow. *Journal of Urban Planning and Development*, Vol. 136, No. 1, Mar. 2010, pp. 50–58.
5. Zheng, N., and Geroliminis, N. On the distribution of urban road space for multimodal congested networks. *Transportation Research Part B: Methodological*, Vol. 57, 2013, pp. 326–341.
6. Aboudolas, K., Papageorgiou, M., and Kosmatopoulos, E. Store-and-forward based methods for the signal control problem in large-scale congested urban road networks. *Transportation Research Part C: Emerging Technologies*, Vol. 17, No. 2, 2009, pp. 163–174.
7. Lin, S., De Schutter, B., Xi, Y., and Hellendoorn, H. Fast model predictive control for urban road networks via milp. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 12, No. 3, 2011, pp. 846–856.