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URBAN FREIGHT DISTRIBUTION AND INNOVATIVE LAST-MILE SOLUTIONS FROM A TRAFFIC PERSPECTIVE

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Abstract

URBAN FREIGHT DISTRIBUTION AND INNOVATIVE LAST MILE SOLUTIONS FROM A TRAFFIC PERSPECTIVE

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Urban population growth, the rise of e-commerce, and the increased need for economically and environmentally sustainable solutions represent urban freight distribution's biggest challenges. Traffic and city logistics are often two sides of the same coin, as congestion affects city freight movements and vice versa.

For this reason, it is important to develop comprehensive mobility and traffic management solutions that consider both systems. During the last decade, technology improvements in wireless communication, computational and sensing technologies, have paved the way to a series of mobility and transportation options (e.g., crowdshipping and driverless vehicles) that could transform the landscape of last-mile delivery. The main contribution of this dissertation consists of modeling urban freight impacts on traffic and investigating the potential implications of innovative last-mile solutions.

The first part of this dissertation focuses on the feedback between freight movements and traffic, taking into consideration the impact of passenger vehicles on commercial vehicles, and vice versa. In order to achieve this goal, it is necessary to model trucks' movements and loading/unloading operations with ad-hoc traffic simulations. Most of existing research has focused on analytical, static, or microscopic models, that either lack accuracy or scalability. Hence, this dissertation creates algorithms that couple existing macroscopic traffic flow models with the microscopic behavior of delivery vehicles. This issue is investigated both at single-link and network levels, by

means of a suitable simulation framework. In both cases, applications of the modeling approach for freight traffic and freight demand management are shown.

In the second part of this dissertation the potential impacts of last-mile delivery solutions are evaluated using the developed simulation framework. First, the impacts of alternative City Logistics solutions, such as off-peak deliveries and access restrictions are investigated. Then, the developed modeling framework is extended to investigate a crowdsourced service for parcel deliveries. The effects on traffic and emissions are investigated for the adoption of crowdshipping by carriers delivering parcels in the city center of Rome, Italy. The externalities associated with several strategic (chosen mode) and operational (detour length, parking behavior, and traffic conditions) aspects of this service are analyzed by means of simulation in realistic settings.

Some results allow preliminary considerations about the effects of last-mile delivery solution that can been confirmed in other studies. Other findings, instead, are in line with studies from previous literature that adopted different approaches. The practice of off-peak deliveries, consisting in shifting part of the trips and operations to less congested hours of the day (typically evening and night) has proved to be an effective solution to freight-related congestion in urban settings. Restricting from deliveries specific links or sets of links, instead, could be beneficial only in some situations. Alternative crowdshipping implementation features, such as the transportation mode choice, but also operational aspects (such as availability of parking, optimization of existing trips, and implementation during off-peak hours) can also considerably influence the final traffic and emissions impacts of this service.

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1. INTRODUCTION

1.1 Background

Urban freight transportation plays a fundamental role in the economic development of urban regions, but, at the same time, threatens their livability given the increased road congestion, environmental impacts, and energy consumption.

Due to the many stakeholders involved and their often conflicting objectives, developing sustainable urban freight transportation systems presents several challenges. On the one hand, private stakeholders, like carriers, shippers, and customers, aim at reducing the operational costs while maintaining a high level of service. The last mile of the distribution can account for up to 50% of the total distribution costs (Dablanc and Rodrigue, 2017), and market phenomena like e-commerce and same-day delivery services put additional pressure on carriers to satisfy customers' expectations. On the other hand, public authorities seek to reduce the negative externalities of freight movements, including congestion and pollution.

Freight masterplans and regulations for more sustainable distribution are becoming a common practice in European and American cities. However, it is only since the early 2000s that an emerging research field referred to as City Logistics has been formally investigating "the process of totally optimizing the logistics and transport activities by private companies in urban areas while considering the traffic environment, traffic congestion and energy consumption" (Taniguchi, 2001). Different studies have proposed a series of initiatives, including new regulations, infrastructure improvements, and measures concerning space and time of delivery operations (Taniguchi and Thompson, 2014).

A particularly critical challenge in the City Logistics field is existing city infrastructure's lack of road and parking capacity to accommodate freight transportation, and the resulting high congestion levels. Traffic and freight distribution are often two sides of the same coin, as congestion affects city freight movements and vice versa. In fact, it is well known that urban freight movements have a negative impact on the transportation network because of their lower speed, reduced maneuverability, and frequent stops for deliveries. Double-parking is a common practice in the commercial business districts of major cities and it would probably continue growing with increasing demand for residential deliveries (Chen et al., 2017). Conversely, high levels of traffic delay truck deliveries and compromise the performance and reliability of freight distribution, ultimately increasing the overall costs of the carriers (and the final shipping costs for consumers). During the last decade, technology improvements in wireless communication, computational, and sensing technologies have paved the way to a series of applications aimed at providing a more efficient transportation system (e.g. dynamic route guidance, real-time traffic management, and congestion pricing) and supply chain (e.g. dynamic vehicle routing and fleet and inventory management) labeled as Intelligent Transportation Systems (ITS). In addition, recent technological progress in automated vehicles (e.g. driverless vehicles, robots, unmanned aerial vehicles) could also bring changes in the current delivery models and transform the landscape of last-mile delivery. Finally, the success of sharing economy models is creating the basis for alternative delivery frameworks based on crowdsourcing and cooperation among different carriers and shippers.

In order to properly assess the impacts of freight movements on traffic (and vice versa) and possible City Logistics solutions, it is crucial to explicitly account for the main features of traffic and congestion (hindrance of traffic, temporary capacity reductions, queues formation and propagation). The dynamic nature of the above-mentioned emerging technologies and opportunities especially calls for adequate analysis and modeling tools.

The focus of this dissertation is on models and algorithms for freight traffic and operations, and their applications in the evaluation and optimization of City Logistics solutions. This work places itself at the intersection of two different research areas: the main theoretical component of the presented framework is based on the Traffic Flow Theory, whereas its capabilities and potential applications fit well in the field of City Logistics.

1.2 RESEARCH OBJECTIVES AND MAIN CONTRIBUTIONS

The main objective of this dissertation is to develop tools for traffic simulation of urban freight distribution, and to employ them for the evaluation and optimization of City Logistics measures.

In order to achieve these goals, first it is necessary to reproduce freight movements and loading/unloading operations with ad hoc traffic simulations. Microscopic models reproduce traffic by simulating each individual vehicle and its driving behavior in relation to others. They are well-suited for investigating phenomena, such as overtaking, lane-changing, and merging, and hence complex traffic and infrastructure configurations. In macroscopic models, traffic is reproduced as a fluid by means of variables, such as density (accumulation), flow (throughput), and average speed, and behaves according to the laws of physics. They are well-suited for investigation of large networks and situations where traffic is mainly regulated by signals. There is less agreement about the definition of mesoscopic models, where different features from macroscopic and microscopic models are adopted in order to overcome some of their limitations.

In the realm of macroscopic traffic models, where traffic behaves like a fluid, one of the main challenges of freight traffic simulation consists of coupling existing macroscopic traffic flow models with the microscopic behavior of delivery vehicles. In this dissertation, this is done by developing hybrid algorithms that pair Partial Differential Equations (PDEs) with Ordinary Differential Equations (ODEs). The algorithms are based on the Lighthill-Whitham-Richards (LWR) model, and on the theory of moving and fixed bottlenecks. For an efficient solution in simulations on urban networks the semi-analytical Lax-Hopf method for for solving the LWR model is extended.

Finally, the modeling framework can be employed in the study of two innovative city logistics solutions for the last-mile distribution. The first application consists of the analysis of traffic and environmental impacts deriving from the introduction of a “crowdshipping service.” This type of initiative, which is typically an internet-based service, allows individuals or carriers who walk, bike, or drive to a certain area to perform delivery on their way. In this context, the developed simulation model is used to compare the network effects and operational performance of traditional deliveries with alternative implementations of the crowdshipping concept. The second application integrates delivery robots in the last-mile distribution of parcel deliveries. In this case, the developed simulation model is integrated into an optimization problem to identify the optimal usage of this technology for carriers. In addition, the simulation framework is used to identify potential improvements and threats for the city in terms of traffic and environmental impacts.

At the theoretical level, this research is intended to provide advanced tools to efficiently and accurately reproduce freight movements at link and network level within macroscopic traffic models. Most previous work has focused on analytical, static, or microscopic/mesoscopic models. The analytical or static models are not precise, and only offer an approximate description of traffic, which is not sufficiently accurate to perform traffic optimization and fleet management. The microscopic formulations of mixed flows (regular vehicles and delivery vehicles), while accurate, are not computationally efficient, and for this reason their usage is typically limited to small case studies.

At the practical level, this research aims to investigate emerging urban freight distribution practices and City Logistics schemes with a particular focus on their effects on traffic. The solutions investigated in this dissertation have become only recently a topic of research in the academic literature. Furthermore, the adopted approach allows for accurate analyses of different aspects, such as the actual impacts on traffic and on carriers' operations. To the best of our knowledge, this is a novel approach as most of the existing literature in the field has mainly focused on either the traffic or the supply chain.

1.3 ORGANIZATION

This dissertation is organized as follows (Figure 1):

Chapter 1: Introduction. This chapter introduces the scope of this dissertation and the rationale behind it. The main research objectives and contributions are identified. The outline of the dissertation is described.

Chapter 2: **Future challenges and opportunities for urban freight distribution.** This chapter describes the context of this research. It provides an overview of trends and emerging technologies in urban freight distribution, their implications for different stakeholders, and their possible impacts on mobility and traffic.

Chapter 3: **A fast simulation algorithm for multiple moving bottlenecks and applications in urban freight traffic management**. Slow vehicles, such as trucks and buses (moving bottlenecks) are a major source of congestion and in order to reduce traffic delays, dedicated traffic management solutions could be implemented. Several methods have been proposed in the field of traffic flow theory to compute solutions associated with the presence of moving bottlenecks. One typical challenge encountered in previous studies consists in identifying and modeling features regarding their speed, their discharge flow, and the extent of the queue held back. In this chapter, a semi-analytical approach based on the LWR model for computing solutions associated with an arbitrary number of moving bottlenecks with different features is presented. The problem of computing solutions associated with multiple moving bottlenecks requires solving a coupled ODE/PDE system, and has never been investigated before in the case of multiple bottlenecks. The computational framework proposed is fast and yields exact solutions. It is highly suitable for optimization problems where a large number of traffic estimations need to be performed. Hence, this algorithm is applied to evaluate solutions in two traffic management strategies for trucks: first, joint coordination of traffic lights and trucks' departures on an arterial corridor and, second, parking-loading curbside management strategy for reducing delays associated with trucks' deliveries. An article based on this chapter has been published with the title "A fast simulation algorithm for multiple moving bottlenecks and applications in urban freight traffic management" on *Transportation Part B: Methodological*.

Chapter 4: **A simulation framework for modeling urban freight operations impacts on traffic networks.** This chapter extends the previous work, where freight movements were simulated on a single link, to urban networks. A traffic simulation framework is developed to reproduce freight movements in urban settings with a particular focus on the phenomenon of double-parking. The traffic simulation framework still relies on the LWR model and on the theory of moving and fixed bottlenecks to reproduce delivery operations at the curbside. The traffic component of the model can be coupled with a generic parking model. In the traffic simulation, a novel version of the Lax-Hopf formula is used to perform efficient and accurate simulations of large networks. Given these characteristics, the simulation framework proposed would be highly suitable for the evaluation and development of City Logistics solutions at the network level. Hence, as a secondary contribution, this chapter explores the impacts (in terms of traffic and carriers' efficiency) of two possible sustainable logistic strategies: shifting deliveries to off-peak hours, and restricting certain critical streets from delivery operations. . An article based on this chapter has been published with the title "A simulation framework for modeling urban freight operations impacts on traffic networks" on *Simulation Modelling Practice and Theory*.

Chapter 5: **Study of innovative logistics problems.** An innovative logistic solution investigated consists of crowdshipping. This service allows individuals to undertake shipping jobs during their personal trips. Consumers could seek this service for particular needs, such as same-day deliveries when "traditional" independent carriers are not able to fulfill them or when their costs are too high. Crowdshipping is still a relatively new concept and it could be implemented in different ways: drivers could modify the routes to pick up and drop off packages; public transport users could carry along packages on their trips and drop them off at lockers installed around the stations, and so on. Although some benefits in terms of reduced pollution and congestion could be obtained by replacing dedicated freight trips, the impacts of crowdshipping are unclear and depend on several factors, such as the transport mode used, the match between demand and supply, and possible rebound effects. In this solution, the developed simulation frameworks is employed to evaluate different implementation alternatives. A paper based on this chapter with the title "Potential impacts of crowdshipping services: a simulation-based evaluation" is under review in *Transportation.*

Chapter 6: Conclusion. In the final chapter, the findings and contributions of this dissertation are summarized and some considerations about future research are presented.

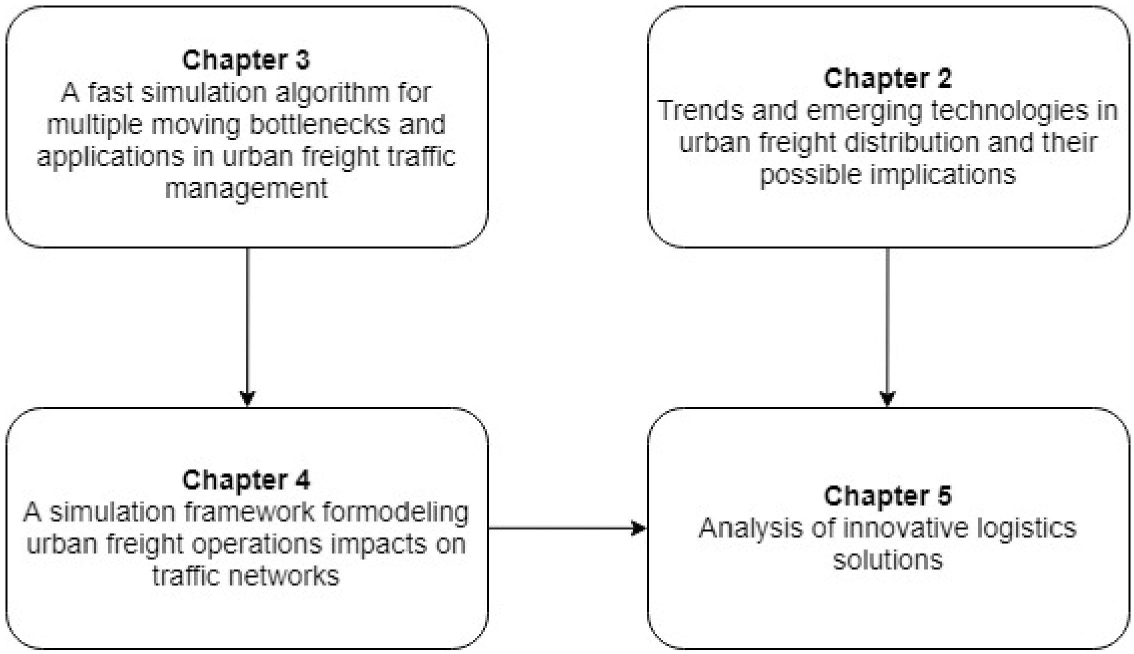

Figure 1: Dissertation schematics

2. OUTLOOK ON FUTURE URBAN FREIGHT DISTRIBUTION

In this chapter, first the issue of last-mile freight distribution and the concept of City Logistics (Section 2.1) are introduced. Then some of the upcoming challenges (Section 2.2) and opportunities (Section 2.3) are identified for the different stakeholders based on the ongoing emerging trends and technologic changes.

2.1 THE LAST-MILE ISSUE

Last-mile delivery represents the final leg of urban freight movements to the end consumer. The final destination could be a retail store, a restaurant, a dweller, or a pickup station. These movements typically occur between distribution center and a final customer, although new online retail and parcel return services have diversified the possible combinations of origins and destinations.

Overall, urban freight distribution involves a very large variety of goods, businesses, and customers. However, the nature of the delivery process that is characterized by different requirements (time and costs) and constraints (dedicated mode and shared infrastructure) is at the root of a series of issues common to moving goods in cities. Specifically, the fact that the different stakeholders involved often have conflicting objectives poses a series of challenges in identifying effective collaborative solutions (Rodrigue et al., 2009).

Public stakeholders (city authorities, city planners, public transport providers) whose first interest is improving social welfare, aim at reducing the negative impacts of freight movements like pollution, congestion, noise, and safety without penalizing the economic activities of cities. Private stakeholders (carriers, shippers, customers) whose primary goal is economic efficiency, aim at improving the quality of distribution services by reducing time and costs.

Since the late 1990s, a new research field at the intersection of economics, policy-making, engineering, and operations research called City Logistics has been exploring solutions: "For totally optimizing the logistics and transport activities by private companies in urban areas while considering the traffic environment, the traffic congestion and energy consumption within the framework of a market economy" (Taniguchi, 2001). Consequently, in the last couple of decades a series of initiatives including new regulations, infrastructure improvements, and measures concerning sharing space and time have been adopted throughout the world, especially Europe and Japan. The reader is referred to Wolpert and Reuter (2012) for an extensive review of City Logistics studies.

While on the one hand current demographic and market trends might worsen the last-mile of freight distribution, on the other hand, technologic advances offer the opportunity to develop newer, more sustainable, and more efficient delivery systems.

2.2 UPCOMING CHALLENGES FOR PUBLIC AND PRIVATE STAKEHOLDERS

Two big challenges for urban freight distribution consist of the increase of urbanization and the expansion of e-commerce. Consequences, such as increased freight traffic and pollution will likely affect the livability of cities and the performance of logistics' key players.

In 2014, more than half of the world population (54%) lived in urban areas rather than in rural areas (United Nations, 2014). By 2045, the urban population is projected to increase by 1.5 times (World Bank, 2018). The pace of growth varies across different regions of the world, with Asia and Africa in the first place because of the highest population growth. Nevertheless, European and North American urban populations will likely increase to 70-80% (European Environmental Agency, 2017; United Nations, 2014). An interesting aspect to consider is the concentration of new city dwellers in medium-sized and large urban areas, eventually leading to the development of mega-cities. By 2030, the number of large metropolitan areas with more than 10 million inhabitants is expected to become 41 (compared to the current 28) (United Nations, 2014). For City Logistics and, in particular, for public stakeholders, such rapid and unplanned growth of urban areas represents a serious threat to the sustainability of freight distribution. An increase of demand for goods and services in cities that are already burdened by scarce road capacity and parking is certainly no good news. In general, unless serious solutions are found for the development of infrastructure and policy measures, congestion and pollution levels will not improve in growing cities, partly because of the increase of freight traffic.

Another threat to sustainable urban freight distribution is represented by the rise of e-commerce and door-to-door services that are determining significant changes in the delivery process. Overall, more direct-to-consumer deliveries are likely to cause lower freight consolidation because of the smaller loads and more frequent deliveries (Taniguchi and Kakimoto, 2003). This shift would inevitably generate a worsening of traffic and parking conditions, given the already limited road network capacity (even though some car shopping trips would be replaced). In addition, as recent research highlights (Visser et al., 2014; Chen et al., 2017), freight traffic and parking issues might arise also in residential areas that could be harder to control by means of regulations (e.g. restricted traffic areas and times). The growth of e-commerce at double-digit rates (around 10% annually in countries like Germany and the US, and more than 25% in Asian countries like China and India according to Capgemini (2013)) calls for action in the near future to address the efficiency of the process and to transfer e-commerce's negative externalities to companies.

The phenomenon of online selling is revealing new challenges for private stakeholders as well, especially for carriers and shippers, as they are faced with increasing last-mile distribution costs. Because of its low efficiency, the last-mile represents the weak link of the supply chain, accounting for up to 28% of the total costs (Rodrigue et al., 2009). There are several reasons behind the high costs of the last mile of transportation (Figure 2), such as low speeds, traffic congestion, lack of parking, and low consolidation. In the case of parcel deliveries, companies are also dealing with the costs related to customers' availability (failed deliveries cost £780 million in 2016, in the UK (IMRG, 2016)) and unpredictability (at least 30% of all products ordered online are returned in the US, according to Invesp's infographic (Invesp, 2016)). These issues are even more prominent for online shopping companies since customers "have an increasingly complex set of expectations regarding speed, flexibility, security and cost of delivery" (Lee et al., 2016). Several companies are struggling to provide high levels of delivery service while keeping their prices as low as possible (or even free), in order to gain customers' loyalty and compete with other companies and traditional "brick-and-mortar" stores. Different surveys have highlighted that a large portion of customers not only prioritize speedy deliveries, but also have a strong preference for free shipping services (Deloitte, 2015; Joerss et al., 2016). Because of the demanded high standards, several e-commerce businesses are facing higher and higher shipping costs. For example, in 2016, Amazon invested $7.2 billion in shipping with an increase of 40% with respect to the previous year investment (Bishop, 2017). In future years, the key players will need to improve their last-mile delivery process, not only to beat the other competitors, but also to guarantee the financial sustainability of their business model.

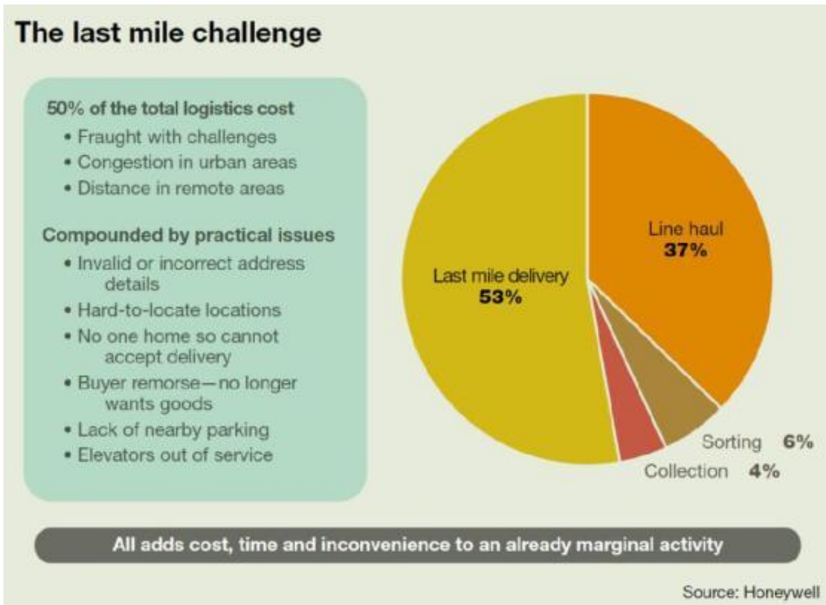

Figure 2: Delivery costs of the last mile (source:Honeywell, 2018)

2.3 UPCOMING OPPORTUNITIES FOR PUBLIC AND PRIVATE STAKEHOLDERS

Freight transport could benefit from the introduction of new business models, technologies, and delivery frameworks based on advances in information and communication technologies. New sharing economy models (Section 2.3.1) and automated technologies (Section 2.3.2) could be adopted by carriers and shippers, in addition to Intelligent Transport System solutions (2.3.3).

2.3.1 Sharing economy models

The sharing economy allows novel delivery approaches by interfacing customers, carriers, and shippers to meet their needs, particularly for goods bought online (McKinnon et al., 2015).

For example, logistics companies might decide to share their assets in terms of infrastructure and fleet (with available capacity) in cooperation with others. The possibility of utilizing spare capacities might result in higher consolidation and eventually a lower number of freight trips. For this reason, this solution is receiving more and more attention in the research field (Krajewska et al., 2008; Audy et al., 2011; Wang and Kopfer, 2014).

The success and expansion of companies like Uber, Lyft, and Didi raises questions about the possibility of integrating last-mile freight transportation with passenger transportation. While such a combination already exists in long-haul transportation (i.e., by sea, air, and rail), it does not usually occur in the short range. Although the utilization of regular passenger modes for freight movements is not entirely new (e.g., CityCargo Project in Amsterdam and Yamato in Kyoto), the usage of internet platforms can considerably harness this process and allow for higher optimization. For example, the people and freight could either travel together or at different times, when vehicles are not used by anybody (Savelsbergh and Van Woensel, 2016). The implementation of such synergies has some potential for improving the efficiency of delivery operations and for reducing dedicated freight trips. However, the final outcomes depend on a series of aspects, such as the level of service provided and integration with existing trips (minimization of detours), and the density of demand. Some initial experiments have been run by partnering companies like Google Shopping Express and Uber and DHL Parcel and Amazon (Blair, 2017), and the first research studies have been investigating conceptual and mathematical models behind this type of delivery frameworks (Li et al., 2014; 2016)

The idea of utilizing traditional passenger modes, such as private vehicles, transit, or bike, and outsourcing services by utilizing others' spare capacity are combined in the concept of crowdshipping. In crowdshipping, individuals traveling to a certain area can perform delivery on their way. In this case, businesses could rely on people to accomplish part of their deliveries. Some recent successful examples of crowdsourcing are the food delivery service UberEats, and same-day delivery platform Deliv. This framework seems very suitable for companies dealing with fluctuating demand and that want to leverage easily accessible, cheaper, and less regulated labor (Joerss et al., 2016). From the perspective of logistics companies, this solution seems promising for improving efficiency and reducing costs (Miller et al., 2017), although it is uncertain whether it could easily scale up to large shares of the freight distribution market (especially for bigger or more expensive items). From the perspective of public authorities, crowdshipping could be beneficial depending on the transport modes utilized by the crowd and on the integration with existing transport flows (Punel and Stathopoulos, 2017). In order for that to become a sustainable option, dedicated freight trips would need to be replaced by public transit, walking, and bike trips (Marcucci et al., 2017).

2.3.2 Automation

Automation will likely change the freight industry thanks to the introduction of self-driving vehicles, drones, and robots.

There are different opinions on the time when autonomous vehicles (AVs) will become publicly available. Nevertheless, it is a fact that major car manufacturers and technology companies are making considerable investments to commercialize partially autonomous vehicles within the next ten years (Muio, 2017). Autonomous driving is going to change significantly people's mobility, and researchers' interest in AVs' impacts on travel behavior and traffic conditions is currently strong. The interested reader can refer to Milakis et al. (2017) for a relatively comprehensive literature review. Still, little investigation has been done on the possible applications of automation to urban freight distribution. Semiautonomous ground vehicles could be used for deliveries as well (Joerss et al., 2016), with a delivery person still needed on the vehicle performing other tasks. It is unclear, however, how this person could move around the truck. A possible alternative could be using autonomous cars as couriers for parcel deliveries. The packages could be placed in different compartments of the vehicle that could be unlocked by the customers at destination with a unique code (DHL, 2014). Along the same lines, some companies are testing a feature that allows control of access to car trunks (Etherington, 2016). This technology could be used by companies to deliver packages to the trunks of customers' cars (DHL, 2015). Although the adoption of AVs might lower shipping costs (by cutting personnel), it is uncertain whether it would lead to increased or lowered levels of congestion and pollution.

Drones or Unmanned Aerial Vehicles (UAVs) could also improve the final leg of delivery operations by delivering small packages in the last mile. The use of UAVs offers several advantages over traditional vehicles. First, drones would be able to perform faster deliveries as they are not constrained by road infrastructure and congestion. They can also more easily access difficult destinations like rural areas and difficult terrains. Since drones represent an appealing opportunity to reduce the costs of the last leg of supply chains, different companies in the field (Amazon, UPS, DHL, and Google) have been testing drone-based solutions in recent years (Hern, 2014; Kim, 2016). On the other hand, deliveries by drones would probably entail only small parcel movements because of their range and weight restriction. Furthermore, their profitability still needs to be thoroughly investigated. For public authorities, drones could help alleviate the pollution and congestion externalities of urban freight transport by replacing road transportation (Stolaroff et al., 2018).

Another automation innovation that could change the landscape of last-mile distribution is robots. Different companies (Starship, Dispatch) are exploring the possibility of using robots to carry parcels, groceries, and food. Robots could be dispatched from hubs, retail outlets or restaurants and once the customers are reached, unlock their compartments by means of codes. Similarly to drones, robots could reduce the environmental and congestion impacts of truck deliveries. Unlike drones, robots are designed to travel on sidewalks and bike lanes, at speeds between 5 and 10 kilometers per hour (Lee et al., 2016). For this reason, their range would be more limited. Also, they might not be able to operate in crowded areas (Markoff, 2015). On the other hand, thanks to their higher capacity they could be used for larger orders or for more deliveries. From a safety and regulation perspective, they also might be easier to employ given their small size and low speed and the fact that they travel on the ground (Pettitt, 2015).

2.3.3 Large Data and Intelligent Transport Systems

The availability of a large amount of information from different sources and the possibility to communicate it in real time has prepared the ground for the adoption of several Intelligent Transport Systems (ITS) solutions (Speranza, 2018). Some ITS could be implemented by public authorities to improve urban freight traffic (traffic management systems), while others could be utilized by shippers and carriers to optimize their supply chain process (freight transport management) (Allen, Browne, & Thorne, 2007). For example, based on real-time traffic conditions, city authorities could implement traffic control measures targeted at freight flows (e.g. managing their access and paths, varying signal timings). Similarly, information about parking availability could be used to improve delivery operations. Traffic and demand data could be employed as well by carriers for dynamic routing in order to reduce their delivery times and improve their reliability. Furthermore, quick communication between shippers, carriers, and customers would allow for more task-courier matching and scheduling of the delivery process. Finally, the large amounts of data about demand could become a valuable source for forecasts and planning of operations (fleet management, efficient inventory management).

Overall, ITS solutions can reduce traffic and congestion due to freight movements and, at the same time, improve the efficiency of delivery operations. The main challenges for the implementation of ITS are: the quick collection and analysis of large volumes of information, for which state-of-the-art analytics methods will be required; and the employment of dynamic and highly accurate data in the decision making process, for which advanced optimization methods will be needed.

3. A FAST ALGORITHM FOR MULTIPLE MOVING BOTTLENECKS AND APPLICATIONS IN URBAN FREIGHT TRAFFIC MANAGEMENT

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3.1 INTRODUCTION

In traffic flow theory, different typologies of "slow" vehicles (or platoons) can be modeled as "moving bottlenecks". These obstructions in traffic streams are usually associated with the presence of buses in urban traffic, and trucks or slower vehicles on highways. All these situations are characterized by a partial blockage of the road that causes a capacity reduction (typically the right lane in right hand driving countries). The concept of moving bottleneck can be extended to fixed bottlenecks, which represent static (spatially) and time varying capacity restrictions that can result, for example, from traffic lights or traffic incidents.

Some main challenges of modeling moving bottlenecks concern identifying and modeling features regarding their speed (depending on the traffic conditions and on the maximum speed of the vehicle), their discharge flow (maximum rate at which vehicles overtake), and the extent of the queue held back. Several studies have highlighted the importance of the effects of moving bottlenecks on traffic (Munoz and Daganzo, 2002; Daganzo and Laval, 2005) and have developed methodologies to include them into existing traffic models. In 1992, Gazis and Herman developed a model based on the conservation of flow, unconditional existence of the flow-density relation, and independence of capacity state from the bottleneck state. Newell (1993; 1998) subsequently proposed the first complete formulation based on the Lighthill–Whitham–Richards (LWR) model in which the moving bottleneck is assumed to behave as a scaled-down version of the freeway's fundamental diagram not influenced by the bottleneck speed. In recent years, Munoz and Daganzo

(2002), Leclerq et al. (2004), and Daganzo and Laval (2005) have proposed more comprehensive formulations of the moving bottleneck problem. Other studies have focused on numerical methods to solve the fixed and moving bottleneck problems within the LWR model (Lebacque et al., 1998; Giorgi et al., 2002; Leclercq, 2007; Laval and Leclerq, 2008). Referring to the "Three-phase traffic theory," Kerner and Klenov (2010) thoroughly explored features of moving bottlenecks,, such as the critical speed at which traffic breaks down. Moving bottlenecks have also been studied in the field of applied mathematics by Lattanzio et al. (2011), Gasser et al. (2013), and Delle Monache and Goatin (2014; 2016), where coupled PDE-ODE models are used to reproduce the dynamics between car traffic flows and slow vehicles.

To date, not many studies have developed methods to simulate an arbitrary number of moving bottlenecks. Daganzo and Laval (2005), and Laval and Leclercq (2008) modeled multiple moving bottlenecks (with exogenous passing rates) by means of a numerical method based on the the Kinematic Waves (KW) theory. Other studies (Leclerc and Becarie, 2012; Laval and Leclercq, 2013; Joueiai et al., 2015) have shown how solving the LWR model with different coordinate systems (mesoscopic approach) would allow addressing multiple internal boundary conditions. However, in these models bottleneck trajectories are assumed to be known in advance. In this study, we offer a more general approach that endogenously accounts for the impact of moving bottlenecks on surrounding traffic and the converse. Additionally, we provide an efficient algorithm that allows the simulation of an arbitrary number of moving bottlenecks associated with different maximum speeds. The effects of moving bottlenecks' stops along the curbside can also be incorporated without significant changes in the algorithm.

To achieve this, we propose a new formulation that computes the parameters associated with moving and fixed bottlenecks (trajectories and passing flows) without having to compute the complete solution. This method improves computational times by orders of magnitude over classical numerical schemes, and does not affect the computational accuracy.

As previously mentioned, the problem of computing the trajectories and parameters (passing flows) associated with moving bottlenecks is not straightforward because bottlenecks both influence and are influenced by surrounding traffic. Thus, in order to compute the density map associated with a general problem (involving initial conditions, boundary conditions and bottlenecks), it is necessary to simultaneously compute the solution to the LWR model and the corresponding trajectories of the bottlenecks (that are initially unknown). Since the solution itself affects the trajectories of the moving bottlenecks, this computationally intensive process requires us to map the solution on the entire computational domain.

The algorithm we propose allows, instead, determining the parameters and trajectories of the moving bottlenecks without requiring us to compute the solution on the entire computational domain. The approach is based on an extension of the semi-analytical solutions to arbitrary Hamilton-Jacobi equations introduced in Mazaré et al. (2011). Using semi-explicit solutions, we show that the trajectories of an arbitrary number of fixed and moving bottlenecks can be simultaneously marched forward in time for a very low computational cost. Indeed, when considering piecewise affine initial conditions containing n_i "blocks" (intervals over which the function is linear), the piecewise affine upstream and downstream boundary conditions containing n_u and n_d blocks respectively, and n_b bottlenecks, the future evolution of each bottleneck can be computed by at most ($n_i + n_b$ +2) calculations of explicit functions. Once this set of calculations is done, the future evolution of the moving bottleneck is completely determined, in function of the difference between the current value of the solution to the Hamilton Jacobi equation along the trajectory, and its future value along the predicted trajectory. When this process is marched forward in time, it allows one to simultaneously compute the parameters associated with all moving and fixed bottlenecks of the problem, and to not have to compute the solution everywhere (solutions are only required along the trajectories of the bottleneck, thus greatly reducing the computational time required to solve the problem).

Once identified the parameters and trajectories of all moving and fixed bottlenecks, it is possible to use this information to efficiently compute the solution of the problem everywhere using the Lax-Hopf algorithm whose computational benefits have been described in Claudel and Bayen (2010a). Since the Lax-Hopf algorithm can compute the solution at any point of the space time domain using only initial, boundary, and bottleneck data, this approach is well adapted to optimization problems in which we are only interested in knowing the solutions at a limited number of points (on which the objective function of the problem depends).

This algorithm's very favorable computational error characteristics also render it advantageous. The only errors induced by the proposed scheme are errors related to the discretization in time of the moving bottleneck trajectories when they enter a different traffic regime, and an approximation of the behavior of the bottlenecks around intersections of bottleneck trajectories (if moving bottlenecks overtake each other). Non-event-based numerical methods for moving bottleneck problems (for example, based on LWR (Leclercq, 2007) or on the Variational Method (Daganzo and Laval, 2005)) require discretized moving and fixed bottleneck trajectories, but also use approximate solution methods to solve the LWR equation. Event-based methods (, such as the wave-front tracking method) can be exact, but require the computation of the solution on the entire computational domain (therefore reducing the computational performance in specific applications where the solution is only needed at a low number of points). Furthermore, to date, algorithms based on wave-front tracking are capable of handling multiple moving bottlenecks only in certain scenarios (closed road) and under certain conditions (same features) (Delle Monache and Goatin, 2016).

Thanks to these favorable properties, the proposed algorithm could be used to efficiently tackle complex traffic estimation and control problems characterized by the presence of several trucks or buses. As a main practical contribution of this research, we present the application of the algorithm to evaluate two alternative traffic management strategies for trucks in urban settings by using a macroscopic traffic flow model. The first consists in the joint coordination of traffic lights and trucks departures on an arterial corridor in order to maximize its throughput. The second consists in a parking-loading curbside management strategy for reducing delays associated with trucks' deliveries. The first strategy could be employed around large urban freight traffic generators,, such as airports, marine ports, and container terminals, but also facilities like shopping malls, hospitals, colleges, and universities and government offices (Jaller et al., 2015). The second strategy could be implemented in locations characterized by a significant number of deliveries like central business districts and commercial areas (Patier et al., 2014). In both situations, the proposed traffic management strategies would require some degree of vehicle connectivity and positioning (for example through GPS), which can be employed in connected and autonomous trucks.

The optimization problems are solved by using the Memetic Algorithm (MA) meta-heuristic, an extension of the population-based hybrid genetic algorithms (GAs) that are coupled with a local search procedure that allows for refinements of the solutions. Although several applications of genetic algorithms have been proposed in the field of traffic control, to the best of our knowledge, MAs have not yet been utilized for this typology of problems. This technique is particularly suitable to situations where the objective function cannot be derived analytically, but only by means of simulations. Combining an extensive search of the best zones in the search space (exploration) with a more detailed search in zones with potential better solutions (exploitation) seems to work well for large problems (Cotta 2012). Furthermore, MAs can often provide better results than other well-known approaches like Genetic Algorithm, Tabu Search, and Simulated Annealing (Garg, 2010).

In the remainder of this chapter, we first introduce the background theory adopted in this study for the modeling of moving bottlenecks. Next, we provide a description of the fast semi-analytic algorithm to simulate single moving bottlenecks. We then extend this algorithm to various moving and fixed bottleneck scenarios. Finally, we illustrate the application of the proposed algorithm to the two different optimization problems. We conclude with a number of general remarks and recommendations for future research.

3.2 Analytical solutions to the Hamilton-Jacobi PDE

In this Section we briefly summarize the main features of the macroscopic traffic simulation used to investigate moving bottlenecks. The LWR model and the Hamilton-Jacobi PDE are described respectively in Section 3.2.1 and Section 3.2.2. The generalized Lax-Hopf formula used to solve this problem is presented in Section 3.2.3 and the formulation of initial, boundary and internal conditions is provided in Section 3.2.4. In the presence of moving bottlenecks, parameters like speed and passing rates cannot always be easily derived because of the influence of surrounding traffic. Hence, in Section 3.2.5 we describe the model to derive internal conditions corresponding to the moving bottlenecks.

3.2.1 The LWR-PDE

We consider a one-dimensional homogeneous section of highway, limited by x_0 upstream and x_n downstream. For a given time t and position x we define the local traffic density $k(x,t)$ in vehicles per unit of length, and the instantaneous flow $q(x,t)$ in vehicles per unit time. The conservation of vehicles on the highway is written as follows (Lighthill and Whitman, 1956; Richards, 1956; Garavello and Piccoli, 2006).

$$\frac{\partial k(t,x)}{\partial t}+\frac{\partial q(t,x)}{\partial x}=0 \tag{3.1}$$

For first order traffic flow models, flow and density are related by the Fundamental Diagram (FD); in this study we adopt triangular FD (Daganzo, 1994). The FD is a positive function defined on $[0,k_j]$, where k_j is the maximal density (jam density). It ranges in $[0,q_{max}]$ where q_{max} is the maximum flow (capacity). It is assumed to be differentiable with derivative $q'(0)=v>0$ (free flow speed) and $q'(k_j)=w<0$ (congested wave speed), and it is defined as follows:

$$q(k)=\begin{cases} v\,k & : \; 0\le k\le k_c \\ -w\left(k-k_j\right) & : \; k_c\le k\le k_j \end{cases} \tag{3.2}$$

where k_c corresponds to the critical density at capacity.

3.2.2 The Moskovitz function

The Moskovitz function expresses the cumulated vehicle count $N(x,t)$ and it represents the continuous vehicle count at location x and time t. In the Moskovitz framework one assumes that all vehicles are labeled by increasing integers as they pass the entry point x_0 of a highway section, and that they cannot pass each other. If the latest car that passed an observer standing at location x and time t is labeled n, then $N(x,t)=n$.

Replacing *k* and *q* with *N* yields to Hamilton-Jacobi PDE (Newell, 1993; Daganzo, 2005a, 2006; Claudel and Bayen, 2010a):

$$\frac{\partial \boldsymbol{N}(\boldsymbol{x},\boldsymbol{t})}{\partial \boldsymbol{t}} - \boldsymbol{q}\left(-\frac{\partial \boldsymbol{N}(\boldsymbol{x},\boldsymbol{t})}{\partial \boldsymbol{x}}\right) = \mathbf{0} \tag{3.3}$$

3.2.3 The generalized Lax-Hopf Formula

The generalized Lax-Hopf Formula is an implicit representation of the solution to a Hamilton-Jacobi PDE. From Aubin et al. (2008), the solution associated with the value condition function *c*, denoted by N_c, is the infimum of an infinite number of functions of the value condition:

$$\begin{gathered} \boldsymbol{N_c} = \boldsymbol{inf}\{\boldsymbol{c}(\boldsymbol{t}-\boldsymbol{T},\boldsymbol{x}-\boldsymbol{Tu}) + \boldsymbol{TR}(\boldsymbol{u})\} \\ \boldsymbol{s.t.}\,(\boldsymbol{u},\boldsymbol{T}) \in [\boldsymbol{w},\boldsymbol{v}] \times \boldsymbol{R}_+ \ \boldsymbol{and}\ (\boldsymbol{t}-\boldsymbol{T},\boldsymbol{x}-\boldsymbol{Tu}) \in \boldsymbol{Dom}(\boldsymbol{c}) \end{gathered} \tag{3.4}$$

where *c(x,t)* corresponds to value condition function defined on the domain $Dom(c)$ and it is defined as:

$$\boldsymbol{c}(\boldsymbol{x},\boldsymbol{t}) = \begin{cases} \boldsymbol{N_{ini}}(\boldsymbol{x}) & \boldsymbol{t} = \mathbf{0} \\ \boldsymbol{N_{up}}(\boldsymbol{t}) & \boldsymbol{x} = \boldsymbol{x_0} \\ \boldsymbol{N_{down}}(\boldsymbol{t}) & \boldsymbol{x} = \boldsymbol{x_n} \end{cases} \tag{3.5}$$

And $R(u)$, which is convex transform associated with the fundamental diagram, corresponds to:

$$\boldsymbol{R}(\boldsymbol{u}) = \sup_{\boldsymbol{k}\boldsymbol{\epsilon}[\mathbf{0},\boldsymbol{k_j}]} (\boldsymbol{q}(\boldsymbol{k}) - \boldsymbol{u}\cdot\boldsymbol{k}) \tag{3.6}$$

This equation is well known in the Hamilton-Jacobi literature and often referred to as Lax-Hopf formula (Aubin et al., 2008; Evans, 1998).

Assuming a triangular fundamental diagram, the calculation of its convex transform *R* yields to:

$\forall \boldsymbol{u} \in [\boldsymbol{w}, \boldsymbol{v}], \boldsymbol{R}(\boldsymbol{u}) = \boldsymbol{k_c}(\boldsymbol{v} - \boldsymbol{u})$	(3.7)

3.2.4 Boundary and internal conditions based on triangular fundamental diagram

The initial conditions represent measurements of density along the link at the beginning of the simulation. The downstream and upstream boundary conditions correspond to measurements of flows at the downstream and upstream end of the link. The internal conditions could represent a variety of measurements *N(x,t)* collected along the link (e.g. vehicles' trajectories), or, in this case, correspond to active fixed and moving bottlenecks.

<u>Definition of initial, upstream, downstream and internal conditions</u>

The initial condition is assumed piecewise linear function and it is defined for each space interval (x_i, x_{i+1}) of measurement by:

$$\boldsymbol{c_{ini_i}}(\boldsymbol{x}) = \begin{cases} -\boldsymbol{k_i x} + \boldsymbol{b_i} & : \boldsymbol{x_i} \leq \boldsymbol{x} \leq \boldsymbol{x_{i+1}} \\ +\infty & : \boldsymbol{otherwise} \end{cases} \tag{3.8}$$

With the above definition, the initial condition can be written as $c_{ini} = \min_i c_{ini_i}$.

Similarly, the upstream boundary condition that is also is assumed piecewise linear, is measured for each time interval (t_i, t_{i+1}) and defined by:

$$\boldsymbol{c_{up_j}}(\boldsymbol{t}) = \begin{cases} \boldsymbol{q_j t} + \boldsymbol{c_j} & : \boldsymbol{t_j} \leq \boldsymbol{t} \leq \boldsymbol{t_{j+1}} \\ +\infty & : \boldsymbol{otherwise} \end{cases} \tag{3.9}$$

With this definition, the upstream boundary condition can be written as $c_{up} = \min_j c_{up_j}$. The downstream boundary conditions are also assumed piecewise linear, with each piece (t_i, t_{i+1}) defined by:

$$\boldsymbol{c_{down_j}}(\boldsymbol{t}) = \begin{cases} \boldsymbol{p_j t} + \boldsymbol{d_j} & : \boldsymbol{t_j} \leq \boldsymbol{t} \leq \boldsymbol{t_{j+1}} \\ +\infty & : \boldsymbol{otherwise} \end{cases} \tag{3.10}$$

This enables us to define the downstream boundary condition function as $c_{down} = \min_j c_{down_j}$, The internal condition corresponding to a fixed or moving bottleneck active on the space-time domain between (x_b, t_b) and (x_e, t_e), can be defined as:

$$\boldsymbol{c_{int}(t,x)} = \begin{cases} \boldsymbol{N_b + \frac{(N_e - N_b)}{(t_e - t_b)} \cdot (t - t_b)} & \boldsymbol{: x = x_b + \frac{(x_e - x_b)}{t_e - t_b} \cdot (t - t_b)\ and\ t \in [t_b, t_e]} \\ +\infty & : \qquad \boldsymbol{otherwise} \end{cases} \tag{3.11}$$

where N_b and N_e respectively denote the values of the label corresponding to the internal condition (Moskovitz function) at the beginning t_b and at the end t_e of the time interval over which the moving bottleneck is active.

One of the major results of Mazaré et al. (2011) is that the solutions associated with each linear piece of the initial, upstream, downstream and internal boundary conditions can be computed analytically as follows:

a) Solution to a linear initial condition

If $0 \leq k_i \leq k_c$, the initial condition imposes a free-flow state.

$$\boldsymbol{N_{c_{ini}}(x,t)} = \begin{cases} \boldsymbol{k_i(tv - x) + b_i} & \boldsymbol{: x_i + tv \leq x \leq x_{i+1} + tv} \\ \boldsymbol{k_c(tv - x) + b_i + x_i(k_c - k_i)} & \boldsymbol{: x_i + tw \leq x \leq x_i + tv} \end{cases} \tag{3.12}$$

else, if $k_c, \leq k_i \leq k_j$, the initial condition imposes a congested state:

$$\boldsymbol{N_{c_{ini}{}^i}(x,t)} = \begin{cases} \boldsymbol{k_i(tw - x) - tk_j w + b_i} & \boldsymbol{: x_i + tw \leq x \leq x_{i+1} + tw} \\ \boldsymbol{k_c(tw - x) - tk_j w + x_{i+1}(k_c - k_i) + b_i} & \boldsymbol{: x_{i+1} + tw \leq x \leq x_{i+1} + tv} \end{cases} \tag{3.13}$$

b) Solution to a linear upstream boundary condition

For an upstream boundary condition ${c_{up}}^j$ defined as (9), the solution component can be expressed as:

$$N_{c_{up}{}^{j}}(x,t) = \begin{cases} c_j + q_j\left(t - \dfrac{x - x_0}{v_f}\right) & : x_0 + v(t - t_{j+1}) \le x \le x_0 + v(t - t_j) \\ c_j + q_j t_{j+1} + k_c\left((t - t_{j+1})v - (x - x_0)\right) & : x_0 \le x \le x_0 + v(t - t_{j+1}) \end{cases} \tag{3.14}$$

c) Solution to a linear downstream boundary condition

For a downstream boundary condition $c_{down}{}^{j}$, defined as (10), the solution component can be expressed as:

$$N_{down}{}^{j}(x,t) = \begin{cases} d_j + p_j t - \left(\dfrac{p_j}{w} + k_j\right)(x_n - x) & : x_n + w(t - t_j) \le x \le x_n + w(t - t_{j+1}) \\ d_j + p_j t_{j+1} + k_c\left((t - t_{j+1})v + x_n - x\right) & : x_n + w(t - t_j) \le x \le x_n \end{cases} \tag{3.15}$$

d) Solution to a linear internal condition

In this study, the internal conditions represent the effects of vehicles or obstructions that modify the trajectory of a specific vehicle. They are represented as piecewise linear functions with two parameters: speed and passing rate that are indicated respectively as the velocity of the moving bottleneck s:

$$s = \frac{(x_e - x_b)}{(t_e - t_b)} \tag{3.16}$$

And as the number of vehicles passing the moving bottleneck per unit time:

$$r = \frac{N_e - N_b}{t_e - t_b} \tag{3.17}$$

Then, for an internal condition c_{int} defined as (11), the solution component can be expressed as:

$$N_{int}(x,t) = (t - t') \cdot (u + v) \cdot k_c + (N_e - N_b) \cdot \frac{(t' - t_b)}{(t_e - t_b)} + N_b \quad : \tag{3.18}$$

$$x \le x_b + v \cdot (t - t_b) \wedge x \ge x_b + w \cdot (t - t_b) \wedge t \ge t_b$$

where t', which corresponds to the capture time in the viability framework from which these formulations are derived (Aubin, et al., 2008), is derived as follows:

$$\boldsymbol{t'} = \begin{cases} \boldsymbol{t - \frac{(x_b + s \cdot (t - t_b) - x)}{(s - v)}} & : \quad \boldsymbol{x_e + v \cdot (t - t_e) \leq x \ \wedge \ x_b + s \cdot (t - t_b) \leq x} \\ \boldsymbol{t_e} & : \quad \boldsymbol{x_e + w \cdot (t - t_e) \leq x} \\ \boldsymbol{t - \frac{(x_b + s \cdot (t - t_b) - x)}{(s + w)}} & : \quad \boldsymbol{otherwise} \end{cases} \tag{3.19}$$

and u corresponds to associated optimal control of the auxiliary dynamical system (Aubin et al., 2008; Bayen et al., 2007):

$$\boldsymbol{u} = \begin{cases} \boldsymbol{-v} & : \quad \boldsymbol{x_e + v \cdot (t - t_e) \leq x \ \wedge \ x_b + s \cdot (t - t_b) \leq x} \\ \boldsymbol{\frac{(x_e - x)}{(t - t_e)}} & : \quad \boldsymbol{x_e + w \cdot (t - t_e) \leq x} \\ \boldsymbol{w} & : \quad \boldsymbol{otherwise} \end{cases} \tag{3.20}$$

The speed of the moving bottleneck (s) and the passing rate (r) cannot be straightforwardly determined in (16) and (17). Indeed, only the initial position and the starting time of each moving bottleneck are known a priori, but not the evolution of the parameters s and r associated with each moving bottleneck, since they depend on the solution itself. For this reason, in the following sections, as main contribution of this study, we show how to compute the evolution of s and r in the presence of several moving bottlenecks, given known initial and boundary conditions, and given the knowledge of maximal velocity, starting time and starting position of each bottleneck.

3.2.5 Modeling single moving bottlenecks as internal conditions

The dynamics of s and r is complex, since the behavior of a moving bottleneck is inherently hybrid, with active and inactive phases depending on the state of traffic. A moving bottleneck becomes “active” when it actually slows down the incoming traffic from upstream. This situation occurs when the traffic flow is sufficiently high to be hindered by the moving bottleneck. Following

Munoz and Daganzo (2004), and Daganzo and Laval (2005), three situations can be distinguished (Figure 1):

1. The moving bottleneck is inactive because there is enough capacity for regular traffic to overtake (region 1 in Figure 3)

2. The moving bottleneck is active because regular traffic is traveling at higher speed and capacity is not enough for everyone to overtake (region 2 in Figure 3)

3. The moving bottleneck is inactive because regular traffic is traveling at a lower speed than the maximum velocity of the bottleneck, because of congestion (region 3 in Figure 3)

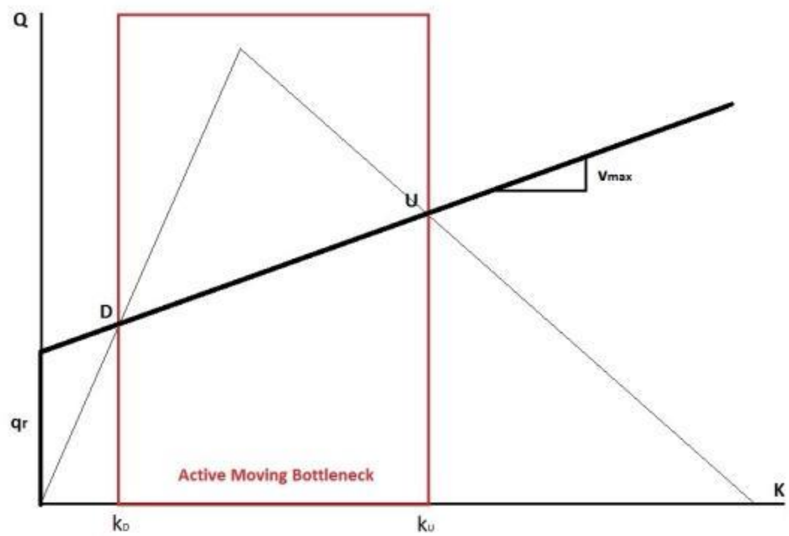

Figure 3: Flow-density relationship of moving bottlenecks according to the Munoz-Daganzo model

In order to identify whether the moving bottleneck is active and derive its corresponding internal conditions we adopted the following approach based on the difference of cumulated flow between two consecutive points along the trajectory of the moving bottleneck:

Choose an arbitrary time step Δt

Calculate the values of the Moskovitz function for: $N\ (x_0, t_0) = N_0$ and $N\ (x_0 + v_{max}\Delta t, t_0 + \Delta t) = N_1$, where (x_0, t_0) corresponds to the position of the moving bottleneck in the end of the previous time interval, and v_{max} corresponds to the maximum speed of the moving bottleneck.

Identify the three abovementioned cases based on the flow between the two consecutive points (ratio between the difference of the Moskovitz function and time):

$$\rho = \frac{(N_1 - N_0)}{\Delta t} \tag{3.21}$$

$0 < \rho < q_r$ → inactivity due to low volumes (traffic is too light)

$\rho > q_r$→ activity

$\rho < 0$→ inactivity due to congestion (traffic is slower than the maximum velocity of the bottleneck)

In the above, q_r corresponds to the maximum passing rate of the moving bottleneck, which is the maximum flow that can ever pass the moving bottleneck going at its maximum speed. The formulation of q_r is based on the model by Munoz and Daganzo (2004) and it corresponds to:

$$\boldsymbol{q_r} = \frac{(\boldsymbol{u} - \boldsymbol{v_{max}}) \cdot \boldsymbol{k_c} \cdot (\boldsymbol{n_l} - \mathbf{1})}{\boldsymbol{n_l}} \tag{3.22}$$

where u stands for the free flow speed, k_c is the critical density and n_l is the number of lanes.

Only in the case of active moving bottlenecks, a new internal condition with speed $s = v_{max}$ and overtaking rate $r = q_r$ is defined and stored. The internal condition applies between times t_0 and $t_0 + \Delta t$, and between positions x_0 and $x_0 + v_{max} \cdot \Delta t$, with beginning and end values of N_0 and $N_1 = N_0 + q_r\Delta t$.

In case of activity over several consecutive intervals (Δt), only the values of the Moskovitz function at the onset and end of activity, as well as the corresponding times and positions, are stored as internal conditions c_{int}.

In case of inactivity of the moving bottleneck due to congested conditions, the moving bottleneck travels at the speed of the surrounding traffic (which is less than its maximal speed), given by:

$$s = \frac{-w \cdot (k_0 - k_j)}{k_0} \tag{3.23}$$

where w corresponds to the congested speed, k_j corresponds to the jam density and k_0 corresponds to the density of the traffic around the bottleneck.

Finally, if the moving bottleneck is inactive due to low flow conditions, its velocity is set to v_{max}. Hence, the moving bottleneck's trajectory can be summarized by the following ODE:

$$\dot{x} = s(k(x,t)) \tag{3.24}$$

where the speed *s* of the moving bottleneck corresponds to:

$$s = \begin{cases} v_{max} & : \ k \leq k_U \\ \dfrac{-w \cdot (k_0 - k_j)}{k_0} & : \ else \end{cases} \tag{3.25}$$

And where k_U and k_D are the density values defining the region for which the moving bottleneck becomes active as shown in Figure 1. The moving bottleneck's label N_{mb} is given by the following ODE:

$$\dot{N_{mb}}(t) = f(k(x,t)) \tag{3.26}$$

where *f(k)* corresponds to:

$$f(k) = \begin{cases} q_r & if\ k_D < k < k_U \\ 0 & else \end{cases} \tag{3.27}$$

The algorithm for the computation of internal conditions associated with a single moving bottleneck can be summarized as the pseudocode below (Algorithm 1).

Algorithm 1: Pseudo-code for the computation of internal conditions associated with a single moving bottleneck

Input: (x_1, t_1, x_2, v_{max}) ***moving bottleneck;***	*Input initial position and time, final position, and performance characteristics of the moving bottleneck*
Input: (v, k_c, k_j, n_l)	*Input list of fundamental diagram parameters*
Input T	*Input simulation time horizon*
$q_r=(v-v_{max})*k_c*(n_l-1)/n_l$;	*Derive maximum passing rate for the moving bottleneck, given the number of lanes of the road*
$t_0 = t_1$ $x_0 = x_1$	*Initialize bottleneck time* *Initialize bottleneck position*
while $t_0 \leq T$ *and* x_0	*While the bottleneck vehicle is still on the computational domain*
$t_1 = t_0 + \Delta t$ $x_1 = x_0 + v_{max}\Delta t$	*update time* *update position*
$N_0=\inf\{N_{ini}, N_{up}, N_{down}, N_{int}\}$ ***calculated at point*** (x_0,t_0) ***using initial, upstream, downstream and currently defined internal conditions*** $N_1=\inf\{N_{ini},N_{up}, N_{down}, N_{int}\}$ ***calculated at point*** (x_1,t_1) ***using initial, upstream, downstream and currently defined internal conditions***	*Calculate Moskovitz function at the previous and new positions of the moving bottleneck*
if $(N_1 - N_0)/\Delta t > 0$ ***then*** ***if*** $(N_1 - N_0)/\Delta t < q_r$	*If bottleneck is inactive due to low flows*
$t_0 = t_1$ $x_0 = x_1$	*Update time* *Update position*
Else	*If bottleneck is active*
Add new internal condition with parameters $\{N_b, x_b, t_b; N_e, x_e, t_e\}$	*Store new internal condition*
$t_0 = t_1$	*Update time*

$\boldsymbol{x_0 = x_1}$	*Update position*
end if	*If bottleneck is inactive due to high congestion*
Else	
	Compute actual speed of bottleneck
derive speed s from Equation $\frac{-w\cdot(k_0-k_j)}{k_0}$	*Update time* *Update position*
$\boldsymbol{t_1 = t_0 + \Delta t}$ $\boldsymbol{x_1 = x_0 + s\Delta t}$	
end if	
end while	

To illustrate the capabilities of Algorithm 1, we present the following example of a stretch of a two-lane road of length 3000 m characterized by some arbitrary initial and boundary shown respectively in Table 1 and Table 2. A moving bottleneck entering at $x = 1500\ m$ and $t = 150\ s$ with $v_{max} = 5\ m/s$ is included in the simulation (red trajectory in Figure 2). The following parameters characterizing the triangular fundamental diagram are chosen: $v = 30\ m/s$, $k_c = 0.04\ \ veh/m$, $k_j = 0.2\ veh/m$.

Table 1: Upstream and downstream boundary conditions

i	x_{i-1}	x_i	k_{ini}
1	0	1000	0.04
2	1000	2000	0.02
3	2000	3000	0.04

Table 2: initial conditions

i	t_{i-1}	t_i	q_{up}^i	q_{down}^i
1	0	40	1.0	0.9
2	40	180	1.0	0.2
3	180	300	1.0	0.9

The simulation, which was performed on Matlab with a 2.3 GHz processor, required about 0.70 seconds, of which less than 0.03 seconds are spent computing the parameters of the internal conditions and the trajectory of the moving bottleneck. The rest is used to compute the solution on the entire on a rectangular grid of resolution one second and ten meters, and to display the corresponding results. The results of the simulation are shown in a space-time-density diagram (Figure 4).

This simulation illustrates the benefits of the method over existing numerical schemes. Different numerical schemes have been proposed to model moving bottlenecks (, such as first order numerical schemes (Daganzo and Laval, 2005; Leclercq, 2007), variational schemes (Daganzo, 2005), or wave-front tracking schemes (Henn, 2005), although they all require the solution to be computed everywhere on the computational domain. For example, the Godunov scheme (first order) requires us to compute the solution on the entire computational grid, and so does the Variational theory (in which bottlenecks are encoded as shortcuts in the computational grid). Similarly, wave-front tracking methods require the solution to be computed on the entire computational domain. Since most optimization problems in transportation do not require us to know the solution everywhere on the computational domain, this is a significant advantage as it allows us to first compute the parameters of all moving bottlenecks, and then compute the exact solution at the few points of the computational domain needed to determine the objective to be optimized, corresponding to a significant improvement in computational time and complexity.

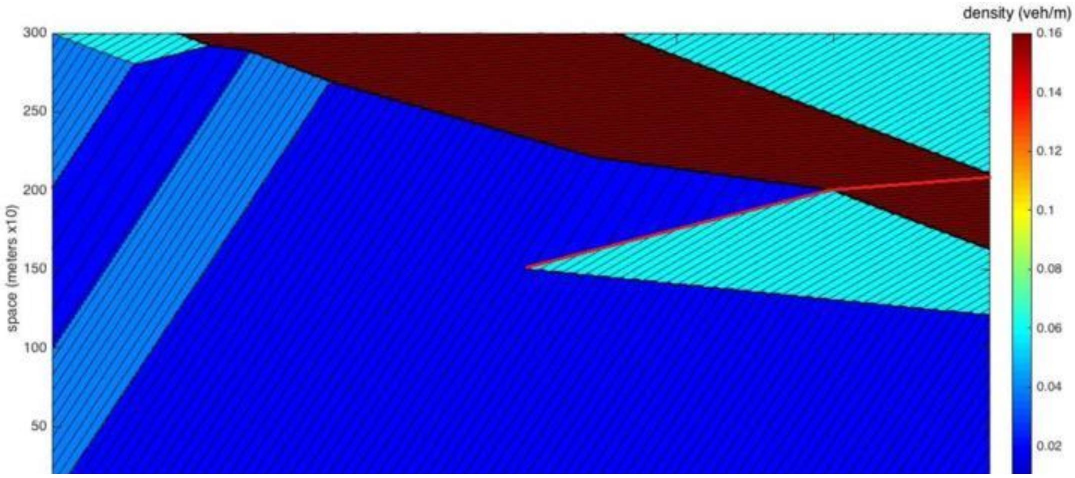

Figure 4: Space-time-density diagram representing the results of the test stimulation. In this simulation, the trajectory of the moving bottleneck is shown in red

3.3 Fast algorithm to compute multiple bottlenecks

In this section, after a brief discussion on the complexity of the problem (Section 3.3.1), we present an extension of the previous algorithm (Algorithm 1) to the model an arbitrary number of different bottlenecks. The algorithm is based on the properties of inf-morphism and domains of influence of traffic flows (Section 3.3.2) and it is able to cope with moving bottlenecks overtaking each other (Section 3.3.3). The algorithm is described and compared to other analytical schemes in Section 3.3.4 and Section 3.3.5.

3.3.1 Background

The necessity of modeling the impacts of multiple trucks, buses and other kinds of slow moving vehicles on traffic has been recognized and increasingly emphasized in the last twenty years in the field of Traffic Flow Theory. To our knowledge, all these efforts have been made to study the effects of a single moving bottleneck, or moving bottlenecks for which the parameters (activity, velocity) are determined before the simulation. The objective is to include these into current traffic models,, such as the LWR model. Extending previous work to an arbitrary number of moving bottlenecks (without relying on continuous flow approximations as in Liu, et al., 2015) implies several challenges, consisting in dynamically computing several trajectories-since moving bottlenecks can both affect and be affected by surrounding traffic and accounting for their interactions accurately and efficiently from a computational perspective. In this section, we describe how a fast algorithm based on the Lax-Hopf algorithm outlined earlier can be used to compute the solution associated with multiple moving (and fixed) bottlenecks.

In order to derive multiple internal conditions associated with several (active) moving bottlenecks, while accounting for their interactions and different properties, we propose a strategy based on two important properties of the solutions to Hamilton-Jacobi equations: the existence of a domain of influence for each internal condition, and the inf-morphism property of solutions.

3.3.2 Inf-morphism and domains of influence

The inf-morphism property implies that we can dynamically update the number of moving bottlenecks considered in the simulation problem, without having to re-compute the solution entirely. The domains on which the solution has to be re-computed are the domains of influence of the bottlenecks, which are the set of points that can be reached by characteristics with speeds ranging from $-w$ to v, and originating on the internal condition (moving bottleneck trajectory).

Indeed, for each position of the moving bottleneck, it is possible to identify its region of influence in the space and time dimension delimited by the congested and free-flow speed in the triangular fundamental diagram (respectively equal to w and v). Whenever the moving bottleneck i at the position (x_i,y_i) enters in the domain of influence of the moving bottleneck j at the position (x_j,y_j), the derivation of internal conditions has to be performed along the trajectory of moving bottleneck j. This stepwise computation can be repeated back and forth among several moving bottlenecks until the simulation is completed. Algorithm 2 summarizes this process, for an arbitrary number n_b of moving bottlenecks with (possibly distinct) maximum speeds $v_{mb,i}$, entering the road at $(x_{1,i},t_{1,i})$ and leaving at $x_{2,i}$.

3.3.3 Passing bottlenecks and Zeno effect

The model used in this study corresponds to the coupling of a PDE (the LWR equation) with an ODE describing the evolution of the slow vehicles. The latter is hybrid, in the sense that the slow vehicles can only be in the three possible states outlined earlier. As with all hybrid systems, the dynamics can sometime exhibit the Zeno effect (Johansson et al., 1999). An execution of a hybrid system is called Zeno, if it takes infinitely many discrete transitions (and therefore computational loops) to solve the problem over a finite time horizon. In the present situation, the Zeno effect arises when bottlenecks are passing each other, as illustrated in Figure 5. In this situation, their respective domains of influence impose an upper bound on the time step used to update the position of each bottleneck (to ensure that the final position of one bottleneck is always outside the domain of influence of the other), and this upper bound becomes infinitely small as their paths come to intersect. This effect complicates the implementation of the algorithm as it can lead to infinite loops, if we want an exact solution. To solve this problem, we adopt a constant time step for the computation of the trajectories associated with moving bottlenecks: this allows the execution to be complete over a finite (and bounded above) number of steps, at the cost of computational accuracy, since this introduces an approximation of the behavior of both bottlenecks when they intersect each other.

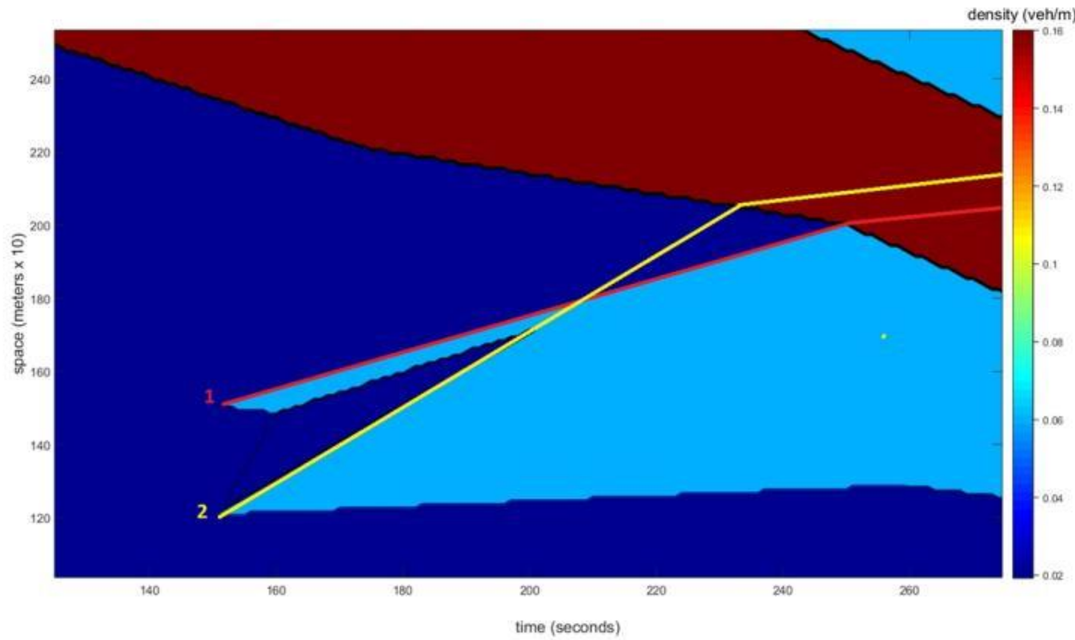

Figure 5: Space-time-density diagram showing the simulation of two overtaking moving bottlenecks

3.3.4 Algorithm

The corresponding pseudo-code is shown as Algorithm 2.

Algorithm 2: Pseudo-code implementation for the computation of internal conditions associated with n_b multiple moving bottlenecks

Input: $(x_{1,i}, t_{1,i}, v_{max,i})\ \forall\ i \in [1, n_b]$	*Input initial position and time, final position, and performance characteristics of moving bottlenecks*
Input: **(*v*, k_c, k_j, n_l)**	*Input list of fundamental diagram parameters*
Input T	*Input simulation time horizon*

$q_{r,i}=(v-v_{max,i})*k_c*(n_l-1)/n_l$;	*Derive maximum passing rate for each moving bottleneck*
b={1,…,n_b}	*Initialize bottlenecks list*
$\boldsymbol{t_i = t_{1,i}}$ $\boldsymbol{x_i = x_{1,i}}$	*Current time for each bottleneck* *Current position for each bottleneck*
while $\boldsymbol{b} \neq \emptyset$	*While some bottleneck vehicles are still on the computational domain*

for $\boldsymbol{i} \in \boldsymbol{b}$
  if $\boldsymbol{t_i > T}$ ***or*** $\boldsymbol{x_i \geq x_{max}}$
  $\boldsymbol{b = b} \setminus \{\boldsymbol{i}\}$
 end
end
	Eliminate bottlenecks that have left the computational domain

l=b	*Initialize list of bottlenecks that are not influenced by others (and that can thus be computed)*

for $\boldsymbol{i} \in \boldsymbol{b}$
 for $\boldsymbol{j} \in \boldsymbol{b} \setminus \{\boldsymbol{i}\}$
    if $(\boldsymbol{t_i}, \boldsymbol{x_i}) \in \boldsymbol{D_j}$ ***($\boldsymbol{D_j}$ domain of influence of bottleneck j)***
      l=l \ {i}
    end
end
end
	Compute list of bottlenecks that are not influenced by others

if $\boldsymbol{l} \neq \emptyset$	*If there are moving bottlenecks that are not influenced by others*

while $\boldsymbol{l} \neq \emptyset$
      pick $\boldsymbol{i} \in \boldsymbol{l}$
      compute propagation of moving bottleneck (according to Algorithm 1)
      $\boldsymbol{l = l} \setminus \{\boldsymbol{i}\}$
  end while
	Propagate these bottlenecks according to Algorithm 1

else	*If none of the bottleneck is outside of the zone of influence of all others (bottleneck intersection)*
Identify intersecting bottlenecks, and propagate them approximately according to Algorithm 1	
end	

end while

An example of the application of Algorithm 2 is illustrated in the sequence of simulations in Figure 4, where the different steps of the computation of the solution are shown for a pair of moving bottlenecks (indicated by letters A and B). First, the trajectory of moving bottleneck A and its impact on traffic are computed till it intersects the domain of influence of moving bottleneck B (Figure 6a), indicated by the green lines (Phase 1). Likewise, the solution associated with moving bottleneck B can be computed till it reaches the domain of influence of moving bottleneck A at its last position in the space and time (Figure 6b). The procedure is repeated back and forth till the moving bottleneck leaves the road (Figure 6c) or the simulation ends (Figure 6d).

A more general example involving ten moving bottlenecks having different speeds (Table 3) and three fixed bottlenecks (representing constant red cycles of a traffic light) on the same link used in the previous cases for a time span of 300 seconds, is illustrated in Figure 5. The simulation requires about 0.15 seconds for the computation of the internal conditions and 2.2 seconds for the computation of the solutions. The Moving bottlenecks' trajectories were obtained using a time and space resolution of one second and ten meters. These results confirm the efficiency of the algorithm.

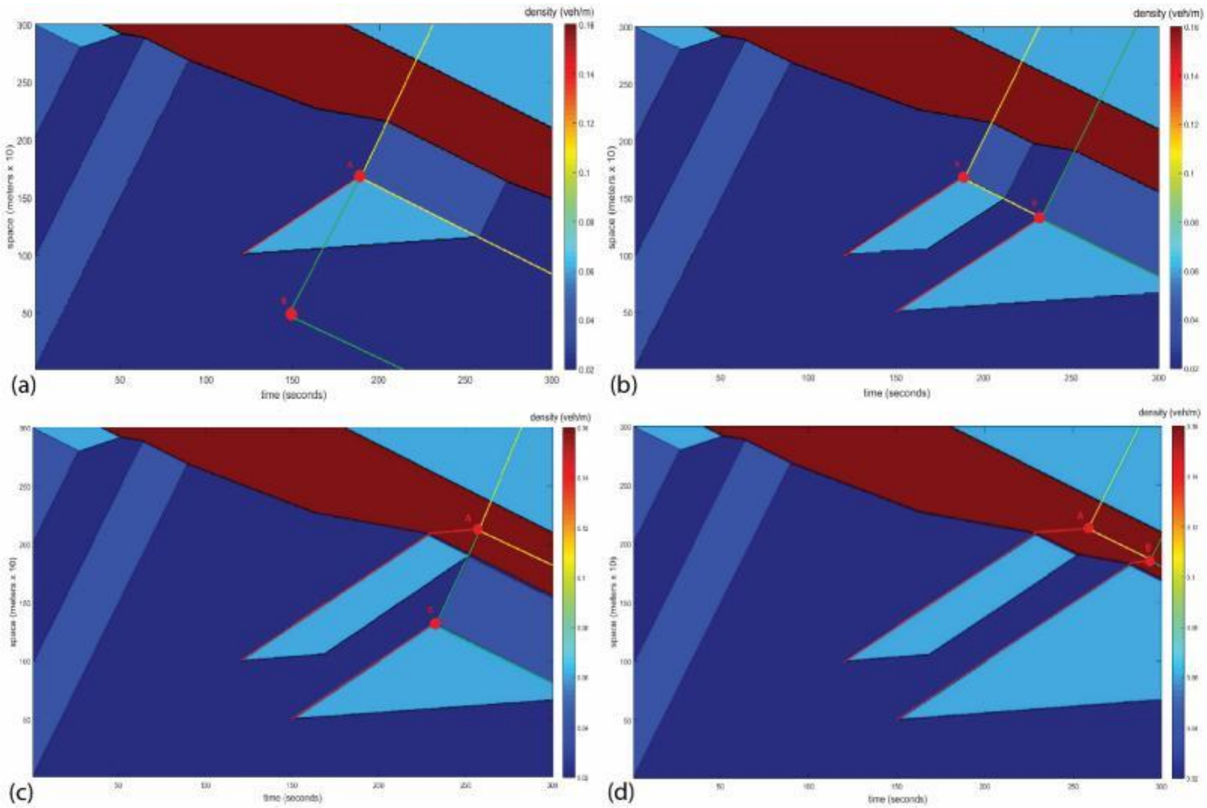

Figure 6: Example propagation of two moving bottlenecks. In (a), moving bottleneck A intersects the domain of moving bottleneck B. The algorithm continues propagating both bottlenecks (b, c) until both bottlenecks have left the computational domain (d)

Table 3: Moving bottleneck features

i	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
x_1	2000	1000	1000	1600	1200	2000	800	1500	1500	1000
t_2	60	20	50	150	120	220	180	270	330	320
v_{max}	5	8	10	10	8	12	10	8	5	5

3.3.5 A performance comparison with other numerical schemes

One of the greatest advantages of the proposed approach over other numerical schemes is its exactness: because the solutions are computed analytically, no approximation is required to determine the parameter of the internal conditions. Once these parameters are known (exactly), we can also compute the solution associated to the problem on any computational grid, following from Mazaré et al. (2011). While the Variational Theory (dynamic programming) also yields exact results in certain conditions (lopsided grid and fine-meshed grid), these conditions are not satisfied in practice as there is no guarantee that the beginning or the end of an internal condition will fall exactly on a grid point, causing errors.

A second advantage of the present formulation is the fact that one does not need to compute the solution everywhere on the computational grid to determine the parameters of the fixed bottlenecks. This represents an important advantage in optimization: if the objective function of the optimization problem requires the solution to be evaluated in m points, and if the problem contains n internal conditions, p initial conditions, the total number of required computations is bounded above by: $(p+2)(\sum_{i=1}^{n}(1+i)+(1+n)m)=(p+2)(n+\frac{n(n+1)}{2}+(1+n)m)$. Indeed, $(p+2)(1+n)m$ is an upper bound on the required number of computations to evaluate the solution in m points, and $(n(n+1))/2$ is an upper bound on the number of computations required to determine the parameters associated with all n internal conditions. In practical problems, both n and m are low. The number n corresponds to the number of red signal phases in the problem, while m represents the number of points needed to evaluate the objective function, which is also low in several important cases. For example, maximizing the outflow over the time horizon requires the evaluation of the solution in two points (m=2). Other algorithms, such as the Godunov scheme (or equivalently the Cell Transmission Model (Daganzo, 1994; Daganzo, 1995) require the computation of the solution over the complete computational grid, which can require a much higher number of computations (depending on the desired accuracy). The algorithm proposed by Leclercq and Becaire (2012) can be extended to multiple bottlenecks scenarios, and has a lower upper bound on its number of operations: $2(n + \frac{n(n+1)}{2} + (1+n)m)$, though this specific algorithm does not consider initial conditions.

3.4 Application to traffic optimization problems

The capabilities of the traffic simulation algorithm for moving bottlenecks are shown in two optimization problems solved by means of the heuristic MA, described in Section 3.4.1. The first one consists of control of inflow truck traffic into a main arterial combined with a traffic signal control (Section 3.4.2), while the second one consists of real-time curbside management for truck deliveries in urban environments (Section 3.4.3). In these tests, we assume that the initial and boundary conditions are known (and arbitrary). Though real world applications of traffic management involve multiple connecting links, for the purpose of this dissertation, we investigate the performance of the fast simulation algorithm in two problems involving a single link. In both cases, each moving bottleneck is characterized by different features (maximum speed, entry times) in order to add complexity. The results for both optimization problems are presented in Section 3.4.4.

3.4.1 Memetic Algorithm

Similarly to GAs, MAs are very flexible as they do not they do not require any knowledge of the gradient and they can avoid getting stuck in local optima (Teklu et al., 2007). In addition, MAs are more suitable to simulation-based frameworks as derivative-based optimization methods require the knowledge of the analytical form of the problem. For these reasons, GAs have been already employed to solve different joint traffic control and assignment problems (Foy et al., 1992; Lee and Machemehl, 1998; Yin, 2000; Ceylan and Bell, 2004; Teklu et al., 2007). In this study, the MA adopted consists of the following steps:

Step 0 (Initial Population): Generating a population of *n* random solutions satisfying the problem constraints (if any). The fitness value of each solution (according to the optimization problem) is calculated by performing a simulation with the fast algorithm presented in the previous section.

Step 1 (Parents selection): Parents are chosen by means of the tournament selection procedure, which consists in the selection of best performing solutions among a restricted pool of randomly chosen solutions from the population.

Step 2 (Breeding): Children are derived by means of a two-point crossover procedure. In case of combinatorial optimization, “Order 1 Crossover” is used, which is an ordered crossover method applicable where direct swap is not feasible.

Step 3 (Mutation-Local Search): The traditional mutation operators like swapping or moving some nodes are replaced by a local search (LS) procedure LS. The LS scan a series of decision variables and performs alternative operations to check whether the solution can be improved. If so, the mutated solution replaces the original one. The LS procedure occurs with a certain predefined probability. The LS consists of testing a series of simple moves performed sequentially for all chromosomes belonging to a randomly chosen child solution. The first move (M1) consists of a simple swap between two consecutive chromosomes. The second move (M2) consists of replacing the chromosome with the unused parent’s chromosome. If any move yields to an improvement of the solution, the LS is terminated and the mutated solution becomes part of the new population.

3.4.2 Joint coordination of traffic lights and trucks departures problem

The first application corresponds to the managing the entrance of slow vehicles on a main arterial with a traffic light downstream. Such a situation might occur at the merging of roads characterized by significant presence slower vehicles (e.g. major road connectors from ports, shopping malls, plants). The coordination between the traffic lights and the trucks could be achieved through Connected Vehicle (CV) technology, for example by issuing real time guidance information to the slow vehicle drivers.

In this optimization problem, the objective function corresponds to the total outflow, calculated as the cumulative number of vehicles at the downstream end of the link N_d. In this problem, the total outflow depends on the entry times of *i* trucks (t_i) and the on the signal settings $\varphi_j = (c, \phi)$, where c and ϕ correspond respectively to the cycle time length and the green time length of traffic signal j. Hence, the optimization problem is characterized by (3×j) decision variables. Each solution corresponds to an array specifying the entry times of the trucks, and the cycle length and green time of the traffic light. Hence the problem can be expressed as:

$$\max_{t_i, \varphi_j} N_d(t_i, \varphi_j)$$

subject to:

1. $t_{i,min} \leq t_i \leq t_{i,max}\ \forall i \in I$ (moving bottlenecks' entry times constraints)
2. $\varphi_j(c, \phi) \begin{cases} c_{min} \leq c \leq c_{max} \\ \phi_{min} \leq \phi \leq \phi_{max} \end{cases} \quad \forall j \in J$ (cycle times and green times constraints)

The initial scenario consists of a 300 meters with a traffic light situated at the downstream end of the link. A time period of 600s (10 minutes), during which 10 trucks enter from the location upstream the link, which represents a significant source of truck traffic. Each truck enters the link at a different time and it is characterized by a different maximum speed (Table 4). The traffic light is characterized by an initial cycle time of 120s and green time of 72s. A time step of 2s is used for the simulation. The boundary and initial conditions are reported respectively in Table 5 and Table 6. The following parameters characterizing the triangular fundamental diagram are chosen: $u = 20\ m/s$, $k_c = 0.04\ veh/m$, $k_j = 0.12\ veh/m$.

Table 4: Moving bottlenecks' characteristics in the first optimization problem

Moving bottleneck	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
Entry time (s)	20	100	150	220	260	300	330	370	420	500
Maximum speed (m/s)	8	11	5	8	5	6	12	7	9	10

Table 5: Upstream and downstream boundary

i	t_{i-1}	t_i	q^i_{up}	q^i_{down}
1	0	300	0.4	0.8
2	300	600	0.8	1.2

Table 6: Initial conditions

i	x_{i-1}	x_i	k_{ini}
1	*0*	*150*	*0.01*
2	*150*	*300*	*0.02*

3.4.3 Parking-loading curbside management strategy

The second application consists of a real-time curbside management for trucks deliveries in complex urban environments with signalized streets. Since traffic conditions can rapidly change and the presence of capacity reductions can yield to queue formation and spillback phenomena, the negative impact of trucks is minimized by re-allocating their delivery locations. This task could be ideally accomplished by means of traffic controller.

In this case, the problem is formulated again, as a maximization of total outflow. Thanks to the MA optimization framework, minimization of delay and queue could be alternatively adopted as objectives without difficulty. Unlike the previous case, the decision variables consist only of the delivery locations d_i of trucks *i*. The available locations for deliveries correspond to “slots” of length *l* each (20 meters). Hence, the problem turns into a combinatorial optimization problem. Each solution corresponds to an array specifying the delivery locations of each truck. No specific constraint is applied, except for the exclusion of already occupied locations from the range of available ones when assigning subsequent trucks.

We investigate this problem on the same road stretch analyzed before and for the same period of time (600s), using a time step of 2s. In this case 10 trucks enter at random times and stop at the curbside for deliveries for a random period of time between 60s and 200s. Each truck is characterized by a randomly assigned different speed, preferred delivery location and duration (Table 7). Like in the previous problem, the traffic light is characterized by an initial cycle time of 120s and green time of 72s. The boundary and initial conditions are the same as those reported in Table 5 and Table 6. Also the parameters adopted for the fundamental diagram are unchanged from the previous case.

Table 7: Moving bottlenecks' characteristics and delivery stops description in the second optimization problem

Moving bottleneck	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
Entry time (s)	20	50	70	90	120	180	220	280	320	400
Maximum speed (m/s)	7	5	5	5	7	5	5	7	5	7
Delivery location (m)	90	150	110	130	70	90	170	130	210	190
Delivery duration (s)	60	120	100	150	90	200	100	60	120	60

3.4.4 Results

The traffic flows corresponding to the case study before and after the optimization procedure for the first and second optimization problem are shown respectively in Figure 5 and Figure 6.

The evolution of the fitness function through several generations in both optimization problems suggests the designed MA converges to a maximum/minimum rather quickly (between the 10th and 15th iteration) regardless of the input parameters used (mutation rate probability, tournament size). From a computational perspective this result implies that the optimization algorithm can be limited to fewer generations without compromising the quality of the results. More interestingly, as several tests concerning the size of the population of the MA show, the quality of the solution does not seem to be largely affected (Table 8 and Table 9). Indeed, in the first problem, increasing the size of the population from 20 to 50 seems to improve only by 2-3 percent the fitness function (on average), at the expense of the computational time, which is almost tripled. Similarly in the second problem, for an improvement of less than 2 percent, more than twice the computational time is required.

The required computation time to calculate the objective function for each of the solutions created during the breeding procedure and accomplished by means of traffic simulation, varies between 0.05 and 0.13 seconds depending on the complexity of the problem.

Overall, this analysis suggests that, for optimization problem involving up to ten moving bottlenecks and one traffic light, it is possible to obtain fairly satisfactory solutions in a few tens of seconds, thanks to the fast algorithm introduced earlier, which we use to compute the solutions associated with multiple moving bottlenecks.

Table 8: Computational performance of the algorithm for different population sizes (average across 20 tests) in the first problem

	Outflow (veh)	*Solution improvement (%)*	*Computation time (s)*
Population 50	281	10.6	14.5
Population 30	278	9.4	9.2
Population 20	275	8.2	6.3

Table 9: Computational performance of the algorithm for different population sizes (average across 20 tests) in the second problem

	Outflow (veh)	*Solution improvement (%)*	*Computation time (s)*
Population 20	144.0	16.1	43
Population 30	144.6	16.6	65
Population 50	145.8	17.5	105

As can be seen from Figure 5 and Figure 6, the proposed numerical scheme yields almost exact solutions, with no numerical diffusion nor approximations in the computation of the density. The only errors introduced by the numerical scheme are related to the integration of the ODE corresponding to the vehicle trajectory, which is performed at discrete points. Since the solutions do not need to be computed everywhere as part of the optimization, the proposed scheme is considerably faster than other numerical schemes. For example solving the problem using the Godunov scheme on a 300×600 computational grid (as shown in Figure 7and Figure 8) would require 180,000 computations per solution of optimization, while the proposed numerical scheme requires only 1,030 computations per cycle in average.

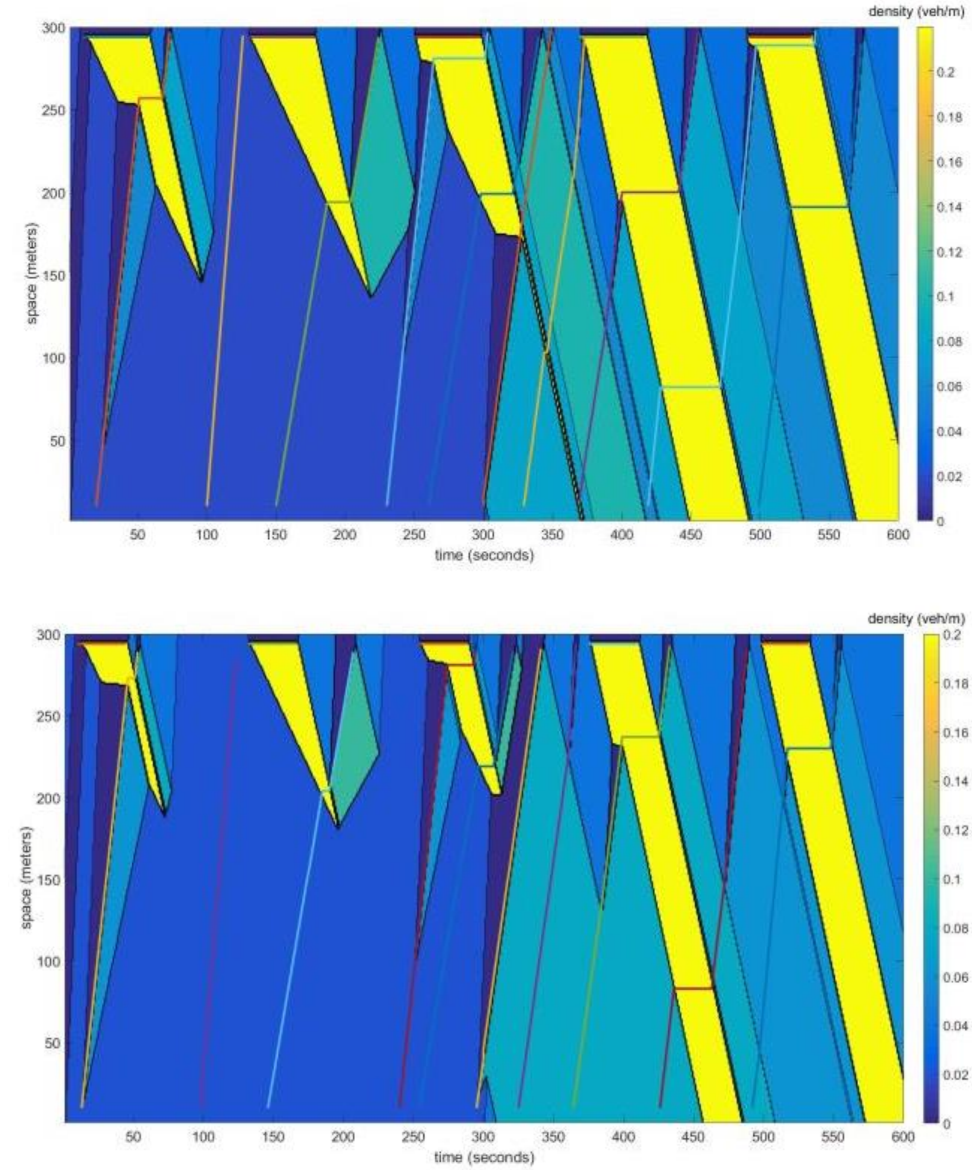

Figure 7: Space-time-density diagram corresponding to the first case study before (above) and after (below) the optimization

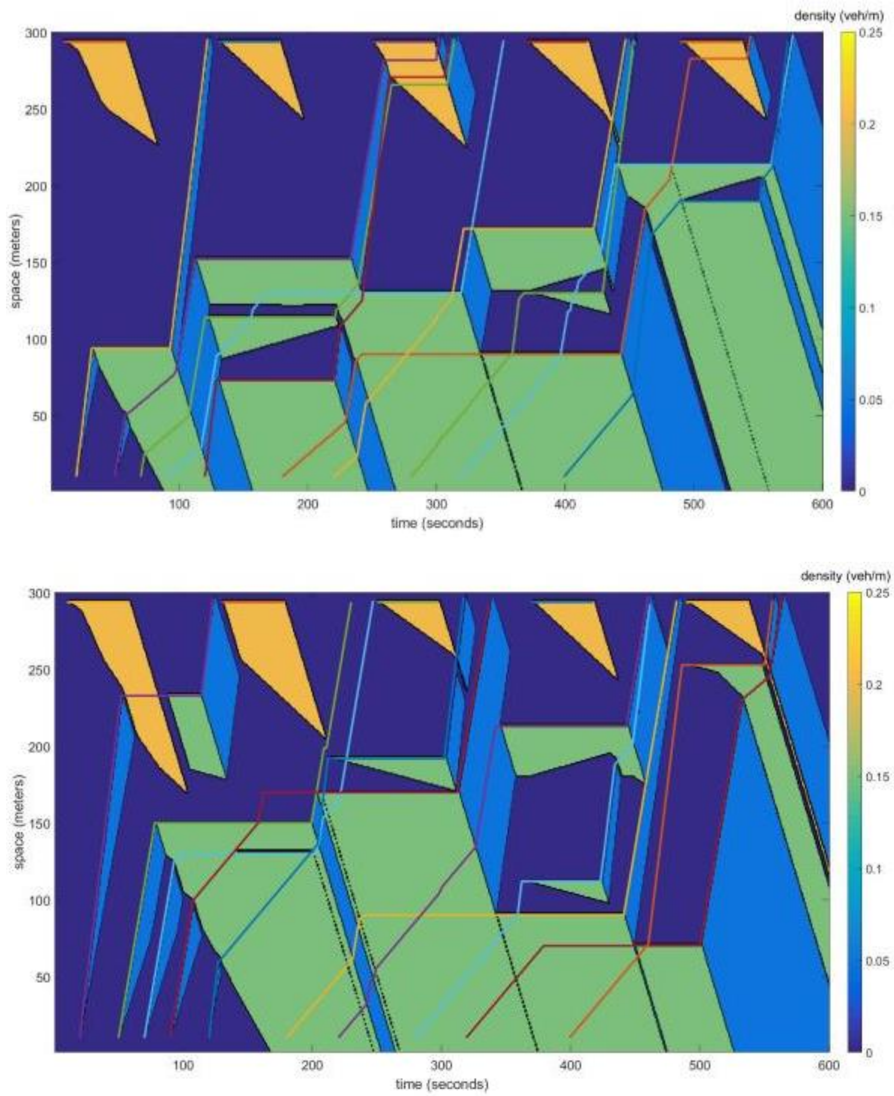

Figure 8: Space-time-density diagram corresponding to the second case study before (above) and after (below) the optimization

3.5 CONCLUSION

This chapter proposes a new semi-analytic numerical scheme that can be used to perform traffic simulations with the LWR model given initial, upstream, and downstream boundary conditions, as well as an arbitrary number of moving bottlenecks modeled as internal conditions.

Without relying on continuous flow or multi-class approximations, this scheme endogenously and efficiently accounts for the interaction between several moving (and fixed) bottlenecks and surrounding traffic. This numerical scheme is based on a Hamilton-Jacobi formulation of the LWR model, and results from the properties of the solutions to Hamilton-Jacobi equations and, in particular, the inf-morphism property.

This semi-analytic numerical scheme is very accurate and very fast (fractions of a second to compute the internal conditions corresponding to several moving bottlenecks). Since it allows one to determine the trajectories of all moving bottlenecks without having to compute the solution on the entire computational domain, it is also very adapted to optimization problems. Other potential applications of this algorithm for include the integration of simulations into problems like model predictive control and optimization of trajectories.

In the second part of the chapter, the benefits of this algorithm are demonstrated in two different optimization problems where fast simulations were required to evaluate the quality of the solutions. The two problems are solved by means of the MA heuristic, which is a combination of evolutionary (, such as GAs) and local-search methods. This approach is relatively new in the field of transportation engineering and is particularly suitable for connected and autonomous vehicles (C-AVs). It would enable C-AVs to dynamically modify their speeds in conjunction with signal timing and their delivery locations in order to minimize congestion. As the results of different tests confirm for the two applications presented, the MA can achieve significant improvements (between 8 and 17 percent) in relatively short times (between 6 and 105 seconds).

The traffic optimization problems presented in this study are particularly designed to reduce the negative traffic impacts of trucks. While this issue has been widely acknowledged by both academics and practitioners (Allen et al., 2000; Dablanc, 2007; Jaller et al., 2013; USDOT, 2017), little has been done in regard to traffic management dedicated to this typology of vehicles. With the oncoming technologic improvements in wireless communication, as well as computational and sensing technologies (Intelligent Transport Systems), the real world implementation of these strategies is a feasible possibility.

4. A SIMULATION FRAMEWORK FOR MODELING URBAN FREIGHT OPERATIONS IMPACTS ON TRAFFIC FLOWS

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The authors confirm the contribution to the paper as follows: Study conception and design: Simoni, M.D., Claudel, C.G.; Data collection: Simoni, M.D.; Analysis and interpretation of results: Simoni, M.D.; Manuscript preparation: Simoni, M.D., Claudel, C.G.

4.1 INTRODUCTION

Efficient and accurate simulation models are critical for investigating the effects of urban freight distribution on traffic congestion and identifying appropriate travel demand and traffic management solutions. Urban freight distribution represents a major challenge in metropolitan areas. In the U.S., freight traffic accounts for 18% of the congestion costs, although they only represent 7% of urban travel (Schrank et al., 2015). Considerable pressure to find efficient and sustainable practices has been building up, particularly in recent years as urban deliveries continue growing with double-digit rates (Joerss et al., 2016). Among the different externalities associated with the last-mile of the delivery chain (pollution, congestion, safety), the limited parking availability for commercial vehicles is certainly a critical issue (Jaller et al., 2013; Nuzzolo et al., 2016). A survey by Kawamura and Sriraj (2016) conducted in Chicago showed that trucks were illegally parked more than 28% of the time compared to 3% for passenger vehicles. Furthermore, recent studies have shown that the volume of deliveries and parking violations in residential and mixed land-use areas are comparable to those in commercial areas (Wang and Zhou, 2015; Chen et al., 2017).

In this chapter, we present a hybrid traffic simulation-based framework suitable for the evaluation of last-mile urban freight operations and urban freight traffic policies. While analytical and statistical models provide a good indication of the consequences of last-mile delivery movements, their traffic impacts can be accurately identified only through traffic simulations. When considering urban settings, characterized by high levels of traffic and signals, it is important to dynamically reproduce phenomena like the formation of queues and congestion spillbacks over the network. In this dissertation work, we choose a macroscopic flow model to reproduce the behavior of all traffic except for the delivery vehicles that are represented microscopically. Because of its macroscopic features, the proposed framework is computationally efficient and requires short simulation times (in the order of seconds) to reproduce traffic and deliveries on large networks. For this reason, unlike microscopic and mesoscopic models (see Section 1.2 for their definition), such a framework would be practical for studies requiring large numbers of simulations, such as optimization and real-time control problems. At the same time, since freight distribution is reproduced at a microscopic level, the framework also allows for detailed analyses of last-mile operations. As shown in this study, it is possible to couple the traffic simulation with a parking model to reproduce on-street parking and double-parking behavior of delivery trucks.

The proposed approach is derived from the Traffic Flow Theory, more specifically from the macroscopic Lighthill–Whitham–Richards (LWR) model (Lighthill and Whitham, 1955; Richards, 1956) and from the concept of "moving bottlenecks" (Gazis and Herman, 1992; Newell, 1993, Munoz and Daganzo, 2002). Freight movements can be reproduced as moving bottlenecks traveling across the network, which become "temporary fixed bottlenecks" when they perform deliveries (under certain conditions). Tracking the position of the delivery vehicles within the network is crucial to properly analyze their delivery operations. Thus, the delivery tours are integrated into a network simulation so that vehicles can be explicitly tracked along their paths. One of the issues associated with the integration of fixed (and moving) bottlenecks into a macroscopic traffic flow model is the inherent hybrid nature of the bottleneck itself, which affects and is affected by the rest of traffic at the same time. For this reason, evaluating the traffic effects of freight deliveries and other freight-related services like crowdshipping is not a straightforward task. This requires the coupling between a vehicular model, encoded by an Ordinary Differential Equation (ODE), and a macroscopic traffic flow model, encoded by a Partial Differential Equation (PDE). To tackle this issue, we use a novel version of the Lax-Hopf formula, which also allows reproducing delivery operations on the streets arbitrarily (at any internal point of the link and at any time instant of the simulation).

The remainder of this chapter is organized as follows. First, we present a literature review of traffic models and analyses of freight operations in urban settings. Then, we describe the simulation framework, the simulation algorithms and its output. In the second part of the chapter, we present two applications in the City Logistics field where the simulation framework is used to evaluate the effects of possible strategies to tackle freight congestion due to delivery operations. Finally, we present some considerations and conclusions.

4.2 Models and studies of traffic impacts of urban freight movements

Freight movements within cities are a significant source of congestion. Nevertheless, for a long time urban freight traffic operations have been overlooked (particularly compared to the passenger vehicle traffic), and traditional strategies aimed at reducing passenger travel demand were found to be less effective for freight demand.

Freight operations represent a potential hindrance to traffic through double-parking which generates a blockage of the road. Such behavior, also referred to as a fixed bottleneck, determines a capacity reduction in presence of high traffic volumes, and might eventually yield to queues and spillbacks across the traffic network. Deliveries are rather inelastic to parking pricing and enforcement policies (Pluvinet et al., 2012; Halsey, 2013), and there are few practical alternatives to delivery trucks in urban areas (Jaller et al., 2013). City Logistic solutions, such as developing freight facilities (urban consolidation centers), modal adaptation (replacement of trucks with more environmentally friendly vehicles) and concentrating shipments are often hard to implement because of costs, physical constraints and additional delays (Rodrigue et al., 2016). Currently, only a few demand management solutions have been successfully implemented in some European and American cities (Russo and Comi, 2010; Holguin-Veras et al., 2011; McLeod and Cherrett, 2011). While a significant amount of studies has focused on the issue of car parking in urban areas, less attention has been paid to parking of freight vehicles. Only in the last ten years we have seen a growing interest in the last-mile delivery problem which has led to studies on impacts and solutions for last-mile delivery operations (Aiura and Taniguchi, 2005; Patier et al., 2014; Marcucci et al., 2015; Gardrat and Serouge, 2016; Comi et al., 2017; Munuzuri et al., 2017). However, not many of them have adopted or developed frameworks that explicitly account for dynamics between delivery vehicles and general traffic[1].

Chiabaut (2015) uses the Kinematic Wave Theory to investigate analytically the reduction of capacity on signalized arterials due to delivery maneuvers. Amer and Chow (2017) have recently presented an on-street parking equilibrium model to evaluate passenger and freight parking behavior. The effects of double-parking are reproduced as a temporary lane drop, while traffic conditions are evaluated based on the fundamental diagram relationship. Roca-Riu et al. (2017) also adopt an analytical approach to design shoulder lanes that can be dynamically used for delivery on a single link. Another proposed approach for modeling commercial parking consists of a statistical approach based on queueing theory and logistical models based on continuous approximations (Figliozzi and Tipagornwong, 2017).

Other studies have adopted instead, simulation-based approaches, typically by integrating commercial software traffic simulators into delivery operation models. Nourinejad et al. (2014) for example, combined an econometric parking choice model with microscopic simulation using Paramics to evaluate parking policies on a few-blocks scenario in Toronto. Aditjandra et al. (2016) also adopted a microsimulation approach (based on AIMSUN) to analyze in detail the environmental impact of a large freight traffic generator (although they did not consider curbside). Ukkusuri et al. (2016) utilized Transmodeler to analyze the effects of an off-peak delivery program in Manhattan and compare the results with those from a regional travel demand model. Munuzuri et al. (2002) develop their own ad-hoc microsimulation to analyze double-parking and loading/unloading activity on a small network of four links. More recently, Munuzuri et al. (2013) adapted the software, Arena, for microscopic simulation of delivery operations to analyze pedestrian-friendly measures of a street in Seville. Lopez et al. (2016) proposed a framework based

[1] In transport planning practice and research freight flows can be estimated and modeled macroscopically (not looking at the individual unit) by means of static models in “traditional” four-step transport planning models. However, these models do not represent properly traffic dynamics, and the delivery operations.

on microscopic traffic simulation to model deliveries and quantify their impacts on one arterial by deriving a Macroscopic Fundamental Diagram (MFD). As the size of the case studies analyzed shows and as the authors themselves acknowledge, mesoscopic and microscopic simulations, are mainly suitable for the evaluation of small scenarios characterized by a handful of links and intersections. While microscopic models allow for detailed modeling of driving behavior, their computational costs and required calibration efforts often represent a barrier for simulation of larger scenarios.

To the best of our knowledge, there has not been any formal study of network traffic dynamics of urban freight deliveries by coupling macroscopic traffic simulation with fixed and moving bottlenecks. In the following section, we present a simulation framework based on the LWR model and theory of moving bottlenecks.

4.3 Simulation Framework

The proposed simulation framework (Figure 9) of delivery operations combines a detailed number of information on forthcoming deliveries (routes, location and duration of stops) with some general network characteristics (lanes, speed limits, signal settings), and traffic conditions (traffic demand). These inputs are used to derive a detailed description of the freight movements and their impacts on traffic flows. In addition to these inputs and parameters, the simulation of delivery vehicles also requires a (discrete) parking model to describe the likelihood that parking (or double parking) can be found by the delivery vehicle. As such, the dynamics of the traffic flows can be described as a hybrid system, since the ODE describing the evolution of the delivery vehicle is hybrid, with three discrete modes (delivery vehicle traveling in traffic, delivery vehicle legally parked, or delivery vehicle double-parked and restricting traffic). In this study, the entire simulation framework is implemented in MATLAB. The network traffic simulation framework, which is based on a macroscopic link (LWR) and node model is described in Section 4.3.1. The delivery vehicle model that is used to track delivery vehicles' operations is presented in Section 4.3.2, and the parking model adopted in this study is described in Section 4.3.3.

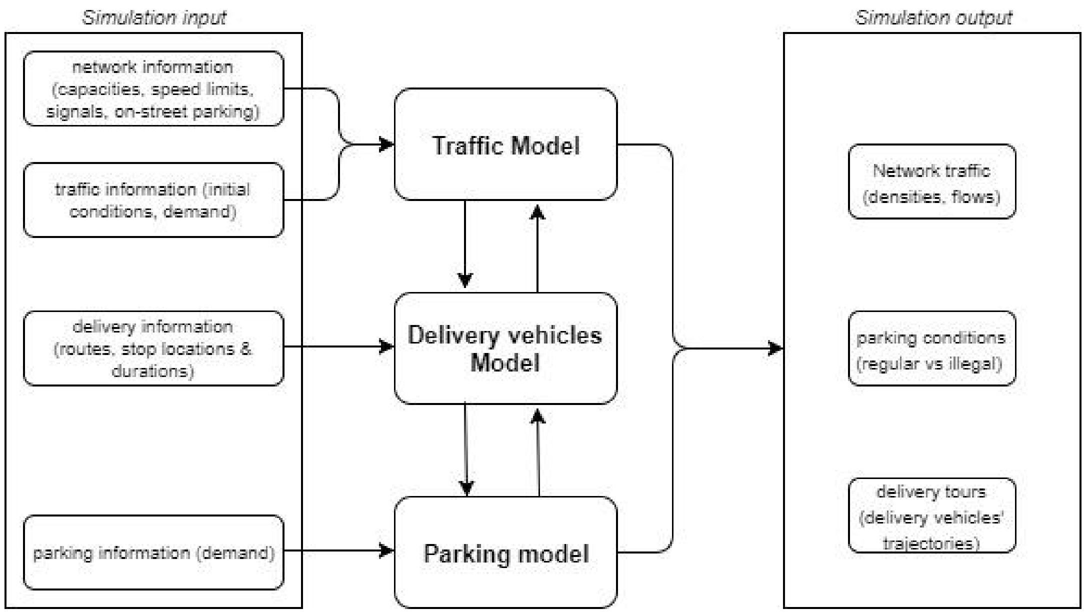


Figure 9: Overview of the simulation framework

4.3.1 Network traffic model

Traffic on road networks is usually modeled by combining a link model that describes traffic flow on a single link, with a node model, which encodes the behavior of traffic at junctions. In this study, we adopt the macroscopic LWR model as the link model, which is solved by means of a Fast Lax-Hopf formula. The link model adopted is the LWR model (Section 3.2.1) which is soved by means of an extension of the Lax-Hopf formula (Section 3.2.2-3.2.3). In the present problem, the function $c(x,t)$ corresponds to peicewise linear initial, upstream, downstream and internal boundary conditions, where each linear piece is defined by:

$$c(x,t) = \begin{cases} c_{ini}^{l}(x) & t = 0,\ x \in [(l-1)\Delta x, l\Delta x] \\ c_{up}{}^{j}(t) & x = 0, t \in [j\Delta t, (j+1)\Delta t] \\ c_{down}{}^{k}(t) & x = L,\ t \in [j\Delta t, (j+1)\Delta t] \\ c_{int}{}^{n}(x,t) & x \in [x_{b,n}, x_{e,n}], t \in [t_{b,n}, t_{e,n}] \end{cases} \tag{4.1}$$

where $(x_b, t_b; x_e, t_e)$ defines the space-time domain of the internal boundary condition.

In the remainder of the chapter, we assume that the initial, upstream, downstream and internal condition functions (4) are all piecewise linear functions. We further assume that the temporal step used to define the piecewise linear upstream and downstream boundary conditions is Δt, and that the spatial step used to define the piecewise linear initial condition of link i is Δx_i .

We consider a problem involving an initial condition $N_{ini}(x)$, an upstream boundary condition $N_{up}(t)$ and a downstream initial condition $N_{down}(t)$. We also assume that the flux function is a triangular Fundamental Diagram with critical density k_c and characteristic speeds within the range$[-w, v]$. Furthermore, we assume an arbitrary number of fixed bottlenecks $N_{{c_{int}}^n}(x,t)$ as defined in (4), whenever delivery vehicles restrict the capacity at their location (see Section 3.3 for further details).

In order to compute traffic flows leaving and entering each link, and assuming that $\Delta t \leq \frac{\Delta x}{v}$ (Courant–Friedrichs–Lewy condition), the solution at the upstream end $N(t,0)$ of the link $[0, L]$ can be computed as:

$$N(0,t) = \begin{cases} \min\left(N_{c_{ini}^{l}}(0,t), N_{c_{ini}^{l-1}}(0,t), N_{{c_{up}}^{j}}\left(0,(i-1)\Delta t\right) + v \cdot k_c \cdot \Delta t, \min_n N_{{c_{int}}^{n}}(0,t)\right) & if\ t \leq \frac{L}{w} \\ \min\left(N_{{c_{up}}^{j}}\left(0,(i-1)\Delta t\right) + v \cdot k_c \cdot \Delta t, {N_{down}}^{k}(0,t), \min_n N_{{c_{int}}^{n}}(0,t)\right) & else \end{cases} \tag{4.2}$$

where $j = i - 1, k = \left\lfloor \frac{t - \frac{x_{n_{ini}}}{w}}{\Delta t} \right\rfloor, l = \left\lfloor \frac{wt}{\Delta x} \right\rfloor$

For any discrete time $t = i \cdot \Delta t$. Where n initial conditions c_{ini}^{l} are identified on blocks of the same length such that $x_i = i\Delta x$ (piecewise). The solution $N(t, L)$ at the downstream end of the link $[0, L]$ corresponds to:

$$N(L,t) = \begin{cases} min\left\{N_{c_{ini}^{l}}(L,t), N_{c_{ini}^{l+1}}(L,t), N_{c_{down}{}^{j}}(L,(i-1)\cdot \Delta t) + v\cdot k_c \cdot \Delta t, \min_n N_{c_{int}{}^{n}}(L,t)\right\} & if \quad t \leq \frac{L}{v} \\ min\left\{N_{c_{down}{}^{j}}(L,(i-1)\cdot \Delta t) + v\cdot k_c \cdot \Delta t, N_{up}{}^{k}(L,t), \min_n N_{c_{int}{}^{n}}(L,t)\right\} & else \end{cases} \quad (4.3)$$

where $j = i - 1, k = \left\lfloor \frac{t - \frac{x_{n_{ini}}}{v}}{\Delta t} \right\rfloor, l = \left\lfloor \frac{vt}{\Delta x} \right\rfloor$

The interested reader is referred to Mazare et al. (2011) for a full formulation of the Lax-Hopf problem and to Appendix I for a formal proof of the FLH for Eq. 4.2-4.3.

The computation of the solutions at the boundaries (Eq.4.2-4.3) can be further simplified. Indeed, the minimum of the internal condition components: $\min_n N_{c_{int}{}^{n}}(0,t)$ and $\min_n N_{c_{int}{}^{n}}(L,t)$ does not need to be computed for all possible values of n, given the following properties:

Property 1: If $j\Delta t > \frac{x_{e,n}}{w} + \Delta t$, then $N_{c_{int}{}^{n}}(0,t) \geq N_{c_{up}{}^{j}}(0, j\Delta t) + v \cdot k_c \cdot \Delta t$

Property 2: If $j\Delta t > \frac{L - x_{e,n}}{v} + \Delta t$, then $N_{c_{int}{}^{n}}(L,t) \geq N_{c_{down}{}^{j}}(L,(i-1)\Delta t) + v \cdot k_c \cdot \Delta t$

The above properties are the consequence of the structure of the solutions $N_{c_{int}{}^{n}}(\cdot,t)$ on the upstream and downstream boundary. They imply that only one internal condition block influence the upstream and downstream boundary conditions at any given time. Hence, the solution at the boundaries (Eq. 4.2-4.3) can be rewritten as:

$$N(0,t) = \begin{cases} \min\left(N_{c_{ini}^{l}}(0,t), N_{c_{ini}^{l-1}}(0,t), N_{c_{up}{}^{j}}(0,(i-1)\Delta t) + v\cdot k_c \cdot \Delta t, \min_{n \mid \frac{x_{e,n}}{w} \leq j\Delta t \leq \frac{x_{e,n}}{w} + \Delta t} N_{c_{int}{}^{n}}(0,t)\right) & if\ t \leq \frac{L}{w} \\ \min\left(N_{c_{up}{}^{j}}(0,(i-1)\Delta t) + v\cdot k_c\cdot \Delta t, N_{down}{}^{k}(0,t), \min_{n \mid \frac{x_{e,n}}{w} \leq j\Delta t \leq \frac{x_{e,n}}{w} + \Delta t} N_{c_{int}{}^{n}}(0,t)\right) & else \end{cases} \quad (4.4)$$

$$N(L,t) = \begin{cases} min\left(N_{c_{ini}^{l}}(L,t), N_{c_{ini}^{l+1}}(L,t), N_{c_{down}{}^{j}}(L,(i-1)\cdot\Delta t) + v\cdot k_c\cdot\Delta t, \min_{n\,|\,\frac{L-x_{e,n}}{v}\le j\Delta t\le\frac{L-x_{e,n}}{v}+\Delta t} N_{c_{int}{}^{n}}(L,t)\right) & if\ \ t \le \frac{L}{v} \\ min\left(N_{c_{down}{}^{j}}(L,(i-1)\cdot\Delta t) + v\cdot k_c\cdot\Delta t, N_{up}{}^{k}(L,t), \min_{n\,|\,\frac{L-x_{e,n}}{v}\le j\Delta t\le\frac{L-x_{e,n}}{v}+\Delta t} N_{c_{int}{}^{n}}(L,t)\right) & else \end{cases} \quad (4.5)$$

In order to model traffic throughout intersections, there is need of a generic macroscopic node model that respects some critical conditions identified by Lebaque and Khoshyaran (2005), Tampere et al. (2011), Flotterod and Rohde (2011) and Bliemer et al. (2014). These requirements are often referred as: satisfaction of links' capacity constraints, conservation of flows, satisfaction of demand distribution constraints, maximization of flows (vehicles should proceed if there is available supply downstream), satisfaction of invariance principle (if the flows are restricted by demands, solutions cannot vary by increasing supplies and vice versa), and non-simultaneity of conflicting flows. In this study, we adopt the greedy "I-HFS algorithm" by Jabari (2016), which respects the abovementioned properties and efficiently derives solutions by staging movements according to any arbitrary priory rules. The algorithm (Algorithm 3) yields realistic solutions in several situations,, such as signalized intersections (with permitted and protected movements) and intersections between major and minor roads. For each node, characterized by I incoming links with potential sending flows $\bar{s}$ and O outgoing links with potential receiving flows $\bar{r}$, a turning proportion matrix $f_{i,o}$ *(I x O)* given a certain priority rule: $P = \{p_1, \dots, p_I\}$, the algorithm can be expressed as follows:

Algorithm 3: Overview of the I-HFS algorithm

Input: $P(\boldsymbol{p_1}, \dots, \boldsymbol{p_I})$, $\bar{\boldsymbol{r}}$, $\bar{\boldsymbol{s}}$, $f_{i,o}$ ***Output:*** $\boldsymbol{q}$	*Priority rules, (vector of) potential inflows, (vector of) potential outflows, turning proportions*
$\boldsymbol{k \leftarrow 1}$ $\bar{\boldsymbol{r}}^{\,\boldsymbol{1}} \leftarrow \bar{\boldsymbol{r}}$ **FOR** $\boldsymbol{k \le \lvert I \rvert}$**:**	*Vector potential receiving flows* *For each outgoing link*
$\boldsymbol{q_{p_k} = min\{s_{p_k}, \min_{o\in O} \frac{\bar{r}^{\,k}}{f_{p_k,o}}\}}$	*Derive actual outflow*
$\bar{\boldsymbol{r}}^{\,\boldsymbol{k+1}} = \bar{\boldsymbol{r}}^{\,\boldsymbol{k}} - \boldsymbol{q_{p_k} \cdot f_{p_k,o}}$	*Update potential receiving flows*

$\boldsymbol{k} \leftarrow \boldsymbol{k}+\mathbf{1}$ **END FOR**	

4.3.2 Parking model

The traffic model can be coupled to a parking model in order to describe parking and loading/unloading behavior of delivery vehicles. Different models, like equilibrium and logit ones can be adopted to reproduce commercial parking behavior, depending on level of aggregation and number of factors considered (parking availability, price, and propensity of drivers of committing infractions). Neither developing a novel parking model nor identifying the most accurate is within the scope of this research, since the traffic model presented in this work, can be potentially coupled to any discrete parking model.

In this study, we integrate into the simulation framework a parking model that can be dynamically applied each time a delivery truck reaches the link of delivery. The model is probabilistic and depends on network infrastructure features, such as the presence of delivery bays (dedicated parking for loading/unloading) and regular parking, and levels of parking demand.

At the time *t* when the vehicle enters the link, it looks for any available delivery bay on the link. In case of failure (such facility does not exist or it is already occupied), it looks for an open or "regular" (on-street) parking spot. The probability of finding regular parking, which depends on the number of lots on the link and on the levels of parking demand, is expressed by means of a binomial distribution. In this version of the model, parking demand is given as input, but in more advanced model it could be derived from surveys or from land-use and travel data. Finally, in case of failure in finding regular parking the vehicles commits an infraction and double-parks. In this model, we assume the delivery vehicles to be rather "inelastic" and more inclined to double-park illegally rather than cruising to find an alternative location for the stop. This is a rather reasonable assumption as carriers mainly cares about proximity to the destination (Amer and Chow, 2017) and typically transfer the overall costs of fines to customers (Hawkins, 2013; Stock, 2014).

The parking model is formulated as follows:

$$\varphi_d = \begin{cases} 0 & if\ b \geq 0 \\ p(1;x) & else \end{cases} \tag{4.6}$$

where φ_d is a binary variable corresponding to double parking of the vehicle, b corresponds to the number of available delivery bays and, the probability of double parking $p(1;x)$ is derived according to the following binomial distribution:

$$p(1;x) = \beta(0, r, p) \tag{4.7}$$

where β stands for the binomial cumulative distribution function given *r* on-street regular parking lots and parking demand p. In this study, we assume p as a given parameter, however it future extensions of the model, it could be derived analytically based on several factors (traffic, time of the day, land use).

The parking model is integrated within the simulation framework as a "parking routine" that is performed each time the vehicle enters the link of delivery. In order to account for changes of availability of commercial and regular lots due to delivery operations, b and r are updated at the beginning and at the end of each delivery.

4.3.3 Delivery vehicle model

There are two main aspects of simulating delivery operations on the urban networks that need to be considered. First, tracking down the vehicles traveling on the network based on real traffic conditions (accounting for signals and queues). Second, modeling the impacts of deliveries on surrounding traffic, when vehicles are double-parked. Delivery vehicle trips can be simulated at individual level by leveraging the cumulative property of the LWR model, while the traffic impacts of double-parking can be modeled as a temporary fixed bottleneck.

In traffic flow theory, capacity restrictions and "slow" vehicles that represent obstructions of traffic stream are respectively referred as bottlenecks and moving bottlenecks. Moving bottlenecks have also been studied in the field of applied mathematics (Delle Monache and Goatin, 2014a,b; Delle Monache and Goatin 2016; Laurent-Brouty et al., 2017), where coupled PDE-ODE models are used to reproduce the dynamics between car traffic flows and slow vehicles. In this study, we consider only vehicles with maximum speed equal to "regular" traffic. This is a reasonable assumption for most of delivery vehicles used by major carriers in urban settings where speeds are already reduced to comply with speed limits. In this case, the main obstruction to traffic flows occurs when delivery vehicles double-park at the curbside to accomplish their delivery. Then, if regular car flows are hindered by the vehicle, the bottleneck becomes active. Depending on the conditions of surrounding traffic, following Munoz and Daganzo (2002) and Daganzo and Laval (2005), it is possible to identify three possible cases where the vehicles can be active or inactive bottlenecks (Figure 10): inactivity due to low traffic volumes ($k \leq k_D$), activity ($k_D \leq k \leq k_U$), inactivity due to high traffic volumes ($k \leq k_U$). Hence, according to the Lax-Hopf formula, the status of the bottleneck is derived according to Eq. 3.21 (Section 3.2.5).

The value of the Moskovitz function for any internal point x' on the link (e.g., where double-parked delivery occurs) at time t' can be calculated by extending the FLH formula, similarly to Jin (2015), as follows:

$$N(x',t') = \begin{cases} \min\left(N_{c_{ini}^{l}}(x',t'), N_{c_{ini}^{l-1}}(x',t'), N_{c_{ini}^{m}}(x',t'), N_{c_{ini}^{m+1}}(x',t'), \min\limits_{n} N_{c_{int}{}^{n}}(x',t')\right) & if \quad vt' \leq x' \leq L - wt' \\ \min\left(N_{c_{ini}^{m}}(x',t'), N_{c_{ini}^{m+1}}(x',t'), N_{c_{down}{}^{j}}(x',t'), \min\limits_{n} N_{c_{int}{}^{n}}(x',t')\right) & if \;\; vt' \leq x' \;\; and \;\; L - wt' \leq x' \\ \min\left(N_{c_{ini}^{l}}(x',t'), N_{c_{ini}^{l-1}}(x',t'), N_{c_{up}{}^{k}}(x',t'), \min\limits_{n} N_{c_{int}{}^{n}}(x',t')\right) & if \;\; vt' \geq x' \; and \;\; L - wt' \geq x' \\ \min\left(N_{c_{up}{}^{j}}(x',t'), N_{down}{}^{k}(x',t'), \min\limits_{n} N_{c_{int}{}^{n}}(x',t')\right) & otherwise \end{cases} \tag{4.8}$$

where $l = \left\lfloor\frac{x'+w\cdot t'}{\Delta x}\right\rfloor$, $m = \left\lfloor\frac{x'-v\cdot t'}{\Delta x}\right\rfloor$, $j = \left\lfloor\frac{t'}{\Delta t} - \frac{L-x'}{\mathrm{w}\cdot\Delta t}\right\rfloor$, $k = \left\lfloor\frac{t'}{\Delta t} - \frac{x'}{\mathrm{v}\cdot\Delta t}\right\rfloor$ with Δx and Δt corresponding respectively to the space step and time step defined in Eq. 4 (boundary conditions). In the specific case of vehicle performing deliveries at the curbside, x_0 corresponds to the position of the delivery d, θ_d within the link, and v_{max} is set to equal to 0 because the vehicle is standstill. We assume that θ_d is in the space interval $[0 + w \cdot \Delta t; L - v \cdot \Delta t]$. Based on that, it is possible to determine whether the bottleneck is active as like in Section 3.2.5.

In this case q_r, which is the maximum passing rate of the fixed bottleneck, the formulation of q_r corresponds to:

$$\boldsymbol{q_r = \frac{u \cdot k_c \cdot (n_l - 1)}{n_l}} \tag{4.9}$$

where u stands for the free flow speed, k_c is the critical density and n_l is the number of lanes. For each time interval the bottleneck is active, a new internal condition $N_{c_{int}}{}^{n}$ is created.

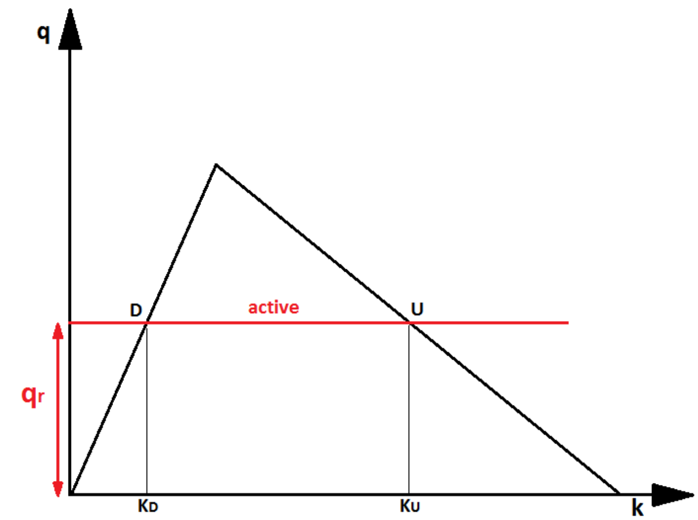


Figure 10: Fixed bottleneck

Some of the main advantages of using the Lax-Hopf computational method compared to other well-known methods, such as the Cell Transmission Model (CTM) (Daganzo,1995) are its accuracy (given its semi-analytical nature) and the possibility of tracking delivery vehicles traveling across each link. Furthermore, delivery operations can be reproduced arbitrarily without any space-time constraint due to the discretization of the model (they can occur at any internal point of the link and do not have to match with the time simulation step). Thanks to these properties, it is relatively straightforward to explicitly track delivery vehicles' trajectories and reproduce their delivery operations without any approximation error. The ability of accurately tracking deliveries along their routes is important in order to consider carriers' perspective on the problem.

4.5 ALGORITHMS AND OUTPUT

The proposed pseudocodes to perform a network simulation while tracking delivery vehicles traveling across the network and inside each link are described respectively in Algorithm 1 and Algorithm 2. For each simulation time step, the inflows and outflows of each network link are calculated using and the delivery vehicles' positions are updated according to the Network Traffic Model and Parking Model (Algorithm 4). Inside each link crossed by any delivery vehicle, the Delivery Model (in conjunction with the link traffic model) is used to derive the trajectories of the delivery vehicles and their corresponding internal conditions in case of double-parking (Algorithm 5). To illustrate the capabilities of these algorithms, we present the following example of a 5-minutes simulation of two delivery vehicles in a simple signalized network of 25 links. The first vehicle, that enters the network from link 1 after 10 seconds, performs a delivery at link 3 and double-parks (since it is not able to find a parking spot), causing a congestion spillback in the upstream links (Figure 11a). In case of regular parking, such vehicle would not produce any traffic disruption (Figure 11b). The second vehicle that enters from link 16 after 10 seconds, performs a delivery at link 12, while being regularly parked. The impacts of double-parking of the first vehicle are also shown at network level, in Figure 12a-b, where the links' densities for a situation of double-parked and a regularly parked delivery are compared with each other after 2 minutes of simulation. In addition to simulating the traffic flow on each link, the proposed algorithm generates detailed information concerning each delivery tour (Table 11), in the form of vehicle trajectories.

Table 10: Algorithm notation

$\boldsymbol{h} \in \boldsymbol{H}$	*link h in the set of H total links in the network*
$\boldsymbol{j} \in \boldsymbol{J}$	*node n in the set of N total nodes in the network*
$\boldsymbol{z} \in \boldsymbol{Z} \subset \boldsymbol{J}$	*Origin node q in the subset of origin nodes Q*
$\boldsymbol{w} \in \boldsymbol{W} \subset \boldsymbol{J}$	*Destination node w in the subset of destination nodes W*
$\boldsymbol{i} \in \boldsymbol{I_j}$	*Inbound link in the set of incoming links into node n*
$\boldsymbol{o} \in \boldsymbol{O_j}$	*Outbound link in the set of outgoing links from node n*
$\boldsymbol{r_h}, \boldsymbol{s_h}$	*Link h demand and supply flow at time t*
$\boldsymbol{q_{h,i}}, \boldsymbol{q_{h,o}}$	*Actual link h inflow and outflow at time t*
$\boldsymbol{\delta_z}(\boldsymbol{t})\ \forall \boldsymbol{z} \in \boldsymbol{Z}$	*Traffic demand in origin node*
$\boldsymbol{\gamma_w}(\boldsymbol{t})\ \forall \boldsymbol{w} \in \boldsymbol{W}$	*Traffic supply in destination node*
$\boldsymbol{N_{ini,l}}$	*Set of initial conditions of link l*
$\boldsymbol{N_{int,l}}$	*Set of internal conditions of link l*
$\boldsymbol{N}(\boldsymbol{x}, \boldsymbol{t})$	*Moskovitz function at the position x and time t*
$\boldsymbol{v} \in \boldsymbol{V}$	*Vehicle in the set of V (delivery) vehicles*
$\boldsymbol{t_v}$	*Entry time of vehicle v in the network*
$\overline{\boldsymbol{\rho_v}}$	*Route r of the vehicle v (vector)*
$\boldsymbol{d} \in \boldsymbol{D_v}$	*Delivery in the set of D delivery tour of vehicle v*
$\boldsymbol{\sigma_d}$	*Link location of delivery d*
$\boldsymbol{\tau_d}$	*Duration of delivery d*
$\boldsymbol{\theta_d}$	*Position of delivery d*
$\boldsymbol{\varphi_d}$	*Binary variable expressing parked or double-parked delivery*
$\boldsymbol{\Pi}(\boldsymbol{v}, \boldsymbol{h}, \boldsymbol{t}, \boldsymbol{N_{v,l}}(\boldsymbol{t}))$	*Data structure to track vehicles across the network. It contains the label of the vehicle, link position, time entered the link, Moskovitz function corresponding to the vehicle v entering link h*
$\boldsymbol{\Phi}(\boldsymbol{v}, \boldsymbol{h}, \boldsymbol{t}, N, \boldsymbol{\varphi_d}, \boldsymbol{\tau_d}, \boldsymbol{\theta_d})$	*Data structure to track vehicles across the link.*

Algorithm 4: Pseudocode for the simulation of deliveries at network level

```
Input: Network G(h,j), N_{ini,l} ∀h ∈ H, V, R_v, D_v, Π = {∅}, Φ = {∅},
Output: q_{h,i}, q_{h,o} ∀h ∈ H, Π

%check if any truck enters the network
FOR v ∈ V:
    IF t<t_v<t+dt THEN:
        {v, ρ_v(1), t_v} → Π
    ENDIF
ENDFOR
%For each time step of the traffic simulation model:
FOR t:
    FOR j ∈ J:
        FOR i ∈ I_j:
            %check if there is any truck within the link
            FOR k ∈ |Π|:
                IF i= Π(k,2) THEN:
                    Π(k,:) → Φ
                    %check if the truck has just entered the link
                    IF t=Π(k,3) THEN:
                        % obtain the value of Moskovitz function when it enters
                        N_{v,h}(t) → Φ(k,4)
                        % check if the truck has a delivery on the link
                        FOR d ∈ D_v:
                            IF i=σ_d THEN:
                                %run Parking Model to derive whether the
                                truck finds parking or double-park
                                CALL Parking Model (Eq.8-9) → φ_d
                                φ_d → Φ(k,5)
                                τ_d → Φ(k,6)
                                θ_d → Φ(k,7)
                            ENDIF
                        ENDFOR
                    ENDIF
                ENDIF
            ENDFOR
            %run extended link model
            CALL Extended Link Model (see Algorithm 3) → r_i, Φ, N_{int,l}
            Φ → Π(k,:)
        ENDFOR

        FOR o ∈ O_j:
            %run regular link model
            CALL Link Model based on Eq. 6-7 → s_i
        ENDFOR

        IF j ∈ Z THEN:
        %compute inflow for origin node
```

$q_{h,i} = \min\{r_l, \delta_j\} \forall l \in I_j$
ELSEIF $n \in W$ ***THEN:***
%compute outflow for destination node
$q_{h,o} = \min\{s_l, \gamma_j\} \forall l \in O_j$
ELSE:
CALL Node Model (see Algorithm 1)→ $q_{h,i}$, $q_{h,o}$ $\forall h \in H$
END IF
END FOR

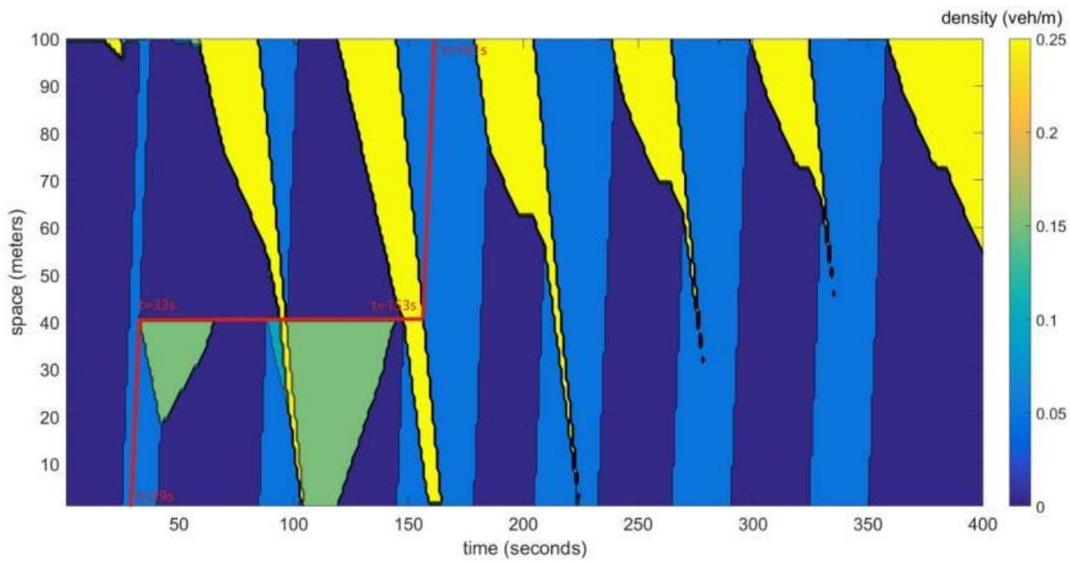
%check if there is any truck leaving any link
FOR $h \in H$ ***:***
FOR $v \in V$***:***
IF $N_{down,h} \geq \Pi(v, 4)$ ***THEN:***
%identify next link in the truck's route and remove it if it is leaving the network
FIND link index k of $\Pi(v, 4)$ ***in*** ρ_v
IF $k < |\rho_v|$ ***THEN:***
$\rho_v(k+1) \rightarrow \Pi(v, 4)$
ELSEIF:
DELETE $\Pi(v, :)$
END IF
END IF
END FOR
END FOR
END FOR

Algorithm 5: Pseudocode for the simulation of Link Model with deliveries
*Input**: t,*** D_v, Φ, ***N(0,[0,t]), N(L,[0,t]),*** N_{ini}, N_{int}
*Output**:*** r_i, Φ, N_{int}

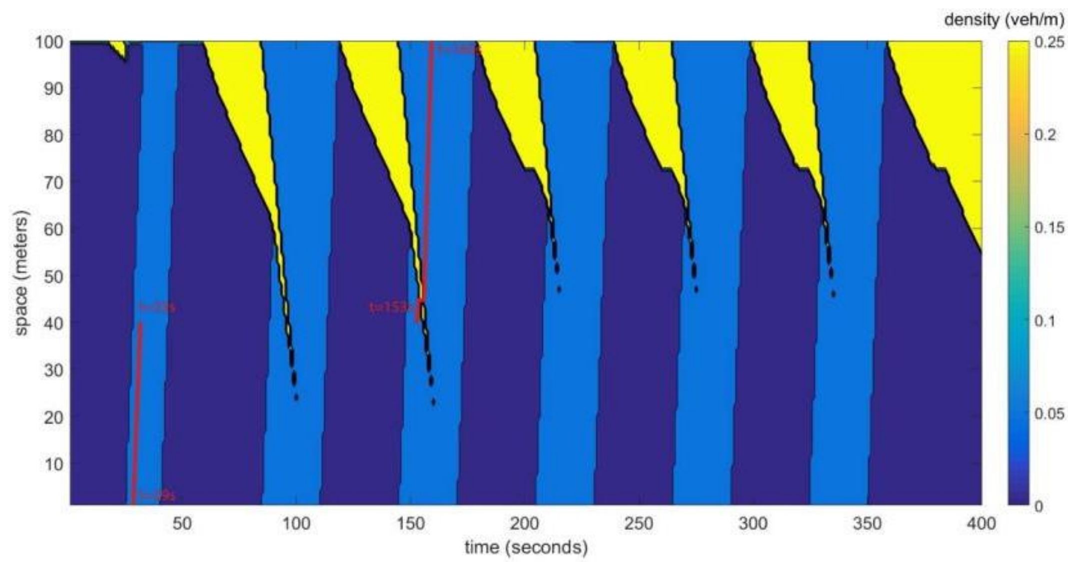
%computation of inflow
Eq.6 → r_i

%check if there are mbs on the link
IF $|\Phi| \geq 1$ ***THEN:***
FOR $j \in |\Phi|$***:***
%check if the mb has a delivery on the link
IF $\Phi(j, :) > 0$ ***THEN:***
%calculate the value of the Moskovitz function at the delivery location
$\Phi(j, 7) \rightarrow \theta_d$
Lax-Hopf Algorithm (Eq. 14)→ $N(\theta_d, t)$
%check if the delivery has started at this interval
IF $N(\theta_d, t) \geq \Phi(j, 4)$ ***THEN:***
%derive exact initial time delivery has started with Bisection Algorithm
Bisection Algorithm → t_{start}
Reset $\Phi(j, 4) = \infty$

```
                                        %check if the vehicle is double-parking
                                        IF Φ(j,5) = 1 THEN:
                                        %check if the vehicle is an active moving bottleneck
                                        Derive N_int based on Eq. 10-11
                                        END IF
                                        %check  if delivery has finished
                                        IF (t − t_start) ≥ Φ(j,6) =THEN:
                                              %calculate new label
                                              Lax-Hopf Algorithm (Eq. 14) → N(θ_d, t)
                                              N(θ_d, t) → Φ(j,4)
                                        END IF
                                  END IF
                            END IF
                      END FOR
                END IF
```

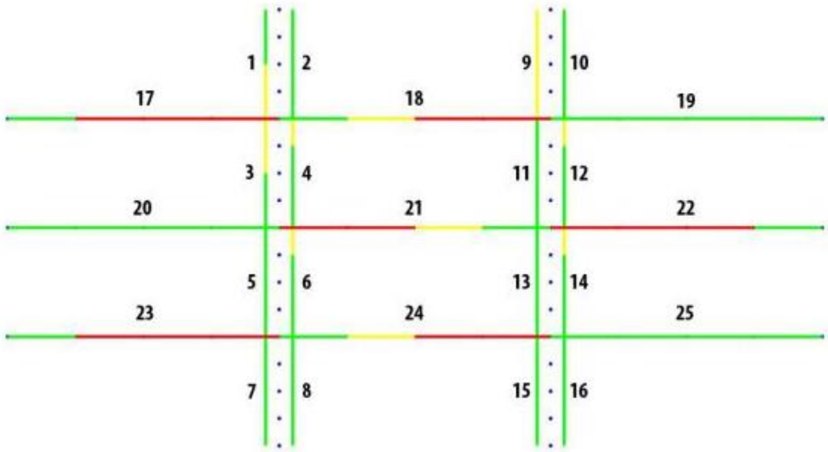


(a)

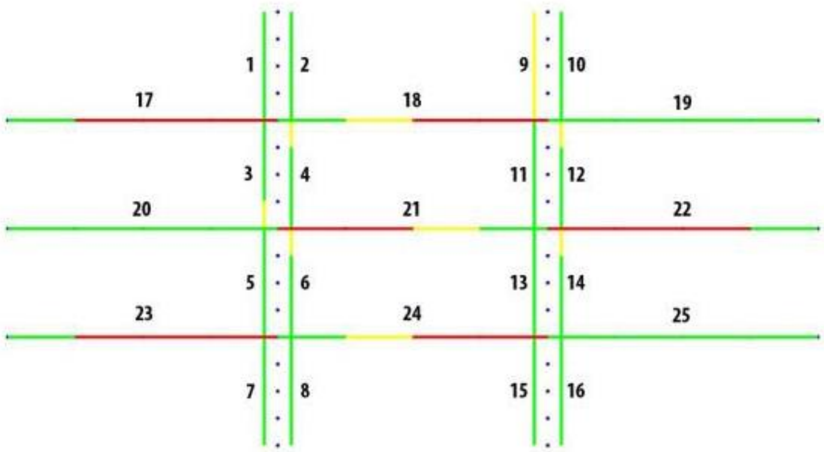


(b)

Figure 11: Space-time-density diagram corresponding to double-parked delivery (a) and regularly parked delivery (b)



(a)



(b)

Figure 12: Network densities at time t=120s corresponding to double-parked delivery (a) and regularly parked delivery (b). Green corresponds to $k/k_c<1$, yellow corresponds to1< $k/k_c<1.5$ and red corresponds to $k/k_c>2$.

Table 11: Delivery tours simulation output

Label	***Entry link***	***Entry time (s)***	***Delivery link***	***Stop location (s)***	***Stop duration (s)***	***Regular parking***	***Exit Link***	***Path***	***Exit time (s)***
1	1	10	3	40	120	No	15	[1,3,5,24,15]	205
2	16	10	12	40	120	Yes	2	[16,14,12,11,21,4,2]	224

4.6 APPLICATIONS

In order to illustrate the potential applications of the developed simulation framework, we present and discuss the results of different simulations representing alternative urban freight distribution scenarios. First, we show the impacts of deliveries on a realistic urban traffic network. Then, by means of the proposed simulation approach, we analyse two possible city logistics solutions: managing the time of deliveries by shifting them to off-peak traffic hours, and managing the curbside space of deliveries by controlling their locations. The first strategy could be achieved by providing incentives or introducing regulations (Holguin-Veras, 2008; Zalewski et al., 2012). One possible way to achieve the second strategy would consist in identifying critical streets or areas where deliveries should be prohibited (Munuzuri et al., 2012). Depending on data availability and information technologies, this measure could be implemented more or less dynamically (in terms of time-windows).

The investigations involve the most central area (about 0.86 square kilometres) of the Austin downtown network (Figure 13). The network is characterized by 201 links and 110 nodes. Each link has between 1 and 3 lanes and the majority of the intersections is signalized (about 90%). For simplicity, in this study, we only model green/red phases and we adopt the same triangular fundamental diagram for all links with: q_{max}=0.4625 veh/s, v=12.5 m/s, and k_j=0.1295 veh/m.

The streets with available regular parking and delivery bays are indicated in Figure 14. Considering the commercial and office land use of the studied area, the occupancy rate of on-street shared parking during the day is assumed 90% between 08:00 and 17:00, decreases to 80% between 17:00-24:00, and reaches 10% between 24:00-06:00 (Litman, 2015).

First, the impacts of different levels of urban freights are investigated during a time window of 20 minutes for an average morning peak hour (8:00-8:20). Information about traffic demand and travel times during different hours of the day is retrieved from the "Bluetooth Travel Sensors - Individual Address Files (IAFs)" (City of Austin Transportation Department, 2017).

Assuming a share between 5%-10% the urban goods traffic in the total traffic (Allen et al., 2014; Nuzzolo et al., 2016) and considering only light-duty and medium-duty deliveries, we simulate a variable number of 25-100 vehicles completing deliveries in the studied area.

Delivery locations and routes can vary considerably depending on type of product (e.g. parcels, groceries) and service provided (e.g. regular VS same day delivery service). In this study, we assume each vehicle to perform a delivery tour with a variable number of stops ranging between 1 and 3 (Punakivi and Saranen, 2001). The delivery tours are calculated by solving a Vehicle Routing Problem (VRP) with fixed origin (entry link) and destination (exit link). The average delivery stop duration is assumed to randomly vary between 1 and 5 minutes based on Munuzuri et al. (2012) and Conway et al. (2016).

Figure 13: Austin downtown network (original source: Google Earth)

Figure 14: Austin downtown regular parking (highlighted streets) and commercial parking (squares)

The effects of delivery operations on traffic flows are measured by three different indicators: the total network efficiency, the average network speed, and the total network delay.

The average network speed $U(T)$ is calculated as a weighted mean of all links' speed u_h calculated at each time step *t* through the simulation T,

$$U(T) = \frac{\sum_t^T \sum_h^H u_h(t) \cdot L_h}{\sum_t^T \sum_h^H L_h} \tag{4.10}$$

where L_h corresponds to the length of link h. The total network efficiency is adopted from Brilon (2000) and expresses the performance of the network as production per time unit, rather than considering demand, capacity and quality of the flows as separate indicators. The Traffic Efficiency is defined as:

$$E = Q(T) \cdot U(T) \quad (4.11)$$

where U represents the average speed (km/h) over the network, and $Q(T)$ the cumulative outflow during the simulation time T(h) measured as:

$$Q(T) = \sum_{h}^{H} \left(N_{down,h}(T) - N_{down,h}(0) \right) \quad (4.12)$$

where $N_{down,h}(T)$ and $N_{down,h}(0)$ correspond respectively to the value of the Moskovitz function at the end and beginning of the simulation, calculated at the downstream end of each link h in the network.

The total network delay $D(T)$, which is expressed as vehicle loss hours is given by the sum of the differences between the cumulative curves of arrivals and departures at each interval Δt, for each link:

$$D(T) = \sum_{h}^{H} \left(\sum_{t=1}^{T} \alpha \cdot \left(N_{up,h}(t + \Delta t) - N_{down,h}(t) \right) \cdot \Delta t \right) \quad (4.13)$$

where α corresponds to an adjustment factor used to correct errors due to time discretizations. The effects of traffic (and indirectly delivery operations) on carriers' efficiency is measured as a proportion of completed tours (where the vehicle performs all the deliveries and exit the network).

4.6.1 Off-peak deliveries

Given the stochastic nature of the parking model, we perform 100 simulation runs per scenario characterized by the same level of freight demand, but with randomized delivery configurations (routes, stops). The time definition (time step) adopted in the simulations corresponds to 2 seconds, which is higher than in most macroscopic network traffic simulations. Each simulation, which is performed on Matlab with a 2.3 GHz processor, requires about 7-10 seconds, depending on the number of delivery operations.

The reference scenario of Austin downtown, during the morning peak, with no delivery is characterized by an average speed of 20.2 km/h, a network efficiency of 65,911 veh-km/h, and a total delay of 382.0 veh-loss hours. For increasing numbers of vehicles performing deliveries in the network, the amount of parking infractions rises and the overall traffic network performance deteriorates significantly, as shown in Table 12. Whereas the available downtown parking supply can accommodate about 39% of the commercial parking demand for a limited amount of deliveries (97 stops), with a 100% increase of freight operations (201 stops) less than 18% of the demand is satisfied.

As expected, changes in traffic performance show a non-linear trend. As the number of deliveries grows, traffic conditions worsen at an increasing rate: an addition of 25 trucks from 75 to 100 has higher impacts than the same increase from 50 to 75. In addition to a general decrease of performance, the overall network travel time reliability diminishes (corresponding to an increase of standard deviation of average speed) as the number of trucks in the system increases. As it is possible to see in Figure 15, the increase of negative skewness indicates a growth of the difference in average network speed between the "worst" and "best" simulations. This corresponds to higher chance of traffic breakdowns (where significant portions of the network are congested) caused by double-parking maneuvres of delivery vehicles.

In line with the traffic results, the efficiency of deliveries seems to be worsened by the delivery operations themselves. The average time to complete one delivery increases by almost 1 minute and the number of incomplete tours increases by about 2% as the number of delivery vehicles entering the network increases from 50 to 100.

Table 12: Impacts on traffic and freight operations of urban freight traffic during the morning peak

	25 trucks	50 trucks	75 trucks	100 trucks
Change of Total Network Delay (%)	0.7	1.6	2.1	3.1
Change of Network Efficiency (%)	-1.1	-1.8	-2.5	-4.4
Change of Average Network Speed (%)	-1.4	-3.1	-4.3	-6.0
Travel Time Variability (σ)	0.739	0.860	0.946	1.026
Average Number of Parking Infractions	34.6	62.1	95.8	133.5
Average Time per Delivery (min)	5.1	5.3	5.6	5.8
Average Incomplete Tours (%)	14.0	14.2	14.9	15.8

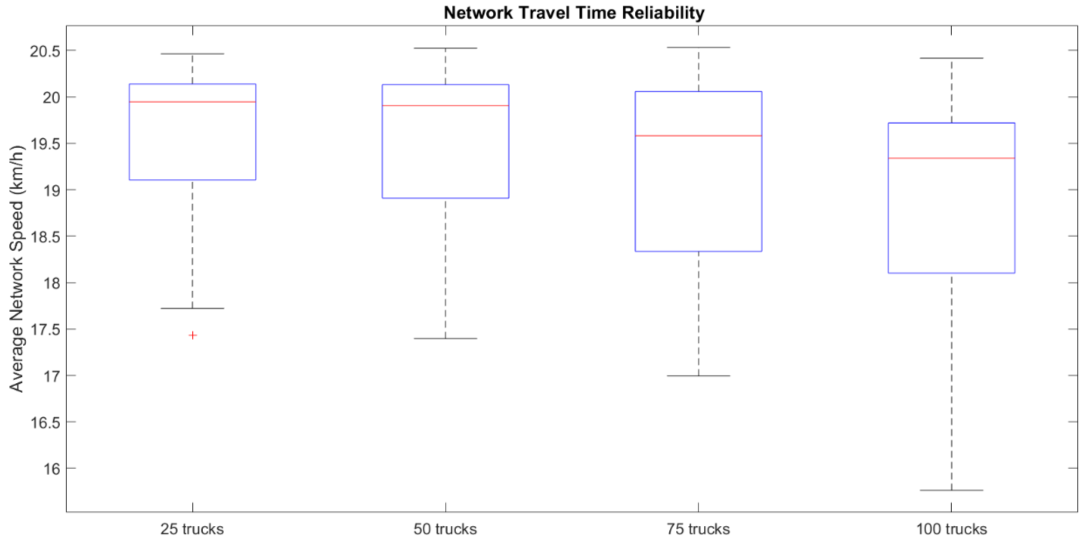


Figure 15: Network travel time reliability for different levels of freight traffic during the morning peak

In order to identify the potential benefits of a shift of delivery operations to the off-peak hours (late evening or early morning), we perform an additional series of simulations for the same levels of freight operations in Austin downtown with nighttime traffic and parking availability. In this case, as shown in Table 13, delivery operations do not yield any significant worsening of traffic conditions (less than 0.2%), regardless of their number. The amount of double-parked operations considerably decreases (by more than 50%) and their impacts are almost none because of the lower levels of traffic. Even for higher levels of freight demand, the average network speed has less than 0.1 km/h variation from simulation to simulation (Figure 16), meaning that the performance of the traffic system is overall stable. This aspect would be particularly important for carriers as reliable travel times would allow for tighter delivery schedules.

The efficiency of carriers' operations is also improved and overall much faster than those in the morning peak (average time for delivery below 5 minutes and about 5% of incomplete tours).

Hence, rescheduling delivery operations from the morning peak hours to off-peak hours, from both traffic and operational efficiency perspective, could determine considerable benefits.

Table 13: Impacts on traffic and freight operations of urban freight traffic during the night

	25 trucks	50 trucks	75 trucks	100 trucks
Change of Total Network Delay (%)	0.0	0.1	0.1	0.2
Change of Network Efficiency (%)	0.0	0.0	0.0	-0.1
Change of Average Network Speed (%)	0.0	0.0	0.0	0.0
Travel Time Variability (σ)	0.013	0.013	0.014	0.015
Average Number of Parking Infractions	12	26	38	55
Average Time per Delivery (min)	4.8	4.9	4.9	4.9
Average Incomplete Tours (%)	4.8	5.8	5.1	4.8

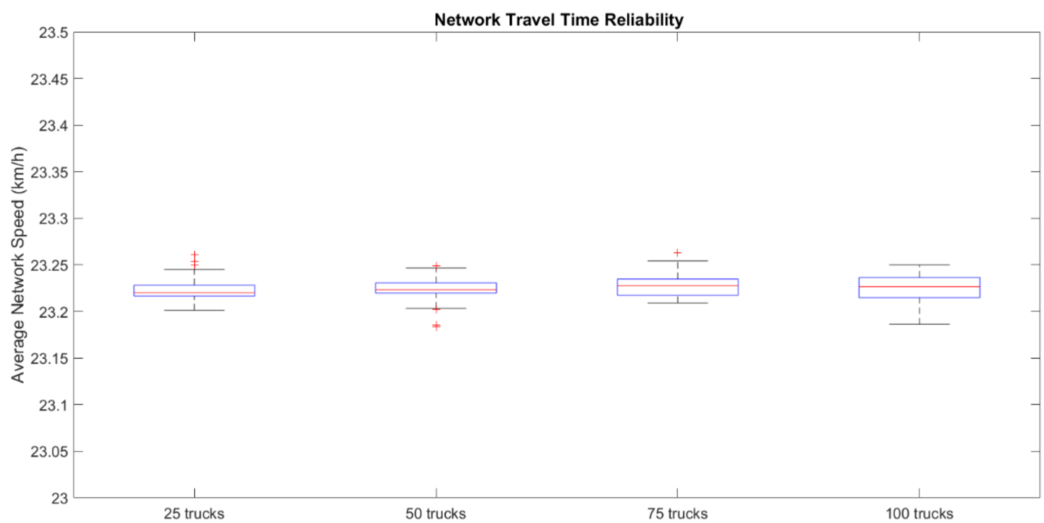


Figure 16: Network travel time reliability for different levels of freight traffic during the morning peak

4.6.2 Delivery interdiction on critical streets

The delivery interdiction on specific links is modeled by modifying the delivery routes with stops on the banned links such that their stop is reassigned to an adjacent link. When the delivery location is modified, the stop duration is increased by 2 minutes per each additional link of distance to account for the increased walking distance between the vehicle and the final destination.

The marginal network effects of restricting deliveries on a single link are investigated by performing a series of network simulations characterized by the Austin morning peak traffic conditions and 100 vehicles performing deliveries within a time window of 20 minutes. In order to provide more reliable results, for each possible link closure to deliveries (only links with 2 or 3 lanes are analyzed) we perform 50 simulations for a total of 6,750 simulations. By means of this procedure, it is possible to map the effects of each link's restriction from deliveries as a change of the average total network speed (Figure 17), although for the majority of the streets, the link's closure determines an overall worsening of network performance (1-3%) because of increased numbers of double-parking infractions and longer stops. However, for about 22% of the analyzed scenarios, the average network speed can be slightly increased by 1-2% (Figure 18). In most of these cases, the improvements occur when the chosen link is characterized by high levels of traffic and its adjacent links can accommodate extra demand. Carriers' delivery performance does not seem particularly compromised by this measure since the delivery tours have similar performance increases and decreases (Figure 19).

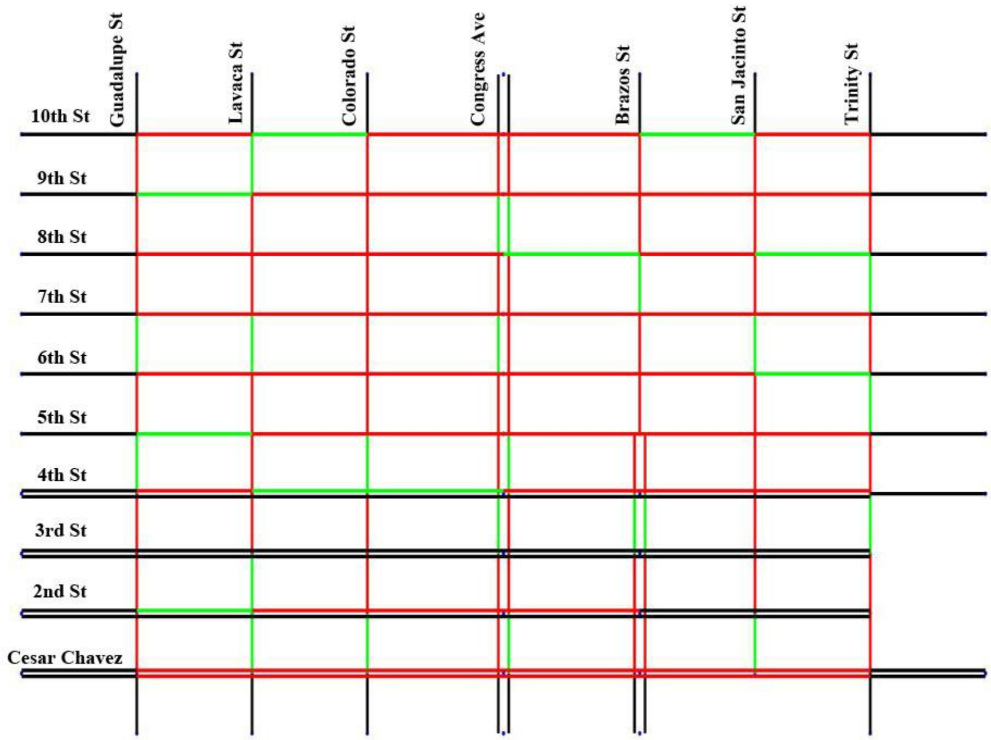


Figure 17: Change of average total network speed per link delivery restriction (red: increase of speed; green: decrease of speed)[2]

[2] Black corresponds to single-lane links that have not been analyzed.

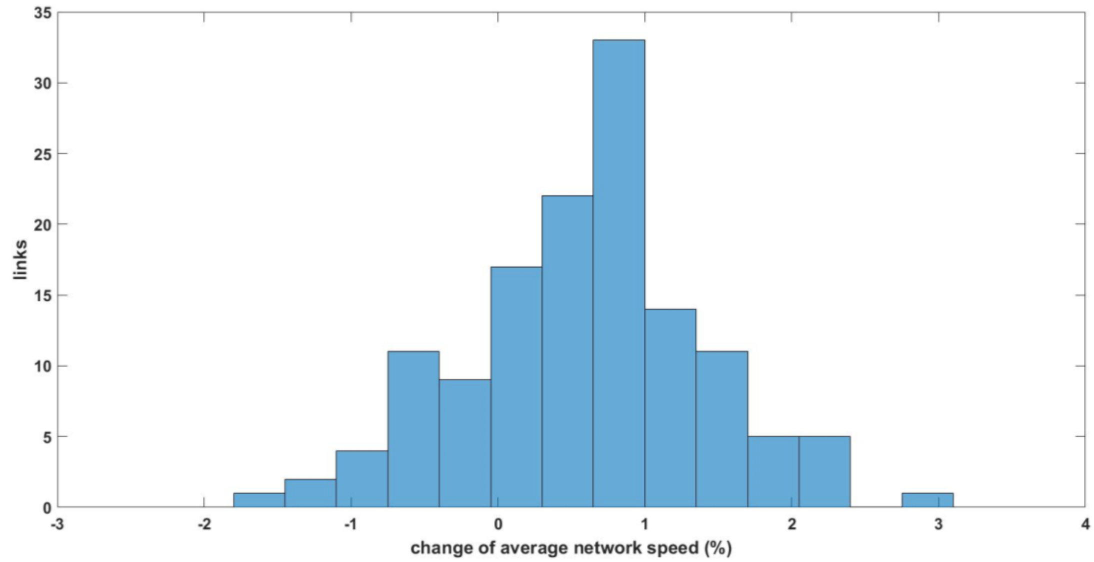


Figure 18: Distribution of changes of average network speed per link restriction

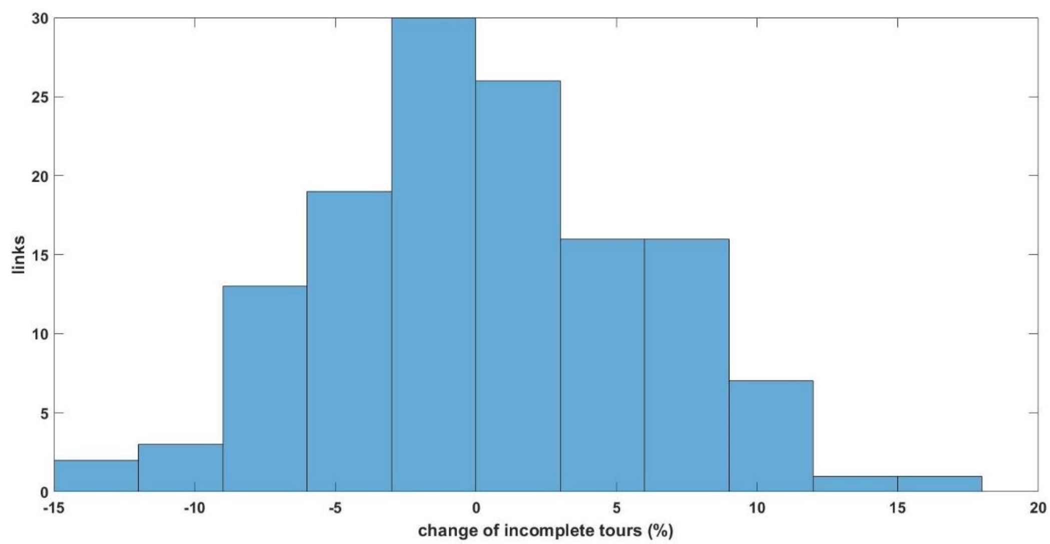


Figure 19: Distribution of changes of incomplete tours per link restriction

Based on the results of this analysis, we investigate the impacts of restricting from deliveries a set including the 5 links that yielded the highest network performance improvements in the previous experiment (Table 14). Interestingly, for high numbers of freight operations (e.g. 100 trucks), the measure does not produce considerable improvements of the network performance (around 0.5%). This result implies that, although the closure of some single links could be beneficial, their effects are not additive when closed in combination with each other. However, as the reduced values of standard deviation indicate, the traffic conditions seem to become more stable. The carriers' performance does not seem to be affected by this measure either, as the average delivery times are unvaried. For relatively low levels of freight demand (below 50 trucks), the benefits of link closure are negligible because of the limited amount of delivery operations on the closed links.

Table 14: Impacts on traffic and freight operations of closure of a set of 5 links from urban freight deliveries

	25 trucks	50 trucks	75 trucks	100 trucks
Change of Total Network Delay (%)	0.7	1.2	1.6	2.8
Change of Network Efficiency (%)	-1.1	-1.5	-1.8	-3.8
Change of Average Network Speed (%)	-1.4	-2.9	-3.6	-5.5
Travel Time Variability(σ)	0.250	0.303	0.280	0.568
Average Number of Parking Infractions	34.6	64.8	96.2	134.5
Average Time per Delivery (min)	5.1	5.3	5.6	5.8
Average Incomplete Tours (%)	14.0	13.2	10.5	16.3

4.7 Conclusion

Urban freight movements have a negative impact on the transportation network because of their lower speed, their reduced maneuverability, and their frequent stops for deliveries. Conversely, high levels of traffic delay truck deliveries and compromise the performance and reliability of freight distribution, ultimately increasing the overall cost of the carriers. The main challenge is that the supply in terms of road and curbside capacity does not usually meet the overall demand of different modes (cars, trucks, buses).

It is important to employ simulation tools that can provide accurate insight into traffic dynamics and delivery operations to properly evaluate policy and traffic management solutions. In this study, we present a (dynamic) traffic simulation framework designed for the analysis of the impact on urban freight operations. Its main characteristic exists in the hybrid nature as it reproduces general traffic behavior at a macroscopic level (LWR model) and urban freight operations at a microscopic level (vehicles are tracked along their routes). The framework leverages on the mathematical properties of the Lax-Hopf solution method of LWR model to compute traffic flows and obstructions created by delivery vehicles that are considered temporary fixed bottlenecks. This simulation framework can effectively reproduce traffic dynamics, such as triggering of congestion, queue spillbacks and interactions with traffic signals all together. Thanks to the high efficiency of its solution method, it can be easily implemented on large networks without having to worry about computational effort (with simulation time in the order of seconds). At the same time, the possibility of tracking vehicles in detail allows a realistic reproduction of the delivery process: operations can occur at any time and point of the link without relying on any space-time discretization. The traffic simulation model can be integrated with any generic (discrete) parking model in order to reproduce delivery vehicles' parking behavior in consistency with the infrastructure supply and demand. In future research, the accuracy of parking behavior could be improved by accounting for traffic patterns, time of day and land use. Furthermore, application of the simulation to real-world case studies would require more detailed information about freight and passenger parking demand from surveys and land-use data.

Thanks to its features, the proposed framework is particularly suitable for the evaluation of City Logistics measures on large networks of both traffic impacts and efficiency of delivery operations. We show that by investigating the impacts of two possible measures for a realistic scenario of downtown Austin: first, moving urban freight delivery traffic from the morning peak to the off-hours, and second, prohibiting deliveries on certain streets. The results of several tests with different freight demands confirm how shifting part of the traffic from the morning peak to the late evening-early morning hours would be beneficial for both a traffic and operational efficiency perspective. Restricting streets from deliveries yields less straightforward outcomes. While, in the majority of cases, closing a link is detrimental, for some vulnerable links, this solution could determine slight improvements. Nonetheless, this strategy does not yield significant improvements for larger sets of links.

The findings from the first application's experiment are in line with the previous literature. The outcomes of the experiments of the second application highlight the complexity of urban freight operations and suggest that the impacts of links closure depend on several factors like network morphology, traffic demand and interactions among delivery operations.

Like nearly all first-order traffic flow models, the single commodity LWR is not suitable to model particular aspects of traffic (acceleration and deceleration, lane-changing) and to reproduce highly mixed traffic flows (with a large freight component of total traffic). Hence, the proposed framework would be mainly suitable for reproducing the effects of a limited fraction of the total traffic demand.

Future work will deal with the application of this framework in more advanced urban freight traffic management and freight transport systems, involving optimization problems and real-time control strategies.

5. POTENTIAL IMPACTS OF CROWDSHIPPING SERVICES: A SIMULATION-BASED EVALUATION

This chapter is currently under review in *Transportation* as “Potential Impacts of Crowdshipping Services: a Simulation-based Evaluation” by Simoni et al (2019).

The authors confirm the contribution to the paper as follows: Study conception and design: Simoni, M.D., Marcucci E., and Gatta, V.; Data collection: Simoni, M.D., Marcucci E., and Gatta, V.; Analysis and interpretation of results: Simoni, M.D.; Manuscript preparation: Simoni, M.D., Marcucci E., Gatta, V., and Claudel, C.G.

5.1 INTRODUCTION

Freight transportation plays a fundamental role in the economic development of cities, but, at the same time, it threatens their livability given the increased road congestion, environmental impacts, and energy consumption. A crucial challenge to sustainable urban freight distribution is represented by the rise of e-commerce and door-to-door services that are determining significant changes in the delivery process.

Overall, more direct-to-consumer deliveries are likely to cause lower freight consolidation because of the smaller loads and more frequent deliveries (Taniguchi and Kakimoto, 2003). This shift would inevitably generate a worsening of traffic and parking conditions, given the already limited road network capacity (even though some car shopping trips might be replaced). The growth of e-commerce at double-digit rates[3] calls for action in the near future to address the efficiency of the process and to internalize e-commerce’s negative externalities. In fact, the European Union is actively promoting research aimed at developing sustainable solutions to growing on-demand logistics (Horizon 2020). The phenomenon of online selling is revealing new challenges for private stakeholders as well, especially for couriers and parcel carriers, as they are confronted with rising “last-mile distribution costs”. Because of its low efficiency, the last mile represents the weak link

[3] Around 10% annually in countries like Germany and the US, and more than 25% in Asian countries like China and India according to Capgemini (2013)

of the supply chain, accounting for up to 50% of the total costs in the parcel delivery market (Dablanc and Rodrigue, 2017).

In recent years, the emergence of sharing economy models has enabled novel alternative services for parcel delivery, such as the "crowdshipping," consisting of a declination of the "crowd sourcing" concept applied to the field of logistics. People can act as non-professional couriers and deliver small items for a monetary compensation (McKinnon, 2016; Rai et al., 2017). In crowdshipping, individuals traveling to a certain area can perform deliveries on their way, and businesses could rely on them to accomplish part of their deliveries. Such integration of personal and freight transport is based on a matching process between demand (for deliveries) and supply (of transportation) through on-line platforms.

Crowdshipping can be implemented in different ways. Like in most of existing services, "crowdshippers" can pick up a parcel and deliver it to the final customers by using privately owned means of transportation (typically a car). Alternatively, crowdshippers can utilize existing public transit services. Due to several factors including the employed mode, the length of detours, and parking behavior, the societal effects of crowdshipping are still uncertain.

From the perspective of logistics companies, this solution seems promising for improving efficiency and meeting the growing demand for faster and cheaper home deliveries. Costs can be reduced thanks to a better use of spare capacity, a potential reduction of delivery trips (Miller et al., 2017), and a more flexible and cheaper on-demand workforce (Punel et al., 2018). In the U.S., some recent successful examples of crowdshipping are the delivery platforms like Deliv, Hitch, and Amazon Flex (Dolan, 2018). However, it is uncertain whether this service could easily scale up to large shares of the freight distribution market (especially for bigger or more expensive items).

From the perspective of public authorities, crowdshipping could be beneficial if properly integrated with existing movements and depending on the mode used by the crowdshippers. Ideally, freight trips would need to be replaced by public transit, walking, and bike trips (Marcucci et al., 2017). If crowdshippers rely on their own vehicles instead, the final number of delivery trips could be reduced only by means of an efficient consolidation and coordination of existing flows. Detours need to be minimized in order to reduce congestion and greenhouse emissions (Paloheimo et al., 2016). However, as often occurs in popular platforms for on-demand transportation services, crowdshippers might provide the service by engaging in new dedicated trips rather than by modifying existing ones (Sampaio et al., 2018). This rebound effect might result in overall worsened conditions (Qi et al., 2016).

Most of the research on crowdshipping has focused on identifying the determinants of the adoption and on modeling preferences for this service (See Section 2). With the exception of a few studies (Paloheimo et al., 206; Buldeo-Rai et al., 2018), no analyses of crowdshipping externalities have been performed. The main contribution of this chapter is to provide a systematic investigation of crowdshipping from a "supply perspective," by analyzing its impacts on congestion and emissions, according to different operational features of the delivery process. In order to do that, we perform a dynamic traffic simulation-based analysis of alternative implementation frameworks. The chapter analyses externalities of crowdshipping services based on private transport or public transit, different levels of matched demand, together with crowdshippers' trip detour and parking behavior.

Dynamic traffic simulation is a valuable resource for providing an accurate indication of traffic and environmental impacts of freight policies. Here, the simulation framework adopted, is consistent with the dynamics of congestion and reproduces delivery operations as temporary fixed-bottlenecks in case of double-parking. Its hybrid nature allows for large-scale analyses and, at the same time, detailed investigations of individual delivery tours and crowdshippers' deliveries. Thanks to this approach, freight related emissions can be accurately estimated at link-level.

The second contribution of this study is to investigate the effects of crowdshipping in a realistic large-scale scenario, by accounting for realistic traffic conditions, availability of commercial bays, and freight demand. For this purpose, simulations are performed for the implementation of crowdshipping in the city center of Rome. The city is very active in finding the most appropriate logistics solutions. This is evidenced by the upcoming Sustainable Urban Mobility Plan where innovative strategies, such as crowdshipping will be considered among the possible interventions.

The interest in this issue is also confirmed by recent research studies already performed in Rome (Marcucci et al., 2017; Serafini et al., 2018).

In this chapter, after a brief presentation of previous research on crowdshipping, we provide a description of the methodological approach used for the evaluation and a description of the case study of Rome. In the second part of the chapter, we present the analysis of alternative scenarios, suggest some policy recommendations and draw conclusions.

5.2 Related Research

Understanding user response to crowdsourced delivery services and developing efficient implementation frameworks is fundamental to measuring external impacts, controlling unintended effects, improving business models and establishing a sustainable service. The body of literature on the topic of crowdshipping is quite limited due to its novelty and the lack of operational and behavioral data.

From a behavioral perspective, it is important to investigate crowdshipping acceptability from both the supply and demand side. Marcucci et al. (2017) investigate attitudes and conditions that might favor participation in crowdshipping initiatives. They perform a survey in the city of Rome, administering a questionnaire to 200 students who can be considered as "early adopters/providers." Results show that there is a large potential consensus in terms of both receiving goods via a crowdshipping service and acting as crowdshippers. Moreover, interviewees require a proof of crowdshipping sustainability to support it. In the same geographical context, Serafini et al. (2018), focusing on crowdshipping services deployed using the public transport network, perform a stated preference survey to identify the most important levers of acting as a crowdshipper. A sampling of metro users have been interviewed and results from discrete choice models reveal that crowdshipping can be a reliable solution to a substantial number of delivery requests. Stated preference data have been used also by Punel and Stathopoulos (2017) who explore "senders' acceptability towards crowdshipping" compared to traditional shipping options. Findings from a US sample suggest the presence of heterogeneous preference patterns more in terms of driver performance attributes than for socio-demographics. Using the same data, Punel et al. (2018) focus on the differences between crowdshipping users and non-users, providing managerial suggestions to logistics companies that help in tailoring the system. Miller et al. (2017) analyze the potential willingness to work as traveler–shipper based on a stated preference survey to a sample of US private car commuters. Results show that specific segments are more prone to crowdshipping and, overall, an increasing marginal rate of payment is needed for longer trips.

From an optimization perspective, some studies have investigated the implementation of crowdshipping in order to improve efficiency of the delivery process. Archetti et al. (2016) consider the addition of occasional drivers (crowdshippers) as a variant of the classical capacitated vehicle routing problem. Wang et al. (2016) formulate the crowd-logistic optimization problem as an extension of a network min-cost flow problem. Kafle et al. (2017) propose a crowdsourced system based on bids and relay points. Arslan et al. (2018) investigate the matching of tasks, drivers, and dedicated vehicles in real time adopting a new variant of the "dynamic pickup and delivery problem" (Savelsbergh and Sol, 1995).

From the perspective of city authorities, Paloheimo et al. (2016) analyze the environmental impacts of a trial crowdshipping library delivery service in Finland and identify an overall reduction of carbon footprint. The fact that a considerable part of crowdsourced delivery trips were done by bike played a significant role in reducing resource use and carbon emissions. Buldeo-Rai et al. (2018) perform a document analysis in combination with interview approach to investigate the externalities of an operational crowd logistics platform in Belgium. Since crowdshippers mainly rely on motorized modes and over half of the crowdshipping deliveries are made by means of dedicated trips, the service does not achieve an overall reduction of external costs.

No study has systematically analyzed the potential impacts of alternative implementation frameworks on traffic and pollution (Table 15). Replacing delivery trips with crowdsourced public transit users would clearly have positive repercussions on environment and traffic. Substituting traditional deliveries with car trips instead depends very much on the possibility of exploiting existing vehicle movements and levels of detour (McKinnon, 2016). In addition, consolidating delivery tours and introducing crowdshipping deliveries at different times of the day could have different impacts, depending on traffic conditions. In this study, by means of a simulation approach, we explicitly consider the influence of all these factors.

Table 15: Qualitative comparison of potential impacts from different delivery frameworks

Framework	Carriers' efficiency	Environmental impacts	Congestion impacts
Regular delivery	Depends on traffic	High	High
Crowdsourced delivery by public transit user	Depends on transit quality of service	Low	Low
Crowdsourced delivery by car user	Depends on traffic	variable	variable

5.3 Modeling and Analysis Approach

The impacts of alternative crowdshipping solutions are investigated by means of dynamic traffic simulation. This approach allows for a detailed representation of the evolution of freight movements (based on congestion) and their interactions with passenger traffic. For each link of the road network, and time interval, it is possible to estimate traffic condition indicators, such as travel times and queues.

In this study, we extend the hybrid simulation framework proposed by Simoni and Claudel (2018) where traffic behavior is macroscopically reproduced at network level, while delivery movements are represented microscopically. Based on the features of this framework, one can reproduce and investigate the impacts of delivery operations on traffic (Section 3.1) and related environmental effects (Section 3.2). The hybrid framework is enhanced to reproduce different crowdshipping services by means of a dedicated simulation module (Section 3.3).

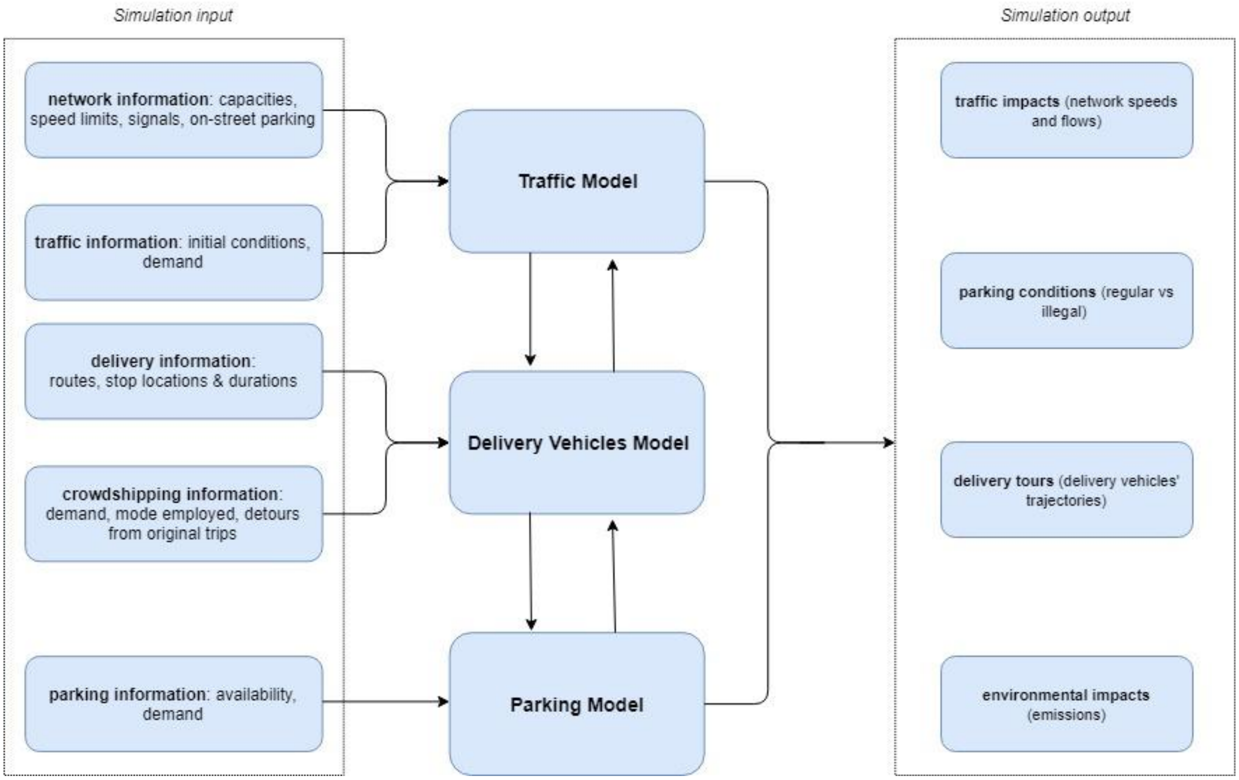


Figure 20: Overview of the simulation framework adopted to evaluate crowdshipping

5.3.1 Traffic and parking

The impacts of freight operations on urban traffic are measured by means of a simulation framework that derives dynamics of traffic flows based on general network characteristics (lanes, speed limits, signal settings) and traffic conditions (traffic demand). Passenger traffic flows are simulated by means of the macroscopic LWR model (Lighthill and Whitham, 1955; Richards, 1956) where road traffic is assumed to follow the main properties of fluid streams. Such a model fairly reproduces traffic congestion phenomena like queue formation and spillback in urban networks, where traffic flow dynamics are mainly determined at (signalized) junctions (Papageorgiou, 1998). A Hamilton-Jacobi partial differential equation (PDE) formulation of the LWR model is solved by using a recent extension of the Lax-Hopf formula (Fast Lax-Hopf) proposed by Simoni and Claudel (2018). This algorithm is suitable for simulation of large traffic networks given any initial and boundary conditions.

Freight movements are reproduced as moving bottlenecks (Gazis and Herman, 1992; Newell, 1993; Munoz and Daganzo, 2002) traveling across the network, which become "temporary fixed bottlenecks" when they perform deliveries. In order to account for the contribution of freight movements to the overall levels of traffic on the network, boundary conditions at the entry links of the network are increased to reflect the additional freight vehicles entered in the network. In addition, the original traffic simulation algorithm is updated such that turning proportions at the nodes are dynamically updated when in the presence of trucks. This approach is in line with the LWR model as it respects the mass conservation law. Based on that, one can explicitly account for the movements of delivery vehicles at each junction, and ultimately reproduce the effects on overall traffic levels of different trip lengths and delivery routes. Since, in this study, delivery vehicles are assumed to have maximum speed equal to 'regular' traffic, the main traffic obstruction occurs when the commercial vehicle stops at the curbside for delivery operations in case of an unavailable dedicated parking place. Each time the vehicle enters the link of delivery, a "parking routine" is performed to check whether there is any unused commercial bay. In case of unavailable parking, the vehicle stops and double-parks, rather than cruising to find an alternative location for the stop. The tendency to illegally park is a rather reasonable assumption as carriers mainly care about proximity to the destination (Amer and Chow, 2017) and typically transfer the overall costs of fines to customers (Hawkins, 2013; Stock, 2014).

Information about parking availability and parking demand for each road of the network need to be provided as simulation input. An example of simulation of illegally parked delivery operation (and its effect on surrounding traffic) is illustrated in Figure 21. During the delivery operation, the vehicle obstructs road's capacity and, when density (of regular traffic) is high enough, it triggers congestion that propagates upstream. Given this level of detail, a large amount of information on forthcoming deliveries (routes, location and duration of stops) is required in order to perform simulations.

Traffic impacts of crowdshippers relying on personal vehicles are modeled similarly to those of delivery vehicles, where the main congestion events are triggered by capacity reductions due to delivery operations. To the best of our knowledge, there are no studies on parking behavior of crowdshippers. It is reasonable to think that crowdshippers would be more inclined than regular drivers to perform deliveries while illegally parked, but also less willing to risk fines than professional commercial drivers who are not (usually) directly affected by parking tickets. Since performing a detailed investigation of crowdhippers' parking behavior goes beyond the scope of this study, here we consider alternative parking attitudes (see Section 4).

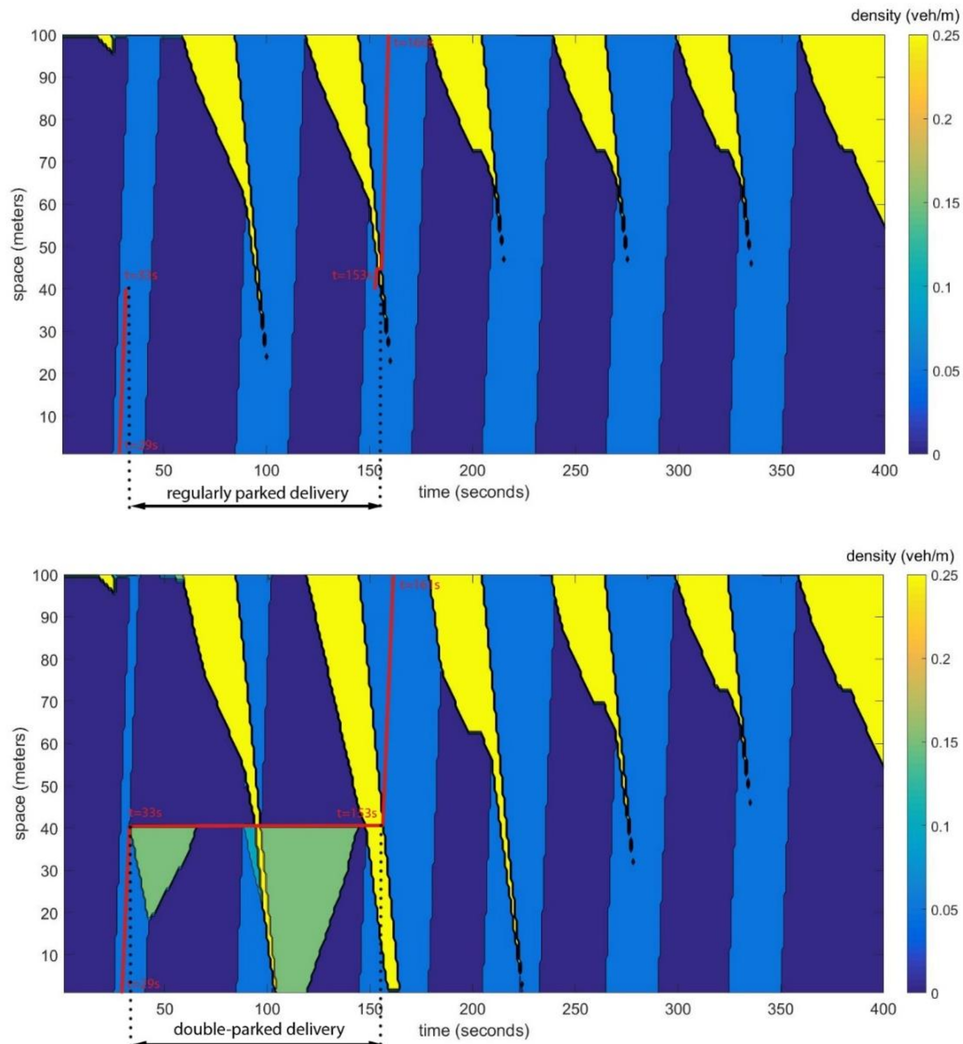


Figure 21: Space-time-density diagrams representing traffic flows in case of (above) regularly parked delivery (below) and double-parked delivery

5.3.2 Carriers' last mile delivery and crowdshipping services

In this study, we evaluate the adoption of crowdshipping for a same-day parcel delivery service performed by carriers in a central area (See Section 4). The last mile delivery process is modeled in three alternative ways: by means of a "traditional" (i.e., existing) delivery service, and by means of two alternative crowdshipping frameworks: a "car-oriented" service and a "public transit-oriented" service, both of which can be integrated into the original one.

In the traditional process, the delivery tours of each commercial vehicle are explicitly modeled by identifying the minimum cost routes given a list of daily customers and the carrier's depot. The problem is formulated as a TSP where the total distance traveled is minimized by adopting Dantzig-Fulkerson-Johnson (DFJ)'s formulation (Dantzig et al., 1954). The obtained routes are then fed into the simulation model.

In the car-oriented crowdshipping service, the driver picks up a parcel from a dedicated pickup station and performs the delivery with his own private vehicle. This type of facility would correspond to depots or stores located in the periphery of the city. In this study, the crowdshipper can perform this service by modifying an existing trip or by means of a stand-alone trip.

In the public transit-oriented service, crowdshippers are existing public transit riders, who pick up parcels at dedicated facilities (e.g., lockers) located at the exit of metro stations or in the surroundings of major transit line stops.

Although it is possible for crowdshipping companies to integrate different delivery modes, for the scope of this study we simulate the two separately. Congestion and environmental impacts of the two services are clearly different. While crowdsourced deliveries made by public-transit users have no direct congestion or environmental externalities, crowdsourced deliveries performed by car users affect traffic and emissions to a different extent, according to factors like the detour from the origin and destination of existing trips, generation of dedicated delivery trips, and parking behavior.

In this study, we assume traditional deliveries could be replaced by a crowdsourced delivery if in the service range for drivers or public transit users. The maximum range for crowdshippers is an exogenous variable that is likely to be determined by the "matching procedure" between demand and supply for crowdsourced deliveries. In this study, crowdshippers and deliveries are considered "matched" *a priori*. A centralized system would dynamically assign delivery orders to crowdshippers, based on their availability and compensation, and depending on customers' willingness to pay.[4] The reader is referred to Wang et al. (2016), Archetti et al. (2016), and Arslan et al. (2018) for novel formulations of the crowdsourced delivery optimization problem. The time required for transshipment operations at pickup stations and depots are not explicitly considered in the model, as we focus on the last mile of the delivery process. In both traditional delivery and crowdshipping services, no delivery failure is considered.

In order to reproduce the crowdsourced delivery process, we embed into the original simulation framework a new algorithm that derives crowdshippers delivery trips (based on randomized existing ones) and integrates them in original delivery framework (by replacing and consolidating existing trucks' tours) based on different input parameters (Algorithm 1). First, customers switching to crowdshipping services are chosen from the original set following a binomial distribution based on the matched levels of demand (input). In case of a transit-oriented service, crowdshipping customers are assigned to the closest transit station. In case of a car-oriented service, customers of the crowdshipping service are assigned to a driver who deviates from his or her original trip in accordance with a maximum detour constraint, and whose new route is fed into the simulation. Original delivery routes are updated in order to account for the different configuration, and in case of significant reduction of customers served (more than 50%), they are also merged together (consolidation) (Figure 22).

Algorithm 6: Pseudo-algorithm for integration of crowdshipping into the simulation framework

Input: ***matched crowdshipping demand (y), initial routes of carriers (ρ_v), delivery sets (D_v), PT stations (Φ), range (r), maximum detour (δ)***

---

[4] This is, indeed, the typical task of crowdshipping platforms. See, for example, *Take My Things* in Italy (www.takemythings.com) and *Hitch* in the US (http://www.hitchit.co/#home).

Ouput: ***new carriers' delivery tours ($\rho_{v'}$), crowdshippers' trips (c_s(o,d))***

% generation of a set S of crowdshipping customers based on crowdshipping demand level y

$\boldsymbol{S = C(n \cdot y, 1)}$

%if crowdshipping is public transit(PT) oriented, assign customer s to the closest PT station (if any)

FOR each s in S:

  FIND φ in Φ such that min(dist{φ, s}):

   IF min(distance{φ, s})≤ r:

    s→s_φ

%if crowdshipping is car oriented, assign detour length τ

FOR each s in S:

$\boldsymbol{\tau = \gamma(0, \delta)}$

%Generate crowdshippers' original trips

FOR each s in S:

  ADD c_s(o,d) such that dist{o,s}+dist{s,d}-dist{o,d} = τ

%update original routes into $\boldsymbol{D'_v}$

FOR d in D_v:

  IF d ∉S:

   ADD d to D'_v

%if number of customers in two routes is lowered by 50% or more, merge them

IF $|D'_v| < 0.5 \cdot |D_v|$:

  ADD D'_v to set V':

    IF $|V'|$==2:

%recompute optimal route $\boldsymbol{\rho_{v'}}$ for new delivery lists

TSP(D_v)→ $\rho_{v'}$

TSP(V')→$\rho_{v'}$

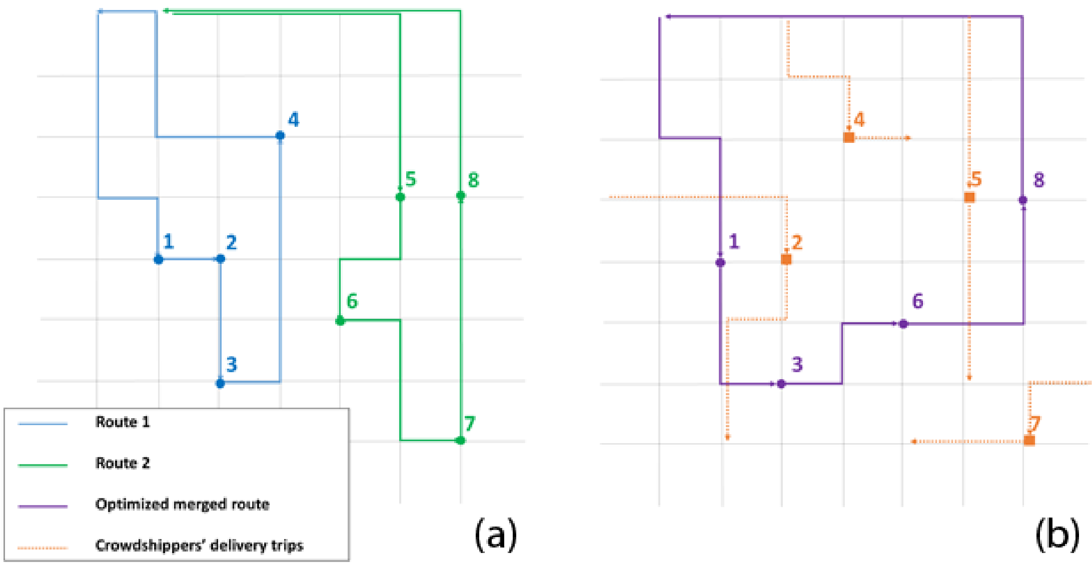


Figure 22:Replacement of truck deliveries by crowdshippers and merging of routes process

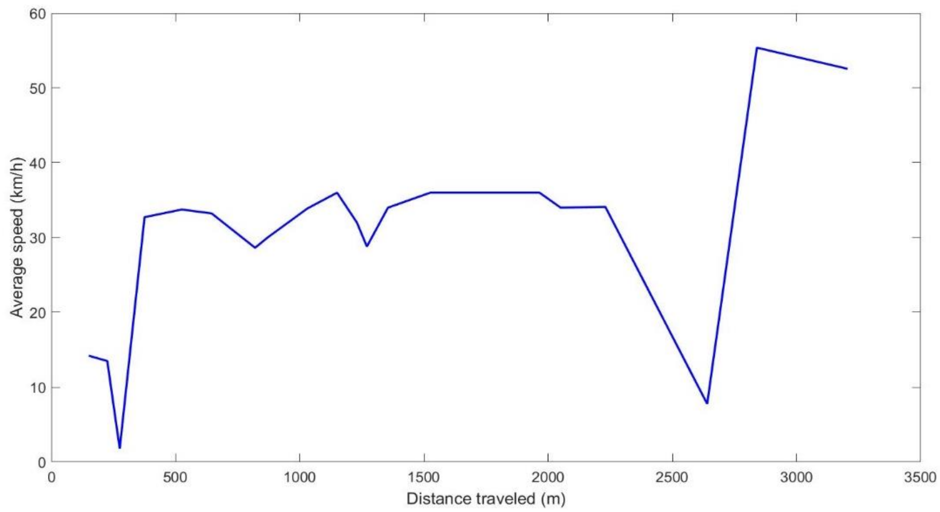
5.3.3 Emissions

The modeling of air pollution emissions due to freight-related movements includes widely used pollutants for measuring air quality standards: CO, NO_x and PM_{10}. These pollutants are derived as a function of the travel speed and distance traveled by each commercial vehicle. Thanks to the adopted hybrid simulation approach, it is possible to identify for each delivery vehicle the emissions produced along its route (Figure 23).

The impacts of travel speed and vehicle technology are derived from an analytical relation proposed by the UK Transport Research Laboratory (Boulter et al., 2009) to obtain the amount of pollutant produced at link level based on the average speed and vehicle's typology. Hence, the cumulative production of pollutant per vehicle P_d (in grams), produced on its delivery route R can be calculated as the following 4th order polynomial function:

$$P_d = \sum_{r \in R} \left[\frac{(a + b \cdot v_r + c \cdot v_r{}^2 + d \cdot v_r{}^3 + e \cdot v_r{}^4 + f \cdot v_r{}^5 + g \cdot v_r{}^6)}{v_r} \right] \cdot d_r \qquad (5.1)$$

where v_r corresponds to the average speed of the vehicle on link r (km/h) of length d_r (km), and the coefficients $\{a, b, c, d, e, f, g\}$ corresponds to empirically derived parameters according to pollutant and vehicle typology. The effects of greenhouse gas emissions (CO_2) are derived based on emissions of the other pollutants that are oxidized in CO_2 by considering them as a constant (Boulter et al., 2008). The resulting speed-emission curves are similar to that of Barth and Boriboonsomsin (2008), which is characterized by a parabolic shape where higher emission rates are determined by low speeds (because of stop-and-go conditions) and higher speeds (because of the higher engine load requirements).



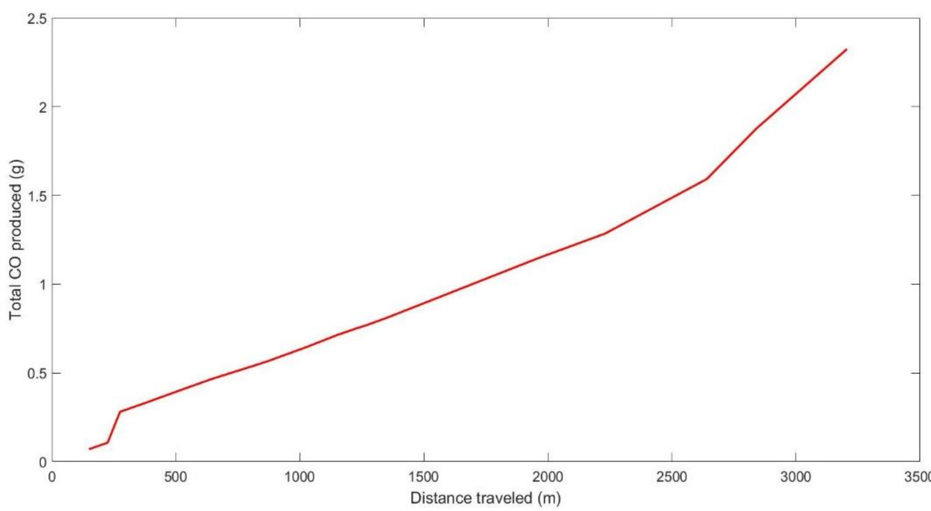


Figure 23: Average speed during a vehicle's delivery tour (above) and corresponding cumulative CO emissions (below).

5.4 CASE STUDY

The impacts of two alternative crowdshipping services are investigated in comparison to a "**Base Scenario**" that corresponds to a realistic simulation of traditional parcel distribution in Rome's freight restricted traffic area (Figure 24a). Despite the access restrictions, the studied area, which accounts for about 73,000 inhabitants, is characterized by serious congestion issues due to an undersized public transport network and a strong car dependency (Marcucci and Gatta, 2017). TomTom (2016) data rate Rome as the 27th most congested city worldwide, with a congestion score or (average) extra travel time of 40%. In this study, we consider only the most central portion of the restricted area (about 5 square kilometers). The simulation's adopted network includes 411 aggregated links with detailed information regarding signalized intersections, number of lanes, and speed limits (Figure 24b). The public transit network considered includes the two major subway lines (Line A and Line B) and 1 tram line (Line 8) with respectively 7 and 3 stops inside the studied area (Figure 24a).

As discussed in more detail in Section 5, in order to account for the influence of traffic and parking conditions on freight externalities we perform network simulations of 60 minutes corresponding to two different times of the day: 10-11 AM, and 2-3 PM. While parking availability in the area is constant throughout weekdays' working hours, during the morning interval the average network speed is about 10% lower than in the afternoon interval.

The simulations are calibrated with real data obtained from the Mobility Agency of Rome, by means of a heuristic optimization process based on a genetic algorithm where the fitness function corresponds to weighted combination of average speed and volume errors (Cheu et al., 1998). The adopted stopping criteria corresponds to a GEH Statistic lower than 5 for 85% of the links, as suggested by the UK Highways Agency's Design Manual for Roads and Bridges (Highways Agency, 1996) modeling guidelines. The resulting simulations are validated by comparing the average travel times between 20 randomly chosen origin-destination couples in the network with estimates from Google Traffic (Google Traffic, 2018). Information about parking infrastructure and parking conditions is obtained from the Municipal Police in Rome, according to which illegal occupancy of loading/unloading bays is around 90%.

In this study, we consider the possibility of adopting crowdshipping services only for packages ordered online. The volume of online ordered parcels distributed in the studied area, based on an on-line daily purchase rate of 2.62% per inhabitant (Serafini et al., 2018), is estimated at 3,500 parcel deliveries per day.

In order to gather additional information about parcel distribution and delivery operations in the area, a set of interviews with major carriers was carried out in connection with the activities performed for the Sustainable Urban Mobility Plan in Rome. Different questions ranging from strategic aspects of delivery tours (stops, length, and times) to operational details (availability of commercial bays) were asked of 12 leading delivery companies operating in the studied area. Based on the collected information, carriers' deliveries and vehicles' delivery tours were modeled as follows: each daily tour accounts for 50 stops corresponding to about 60 deliveries for a total distanced traveled of 60 km (from the main depot); each delivery requires a stop of 3 minutes. These values are in line with Allen et al. (2017), who estimated 72 customers per round and 4 minutes per delivery.

To calculate emissions, we consider delivery light vans for traditional delivery services (category Euro IV) and petrol car Euro IV for crowdshippers. This category represents the largest share of circulating vehicles in Rome (Comune di Roma, 2016).

An investigation of the conditions for public transit passengers to act as crowdshippers and for people to receive goods with crowdshipping (Serafini et al., 2018) is used as a main reference for the implementation of crowdshipping in Rome. Here, crowdshipping demand/supply is estimated and compared, revealing the potential feasibility of this distribution system for different scenarios. In this study, parcels delivered by means of crowdsourced delivery can be collected at dedicated pickup points located at the exit of subway lines in case transit-oriented service, or in the periphery of the city for car-oriented service. In this study we do not consider induced crowdshipping trips. This is a reasonable assumption considering that in order to access the area studied drivers would need to purchase a special pass.

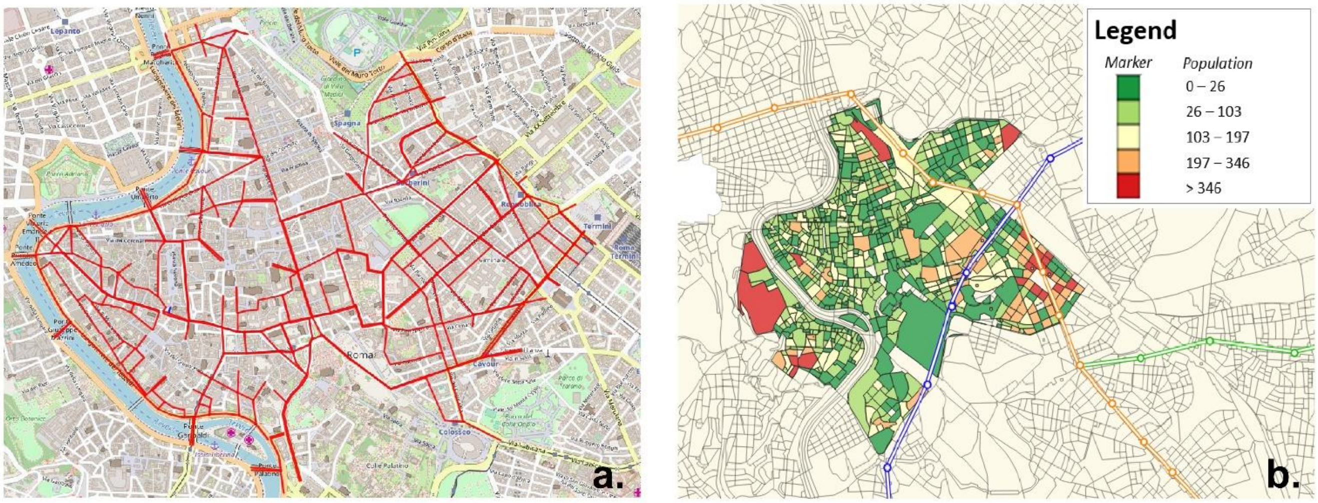


Figure 24: Rome’s traffic restricted area with subway lines (a) and simulation’s network (b)

5.5 ANALYSIS

In this section, we study the impacts of different crowdshipping implementation features on the overall levels of pollution and congestion. Environmental impacts are distinguished in changes of air pollutants (CO, PM_{10}, and NO_x) and greenhouse gases (CO_2). Congestion effects are reported by the change of delay (measured at network level) attributable to crowdshipping operations in comparison to the delay due to traditional delivery operations (marginal delay). Given the random configuration of deliveries and the stochastic nature of the parking model, we perform 100 simulation runs per tested scenario.

First, we evaluate the potential influence of the chosen mode for crowdshipping services. Then, we explore more in detail the effects of operational aspects, such as the length of detour made by and the parking behavior of crowdsourced drivers. Finally, we provide insights into the impacts of crowdshipping at alternative times of the day, characterized by different traffic conditions.

5.5.1 Influence of mode and matched demand

In order to understand the effects of adopting alternative crowdshipping modes, we perform experiments for three different levels of matched demand (10%, 30%, and 50%) by using car and public transit (Figure 25). As expected, for higher levels of matched demand, crowshipping by public transit is beneficial from both an environmental and congestion perspective, showing an increasing trend. It is important to note that, while benefits are almost negligible for low levels of matched demand (particularly in terms of congestion), the gains significantly increase for 30% and 50% of traditional deliveries replaced. This result can be explained by the possibility of achieving higher consolidation of original truck trips. In case of car usage, crowdshipping does not generally determine improvements in terms of pollution and congestion. This result is in line with Buldeo-Rai et al. (2018) who found crowshipping to be unsustainable, especially due to the rebound effect of induced delivery trips. Here, even by considering only existing trips, deliveries made by non-professional drivers determine a worsening of emissions between approximately 3% and 5% and an increase of marginal congestion impact between approximately 6% and 11%. Increasing the number of trips and their length in an already congested area is clearly detrimental. Interestingly, while congestion impacts show an overall increase for higher levels of matched demand, the emissions effects are stable. This effect is due to the increasing savings coming from improved consolidation of truck tours and from replacement of trucks with cars (that are, according to the assumptions, less polluting) in the trip from crowdshipping stations to the city center.

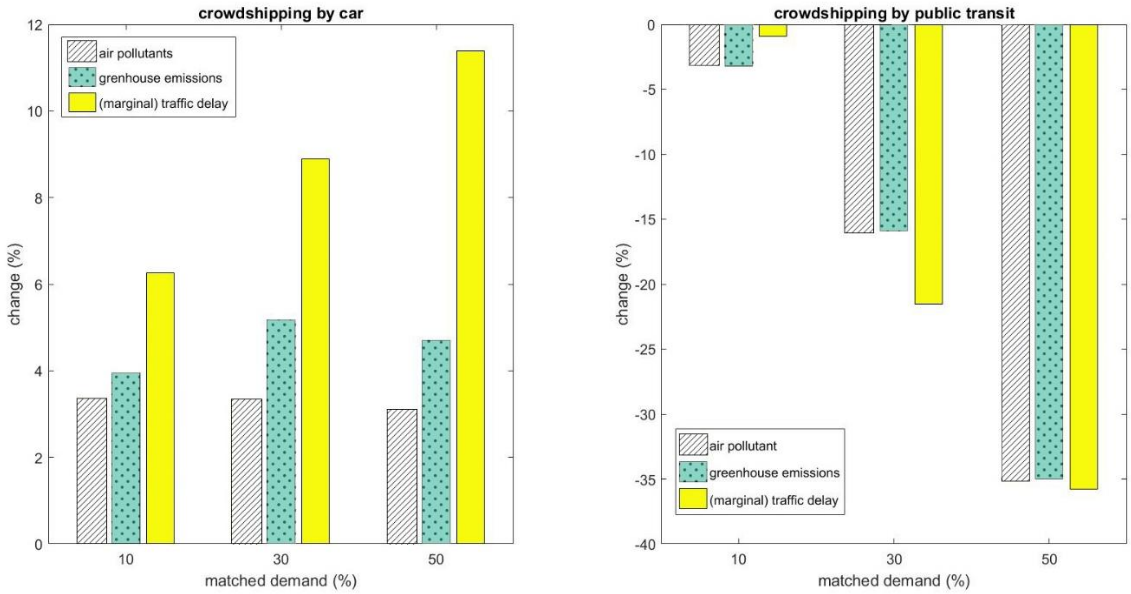


Figure 25: Impacts of employed mode for crowdshipping at different levels of matched demand

5.5.2 Influence of detour length and parking behavior

In order to test the influence of different levels of detour on the overall impacts of crowdsourced deliveries made by car, three alternative maximum ranges of deviation from the original trips (5, 10, and 15 minutes) are tested for the same level of matched demand (30%). The results shown in Figure 26, indicate that, while performing crowdshipping by car could be partially beneficial for deviations below five minutes, it becomes unsustainable for longer detours. Interestingly, for minor detours, the overall marginal delay still increases because of the overall growth of vehicle miles traveled.

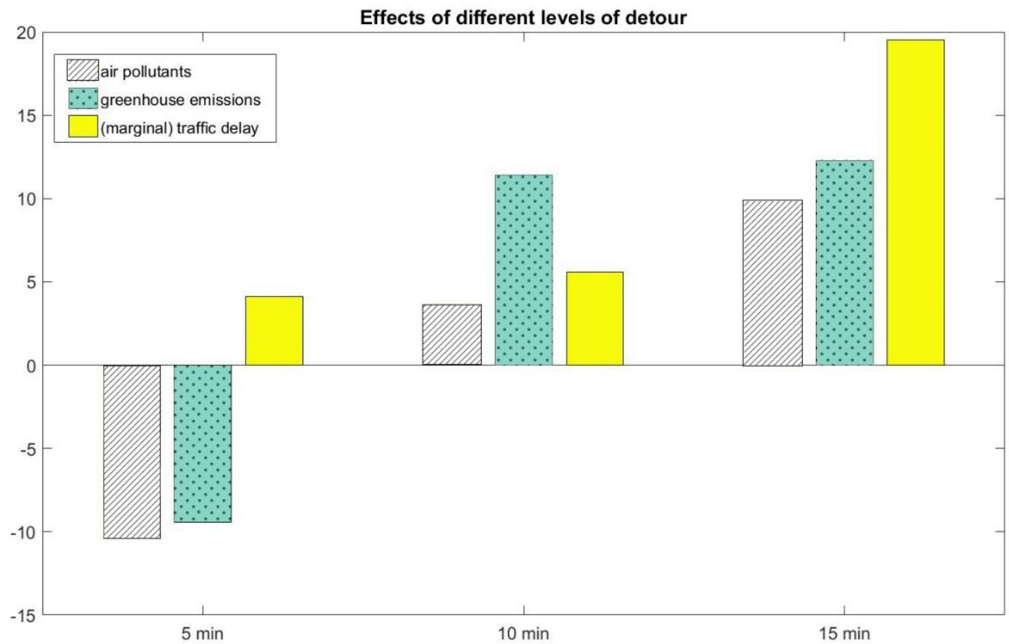


Figure 26: Impacts of different levels of detour

As discussed earlier, there is little knowledge of carriers' parking behavior and even less concerning that of crowdshippers. Here, we investigate the congestion effects of three alternative behavioral trends (which could themselves be the result of several factors, such as infrastructure supply, reward for crowdshipping services, and levels of enforcement): a "conservative" attitude wherein crowdsourced drivers always park legally; an "illegal" attitude wherein crowdsourced drivers always double-park; and a "mixed" attitude wherein legal and illegal parking are equally split. Just as in the previous experiment, we assume constant matched demand equal to 30% of deliveries. The results highlight how parking plays an important role in the final traffic performance of crowdshipping services (Figure 27). While a "mixed" parking attitude would only increase marginal delay by approximately 2% in comparison to a completely "legal" attitude, consistent illegal parking performed by crowdshippers would yield a significant increase of marginal delay (15% in total). The outcome of this experiment shows how the creation of temporary fixed bottlenecks during illegally parked deliveries is a crucial issue for congestion.

Figure 27: Traffic impacts of different parking behavior

5.5.3 Influence of daily traffic fluctuations

In order to investigate the impacts of performing crowdshipping deliveries under different traffic conditions, we conduct the same experiments of Section 5.1 by simulating network traffic between 2 and 3 PM. During this time of the day, traffic congestion is milder than in the previous scenario (traffic delay is approximately 15% lower). As it is possible to see in Figure 28, performing deliveries through crowdshipping at another time of the day, characterized by lower levels of traffic, implies different impacts. In case of crowdsourced deliveries by car, the impacts are still negative; however, increasing the level of matched demand does not increase congestion as in the morning scenario. Interestingly, for higher levels of matched demand (50%), the environmental impacts of crowdshipping by car are close to zero. Given the relatively low levels of traffic and the higher traveling speeds, having more vehicles performing deliveries (and often double parking) does not have significant effects, especially when counterbalanced by increased consolidation and reduced truck trips between the depot and the city center. Crowdsourcing deliveries by using public transit between 2 and 3 PM, shows a similar trend to the experiments performed at 10 AM.

However, given the overall lower levels of congestion, it entails lower benefits in terms of reduced (i.e., marginal) delay. On the other hand, significant air pollutants and greenhouse emissions savings can still be achieved.

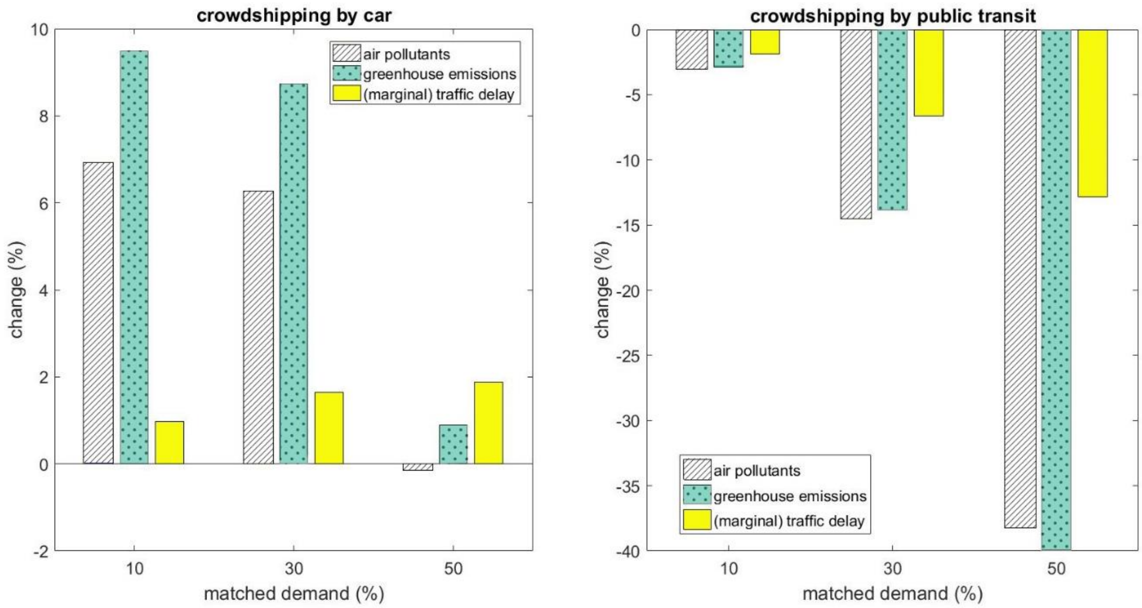


Figure 28: Impacts of crowdshipping for less congested times of the day

5.5.4 Influence of shorter delivery operations

Another aspect of crowdshippers' parking behavior worth of consideration, is the time required to perform deliveries. Smaller vehicles (, such as crowdshippers' cars) in charge of a single delivery might require less time than the larger trucks because of shorter unloading operations. This would translate to shorter delivery durations and lower hindrance to surrounding traffic flows in case of double-parking. On the other hand, as already observed earlier, trucks would have longer stops, but also lower frequency.

In order to investigate the influence of shorter operations of crowdshippers, we test three alternative (crowdshippers') delivery durations (60, 90, and 120 seconds) for the same level of matched demand (30%). The results shown in Figure 29, indicate that, the length of crowdshipper's delivery has a considerable impact on surrounding traffic. For lower delivery durations, crowdshipping's negative impacts can be considerably reduced to the point that very short crowdshippers' operations (1 minute or below) would become overall beneficial to traffic. This outcome shows that increasing the efficiency of crowdshippers' delivery operations could significantly improve the traffic congestion footprint of crowdsourced delivery services. In order to achieve this goal, different strategies to facilitate parcel "drop-off" operations could be made,, such as sending live notifications to the receiver when the crowdshipper is approaching destination or designing dedicated drop-off facilities in the apartment complexes lobbies.

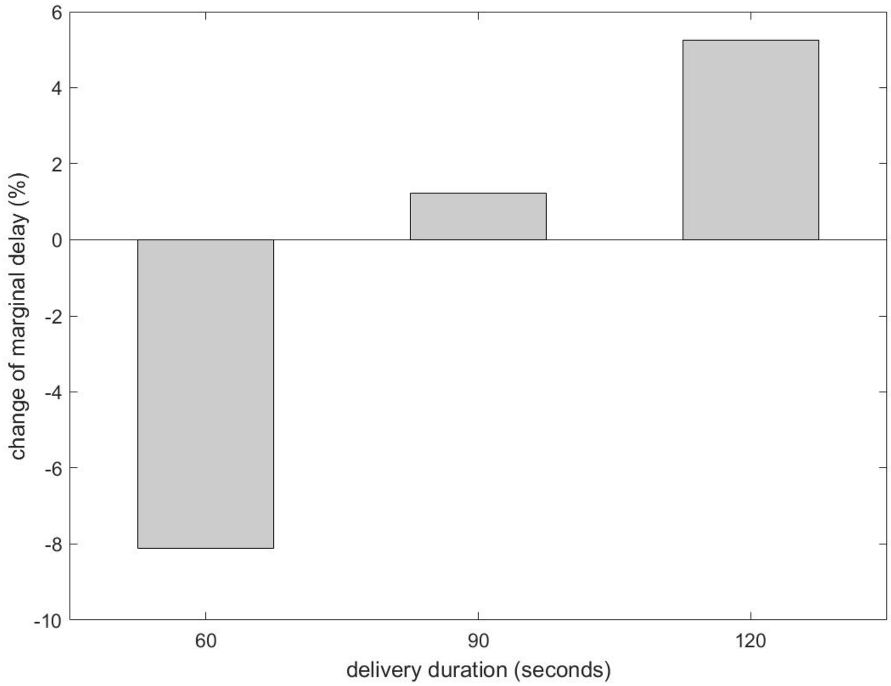


Figure 29: Impacts of shorter crowdshippers' delivery operations

5.5.4 Policy Implications

Thanks to the experiments performed, it is possible to determine a clearer picture of the potential opportunities and threats coming with the implementation of crowdshipping services.

It is interesting to see that even for a "mild" implementation of crowdshipping targeted to a very specific market segment (on-line parcel deliveries) and for relatively low levels of demand, the environmental and congestion effects are already appreciable.

The transportation mode chosen by crowdshippers is fundamental for the overall sustainability of crowdsourced deliveries. While crowdshipping can be beneficial (for the city) when relying on public transit, its impacts are always negative in case of car-based crowdsourced trips. If crowdshipping is implemented by private carriers (or companies) independently, thus leaving *de facto* such transportation choice to crowdshippers, a midway scenario is most likely to occur.

However, without any supporting policy in terms of incentives or regulations, it would be difficult to steer crowdshipping practices in the public-transit oriented direction.

More operational aspects,, such as the range of detour and parking behavior of crowdsourced drivers, are also affecting the overall sustainability of this service. Limiting the deviation of crowdshippers' delivery trips from their original trips and providing adequate parking for crowdsourced deliveries would be important actions to reduce negative externalities. In this context, logistic providers could play a critical role in adjusting the platform operations to obtain a more sustainable use, and public authorities would have the responsibility to identify adequate parking responses to this phenomenon.

Finally, investigating the impacts of crowdsourced delivery at different times of the day has shown how the negative effects of crowdshipping by car are lower during less congested hours. This information could be exploited by policy makers to encourage the use of crowdshipping by public transit particularly during peak hours.

5.6 CONCLUSION

This study investigates, by means of a simulation approach, the potential impacts on traffic and pollution deriving from the implementation of alternative crowdshipping practices. The externalities associated with several strategic (chosen mode) and operational (detour length, parking behavior, and traffic conditions) aspects of this service are analyzed by means of simulation in realistic settings.

Traffic simulation is adopted in order to model more accurately the effects on traffic and pollution of delivery operations dynamic. This modeling approach is relatively limited in the field of City Logistics and, to the best of the authors' knowledge, no systematic simulation-based study of crowdshipping has yet been performed. The adoption of a hybrid traffic simulation seems particularly appropriate for the evaluation of traditional and crowdshipping delivery services, as it reproduces traffic at a macroscopic level, while reproducing delivery operations and crowdshippers' trips at a microscopic level. This approach offers a good compromise between computational performance and the accuracy of the traffic model. Future research could address carriers' and crowdshippers' parking modeling in order to reproduce more accurately their behavior with the support of revealed and stated preference surveys.

The externalities related to crowdshipping are investigated at the network level by analyzing the effects of the implementation of such service in comparison to traditional delivery framework for parcels, in the city center of Rome. The city is characterized by considerable congestion and parking issues and it would greatly benefit from innovative freight distribution solutions. Thanks to available traffic data and information about the parcel delivery process directly obtained from major carriers operating in the area, it was possible to perform realistic simulations corresponding to alternative implementation scenarios. The realism of the experiments could be further increased in future studies, by including more specific information about signal settings and parking, and by adopting a more detailed street network.

The analyses confirm that crowdshipping is a double-edged sword for sustainable freight distribution since, depending on different implementation features, it could result in very different changes in emissions and traffic congestion. The chosen transportation mode by crowdshippers plays the main role in identifying the effects of this solution. Car-based crowdsourced deliveries entail higher negative externalities from both a traffic and an environmental perspective than traditional deliveries. For this kind of crowdshipping, operational aspects,, such as the availability of parking, the optimization of existing trips, and the implementation during off-peak hours can considerably influence the final traffic and emissions impacts.

More research is needed to understand whether the crowdshipping services offered in current market are leaning more towards car-based or public transit-based (or other environmentally friendly) deliveries. Based on that need, ad hoc policy solutions aimed at optimizing existing crowdshippers' trips could be developed and evaluated by a similar simulation-based approach. A possible solution could consist of link and lane tolls in those locations characterized by heavier traffic of crowdshippers. Advanced technologies,, such as "smart vehicles", capable of dissipating shockwaves by means of intelligent control, could be employed to minimize the negative effects of double-parked maneuvers.

6. CONCLUSION

6.1 Summary of contributions

Freight transportation plays a fundamental role in the sustainable development of urban regions. In order to cope with the growth of road freight traffic and other recent mobility trends that are increasing the burden on road infrastructure systems (e.g., e-commerce, urbanization), innovative, sustainable, and efficient solutions are needed. This dissertation focuses on the development of appropriate modeling tools to reproduce traffic movements and operations of commercial vehicles at different levels. Such tools can be employed for the development of advanced mobility solutions and for the evaluation of complex freight-related traffic situations. The main rationale behind this research is that, since dynamic traffic simulation can properly capture the traffic effects of trucks, especially in urban settings, research efforts need to be taken in this direction for modeling and integrating freight traffic into City Logistics. In the context of this research work, it is possible to identify some theoretical contributions in the field of traffic modeling and traffic flow theory (Chapter 3 and 4), and other more practical contributions in the field of transport policy and urban freight distribution (Chapter 5).

6.1.1. Theoretical contributions

In the first part of the dissertation a semi-analytic numerical scheme is developed to reproduce accurately and efficiently interactions between passenger and commercial traffic, which is modeled as moving bottlenecks. Based on the LWR model and on the Hamilton-Jacobi formulation of the problem, the algorithm allows the derivation of trucks' trajectories without having to compute the solution on the entire computational domain. Thanks to this approach it is possible to reproduce several moving bottlenecks traveling on a stretch of road in a broad range of traffic conditions.

As an extension of this work, a simulation framework is developed for modeling the effects of urban freight operations on urban networks. A particular focus is given to the phenomenon of double-parked delivery operations that are modeled as temporary fixed bottlenecks. The main characteristics of the proposed modeling approach resides in its hybrid nature. While regular traffic is modeled macroscopically, delivery vehicles are reproduced microscopically, such that they can be tracked along their routes during the entire simulation. Thanks to the solution method adopted, it is possible to run accurate large-network simulations with relatively low computation times (in the order of seconds) and perform network analyses requiring a large amount of tests.

A further improvement of the modeling framework is proposed in the final part of the dissertation, when crowdsourced delivery services are investigated. In this case, in order to specifically account for traffic increases on links traveled by trucks or crowdsourced carriers, the original traffic simulation algorithm is updated such that turning proportions at the nodes are dynamically updated. Based on that, one can explicitly account for the movements of delivery vehicles at each junction, and ultimately reproduce the effects on overall traffic levels of different trip lengths and delivery routes.

Finally, as a side contribution of this dissertation, not strictly related to the issue of freight traffic modeling, a more efficient version of the Lax-Hopf algorithm is formally derived (Fast Lax-Hopf). Based on mathematical proofs, it is demonstrated that, for calculations of the link's demand and supply, not all the initial conditions are influential, and that, after a certain time, they can be all completely neglected. The results of several experiments confirm that the FLH algorithm is considerably faster than the original version and it does not compromise the accuracy in reproducing congestion phenomena.

6.1.2 Practical contributions

In this dissertation, the modeling approach is employed for the analysis of different freight transportation problems. Some results allow preliminary considerations about the effects of last-mile delivery solution that can been confirmed in other studies. Other findings, instead, are in line with studies from previous literature that adopted different approaches.

Different solutions have been analyzed by means of the *ad hoc* simulation framework in order to reduce the impacts of freight movements, especially of double-parked delivery operations. The practice of off-peak deliveries, consisting in shifting part of the trips and operations to less congested hours of the day (typically evening and night) has proved to be an effective solution to freight-related congestion in urban settings. Several simulation experiments performed in a realistic urban network have shown that this solution would be very effective as well, in increasing the reliability of the system and improving carriers' delivery performance. These results are in line with the previous studies that employed different types of models or used experimental data.

Restricting from deliveries specific links or sets of links, instead, could be beneficial only in some situations. It is not very clear to what extent this measure can be effective in reducing congestion because of the complexity of urban freight operations and the influence of several factors like network topology, traffic demand and interactions among delivery operations.

A full chapter of this dissertation has been dedicated to the evaluation of crowdsourced delivery services and their externalities, by means of simulation. To the best of our knowledge, this is the first work that systematically analyzes the impact of different crowdshipping features at network level. From the experiments it emerges how crowdshipping's alternative implementations could determine very different changes in emissions and traffic congestion. While crowdshippers' transportation mode choice plays the main role in identifying the effects of this solution, other operational aspects (, such as availability of parking, optimization of existing trips, and implementation during off-peak hours) can also considerably influence the final traffic and emissions impacts.

Finally, in the presentation of the fast algorithm for moving bottlenecks, its application in two specific freight traffic optimization problems is discussed. The first one consists of control of inflow truck traffic into a main arterial combined with a traffic signal control, while the second one consists of real-time curbside management for truck deliveries in urban environments. In both cases, a relatively straightforward evolutionary metaheuristic is coupled to the simulation in order to maximize the overall traffic throughput. The results of the experiments indicate that, thanks to the computational efficiency of the algorithm, it is possible to achieve fairly satisfactory solutions in a few seconds. Thanks to the oncoming technologic improvements in wireless communication, as well as computational and sensing technologies (Intelligent Transport Systems), the real world implementation of these strategies is a feasible possibility.

6.2 LIMITATIONS AND DIRECTIONS FOR FUTURE WORK

The simulations and analyses performed in this study present some limitations. Some of them are more related to the nature of the models employed, whereas others derive from the lack of real data.

Throughout the entire dissertation, freight flows and operations are modeled according to an hybrid approach, where main traffic flows are reproduced macroscopically (LWR model), while single trucks' movements are represented microscopically in forms of moving (or temporarily fixed) bottlenecks. While this approach well captures the effects on capacity reduction of slower vehicles, it does not explicitly account for more complex traffic phenomena (e.g., overtaking, weaving, etc.). The main reason behind the choice of this approach lies in its computational efficiency that makes it very suitable for large-scale studies (involving hundreds or thousands of links). This feature is also very important for simulation-based optimization and statistical problems requiring a large number of simulations. Finally, as Papageorgiou (1998) notices, the LWR model works fine in urban signalized networks where most of dynamics are dominated by external events (traffic lights) rather than by inherent traffic flow dynamics. Future work could involve the development of similar methods for more advanced models (e.g., second-order models).

In the proposed traffic simulation framework, it is possible to couple the traffic model with any generic (discrete) parking model in order to reproduce delivery vehicles' parking behavior in consistency with the infrastructure supply and demand. In our study, delivery vehicles are assumed to be rather "inelastic" and more inclined to double-park illegally (when no commercial bay or regular parking is available) rather than cruising to find an alternative location for the stop. Developing more accurate behavioral models or adapting (one of the few) existing ones was beyond the scope of this research and would have required surveys and data from carriers for estimation and validation. In future research, the accuracy of parking behavior could be improved by accounting for traffic patterns, time of day and type of delivery.

From a practical perspective, the majority of the experiments were performed with little of the actual volumes of freight traffic and deliveries made in the studied areas (or none, in the case of Austin). Access to this type of privately owned information is a common problem in this field of study, mainly resulting from a lack of freight stakeholder involvement in urban transport planning and policy making (Ballantyne et al., 2013; Lindholm and Browne, 2013) or from companies' reluctance to share business information. For this reason, a series of assumptions on features of delivery tours (e.g., average stop duration, number of stops and deliveries, total number of trips) had to be made in our simulations (particularly in the Austin scenario). Overcoming this limitation in this type of study (focused on the externalities of freight movements) would require a significant investment of resources to collect data from carriers and by means of fieldwork. Thanks to the possibility of running several simulations, thorough sensitivity analyses could be performed by changing different features of freight deliveries and by randomizing delivery locations.

Besides the research work proposed to address the above-mentioned limitations of this dissertation, some other directions for future research have been identified as well. Within the realm of freight traffic simulation-based optimization, evolutionary metaheuristics,, such as genetic and memetic algorithms have been adopted. It would be interesting to test alternative simulation-based, derivative-free approaches and compare their efficiency with the ones in this dissertation. Possible solutions include adaptive-search and response-surface methods. Methods from machine learning could also be employed to develop heuristics capable of realistic modeling of traffic flows, while retaining good computational efficiency in order to deal with large networks.

Finally, given the deterministic nature of the adopted simulation framework, all the optimization experiments were performed in deterministic fashion with the support of sensitivity analyses. It is known that, in reality, several sources of uncertainty (i.e. traffic predictions, measurements) could affect the final quality of the solutions. Future work could focus on exploring the influence of uncertainty on the optimization, and including it by means of robust optimization approaches.

As to the evaluation of innovative City Logistics solutions, like crowdshipping, it would be interesting to study how the results obtained in this study apply to other cities. In addition to demand for parcel delivery and features of the implemented service, several other factors related to the urban morphology of the road network, availability of parking and commercial bays, and overall traffic conditions might ultimately influence the impacts of this solution.

APPENDIX: FAST LAX-HOPF ALGORITHM

The primary objective of the proposed algorithm is to quickly compute the outflows and inflows at every time step, by using a minimum number of operations, and maintaining exactness. Once the boundary conditions are known on all links, the solutions inside the computational domain can be found by minimizing a number of explicitly computed functions. The Fast Lax-Hopf (FLH) algorithm speeds both the computation of the boundary conditions, and the computation of the solution inside the computational domain.

This algorithm relies on the specific structure of the partial solutions to the Hamilton-Jacobi PDE with triangular fundamental diagrams. From (Claudel and Bayen, 2010a, b), the partial solutions associated with affine blocks are convex (this property is valid for any concave fundamental diagrams) functions of (t, x). Furthermore, (Daganzo 2005) showed that these solutions are Lipschitz continuous on their domain of definition for general diagrams. In the case of a Triangular diagram, it is easy to verify from the expression of the solutions that these solutions are indeed Lipschitz continuous.

Furthermore, the partial solutions associated with linear initial or boundary conditions, for a triangular fundamental diagram, are piecewise linear functions of space and time. This property is very important in the present situation, and would not be true for example in the case of a Greenshields fundamental diagram.

In the present case, we consider a general mixed initial-boundary condition problem on a given stretch of highway limited by upstream and downstream boundaries. We also assume that the boundary conditions that apply on the domain are not known in advance, unlike in the LH case. These boundary conditions have to be computed at each time step through junction models relating the demands of the incoming links to the supplies of the outgoing links, across each junction. These junction models have the effect of coupling the solutions computed over adjacent links. To compute these boundary conditions, our objective is to compute the inputs to the junction models as fast as possible. These inputs are upstream demands and downstream supplies of each link (for a given time step).

let the initial condition be expressed as a piecewise linear function, with each linear piece on intervals (x_i,x_{i+1}) defined by:

$$c_{ini}^{i}(x) = \begin{cases} -k_i x + b_i & : x_i \leq x \leq x_{i+1} \\ +\infty & : otherwise \end{cases} \qquad (1)$$

where $i \in \{ 0, \dots, n_{ini} - 1\}$, with similar definitions for the upstream and boundary conditions (Eq. 7). As described in (Daganzo, 2006), the initial condition must satisfy some growth and continuity conditions:

$$0 \leq k_i \leq k_j \text{ for all } i \in \{0, \dots, n-1\} \qquad (2)$$

$$-k_i x_i + b_i = -k_{i+1} x_i + b_{i+1},\ \ \forall i \in \{1, \dots, n-1\} \qquad (3)$$

Similar growth and continuity constraints apply for the upstream and boundary conditions, in particular the boundary flows are nonnegative and upper bounded by the link capacity.
By the inf-morphism property (Mazare et al, 2011), the solution $N(x,t)$ associated with the Hamilton-Jacobi PDE (3) can be computed at any point (x,t) of the space-time domain using the following formula:

$$N(x,t) = \min\left(\min_{i,j,k} N_{c_{ini}^{i}}(x,t), N_{c_{up}{}^{j}}(x,t), N_{c_{down}}^{k}(x,t)\right) \qquad (4)$$

To compute the downstream boundary block for a given time interval $[t, t + \Delta t]$, we first need to derive the demand of this particular link over the time interval $[t, t + \Delta t]$, defined by $d(t, t + \Delta t) = \frac{N\left(x_{n_{ini}}, t+\Delta t\right) - N(x_{n_{ini}}, t)}{\Delta t}$. The actual flow over the time interval $[t, t + \Delta\, t]$ is then determined using the other demand and of all links connected to this junction, through the chosen junction model.
Hence, assuming that $N(x_{n_{ini}}, t)$ is known, and using the classical LH algorithm (Mazare et al., 2011), we can compute $N\left(x_{n_{ini}}, t + \Delta t\right)$ as:

$$N(x_{n_{ini}}, t+\Delta t) = \min\left[min_{i\le j\le n_{ini}} N_{c_{ini}^{j}}(x_{n_{ini}}, t + \Delta t), \min_{0\le k\le \kappa} N_{c_{up}{}^{k}}(x_{n_{ini}}, t+\Delta t), N_{c_{down}}^{l}(x_{n_{ini}}, t+\Delta t)\right] \quad (5)$$

In (5), κ is defined as $\kappa = \max_{i\in\mathbb{Z}\ s.t.\ x_0+v_f\cdot(t+\Delta t-t_{i+1})\ge x_{n_{ini}}} i$, and $l = \max_{i\in\mathbb{Z}\ s.t.\ t_{i+1}\le t+\Delta t} i$.

For simplicity, we now assume that all boundary condition blocks are defined at regular time intervals (though the algorithm can be extended in a straightforward way for general time intervals), and thus, that $t_j = j \cdot \Delta t$, where Δt is the time step considered. In this situation, we have that $\kappa = \lfloor \frac{t+\Delta t-\frac{x_{n_{ini}}-x_0}{v_f}}{\Delta t} \rfloor$ and $l = \lfloor \frac{t+\Delta t}{\Delta t} \rfloor$. In the original Lax-Hopf method, the process required to compute the downstream boundary condition block at time $t+\Delta t$ is shown in Figure 1.

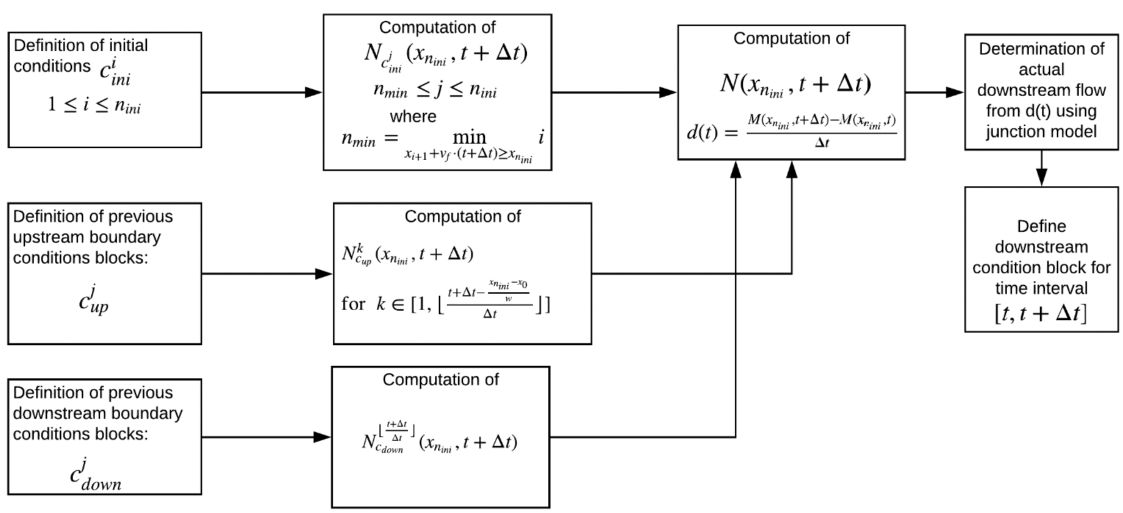


Figure 30:Required operations to determine the exiting flow (downstream) over the time interval [t,+Δt] using the classical Lax-Hopf algorithm

Equation (4) requires the minimization of $n_{ini} + \kappa + 1$ explicitly computed functions to derive the upstream supply of the link when $t + \Delta t \geq \frac{x_{n_{ini} - x_0}}{v_f}$. The objective of the Fast Lax Hopf algorithm is to decrease the required number of operations (in comparison to the Lax-Hopf algorithm), while still computing the average demand and supply functions exactly.

We now introduce a set of rules that allows one to reduce the number of required calculations with respect to the original LH algorithm.

Theorem 1: Let set of n_{ini} initial conditions be defined as in (1). Let us further assume that $N_{c_{ini}^i}\left(x_{n_{ini}}, t'\right) \leq N_{c_{ini}^j}\left(x_{n_{ini}}, t'\right)$ for a time $t' \geq \frac{x_{n_{ini}} - x_{i+1}}{v_f}$, with $i < j$. Then:
$\forall\ t \geq t', N_{c_{ini}^i}\left(x_{n_{ini}}, t\right) \leq N_{c_{ini}^j}\left(x_{n_{ini}}, t\right)$

Proof: using the structure of the solution to initial conditions (Appendix I), we have that both $N_{c_{ini}^j}\left(x_{n_{ini}},\cdot\right)$ and $N_{c_{ini}^i}(x_{n_{ini}},\cdot)$ are defined on $[t', +\infty)$, continuous and convex functions. Hence, both functions have subderivatives (noted ∂_-), and are differentiable almost everywhere on their domain. These subderivatives can be computed from the expression of the initial solutions as follows:

Let $v_i \in \partial_+ Q(k_i)$ (if $v_i \leq 0$ then only the third case of the below equation remains).

$$\partial_- N_{c_{ini^i}}\left(x_{n_{ini}}, t\right)$$
$$= \begin{cases} \{Q(k_i)\} & : \dfrac{x_{n_{ini}} - x_{i+1}}{v_i} \leq t \leq \dfrac{x_{n_{ini}} - x_i}{v_i} \\ \left\{R\left(\dfrac{x_{n_{ini}} - x_{i+1}}{t}\right)\right\} - \dfrac{x_{n_{ini}} - x_{i+1}}{t} \cdot \partial_- R\left(\dfrac{x_{n_{ini}} - x_{i+1}}{t}\right) & : \dfrac{x_{n_{ini}} - x_{i+1}}{v_f} \leq t \leq \dfrac{x_{n_{ini}} - x}{v_i} \\ \left\{R\left(\dfrac{x_{n_{ini}} - x_i}{t}\right)\right\} - \dfrac{x_{n_{ini}} - x_i}{t} \cdot \partial_- R\left(\dfrac{x_{n_{ini}} - x_i}{t}\right) & : t \geq \dfrac{x_{n_{ini}} - x_i}{v_i} \end{cases} \quad (6)$$

Using the Legendre-Fenchel inversion formula (Aubin Bayen Saint Pierre 2008), we have:

$$k \in \partial\_R\left(\frac{x_{n_{ini}} - x_{i+1}}{t}\right) \iff \frac{x_{n_{ini}} - x_{i+1}}{t} \in \partial_+ Q(k)$$

Hence, we have that $\left\{R\left(\frac{x_{n_{ini}}-x_{i+1}}{t}\right) - \frac{x_{n_{ini}}-x_{i+1}}{t} \cdot k\right\} = \{Q(k)\} \subset \{R\left(\frac{x_{n_{ini}}-x_{i+1}}{t}\right)\} - \frac{x_{n_{ini}}-x_{i+1}}{t} \cdot \partial\_R\left(\frac{x_{n_{ini}}-x_{i+1}}{t}\right)$ for $k \in \partial\_R\left(\frac{x_{n_{ini}}-x_{i+1}}{t}\right)$.

The same property can be applied to (6), allowing us to rewrite it as:

$$\partial\_N^i_{c_{ini}}\left(x_{n_{ini}}, t\right) = \begin{cases} \{Q(k_i)\} & : \frac{x_{n_{ini}} - x_{i+1}}{v_i} < t < \frac{x_{n_{ini}} - x_i}{v_i} \\ \left\{Q(k), k \in \partial\_R\left(\frac{x_{n_{ini}} - x_{i+1}}{t}\right)\right\} & : \frac{x_{n_{ini}} - x_{i+1}}{v_f} < t < \frac{x_{n_{ini}} - x_{i+1}}{v_i} \\ \left\{Q(k), k \in \partial\_R\left(\frac{x_{n_{ini}} - x_i}{t}\right)\right\} & : t > \frac{x_{n_{ini}} - x_i}{v_i} \end{cases} \tag{7}$$

We can rewrite $\partial\_N^i_{c_{ini}}\left(x_{n_{ini}}, t\right)$ as $\partial\_N^i_{c_{ini}}\left(x_{n_{ini}}, t\right) = Q(k_i(t))$ where $k_i(t)$ is the set-valued map defined by:

$$k_i(t) = \begin{cases} k_i = \partial\_(v_i) & : \frac{x_{n_{ini}} - x_{i+1}}{v_i} < t < \frac{x_{n_{ini}} - x_i}{v_i} \\ \partial\_R\left(\frac{x_{n_{ini}} - x_{i+1}}{t}\right) & : \frac{x_{n_{ini}} - x_{i+1}}{v_f} < t < \frac{x_{n_{ini}} - x_{i+1}}{v_i} \\ \partial\_R\left(\frac{x_{n_{ini}} - x_i}{t}\right) & : t > \frac{x_{n_{ini}} - x_i}{v_i} \end{cases} \tag{8}$$

It can be verified from this expression that $k_i(t) \leq k_j(t)$ when $i < j$, for $t > \frac{x_{n_{ini}}-x_{i+1}}{v_f}$. Indeed, since $R(\cdot)$ is convex, we have that $a \leq b \implies \partial\_R(a) \leq \partial\_R(b)$, in the sense of the interval order (partial order over the set of intervals of ℝ), and since $i < j$, we have $\frac{x_{n_{ini}} - x_{j+1}}{t} \leq \frac{x_{n_{ini}} - x_j}{t} \leq \frac{x_{n_{ini}} - x_{i+1}}{t} \leq \frac{x_{n_{ini}} - x_i}{t}$.

Hence, we have that $\partial\_N^i_{c_{ini}}(x_{n_{ini}}, t) \leq \partial\_N^j_{c_{ini}}(x_{n_{ini}}, t)$ since (in the sense of the interval order) for all times $t \geq t'$ if $i < j$.

Therefore, given that $N_{c^i_{ini}}(x_{n_{ini}}, t') \leq N_{c^j_{ini}}(x_{n_{ini}}, t')$, we have (by integration) that $N_{c^i_{ini}}(x_{n_{ini}}, t) \leq N_{c^j_{ini}}(x_{n_{ini}}, t)$.

Theorem 2: Let set of n_{ini} initial conditions be defined as in (1). Let a set of upstream boundary conditions be defined as in Eq. 3.14. Let us assume that $N_{c^i_{ini}}(x_{n_{ini}}, t') \geq N_{c^j_{up}}(x_{n_{ini}}, t')$ for some $i \in [1, n_{ini}]$, for some time $t' > t_j + \frac{x_{n_{ini}} - x_0}{v_f}$. We have that $\forall t > t'$, $N_{c^i_{ini}}(x_{n_{ini}}, t') \geq N_{c^j_{up}}(x_{n_{ini}}, t')$.

Proof: given the structure of the solution to boundary conditions, and using a similar reasoning as in the proof or Theorem 1, we have that:

$$\partial\_N_{c_{up}{}^j}(x_{n_{ini}}, t) = \begin{cases} Q(\rho_j) \;:\; x_0 + v_j(t - t_{j+1}) \leq x \leq x_0 + v_j(t - t_j) \\ \left\{Q(k), k \in \partial\_R\left(\dfrac{x_{n_{ini}} - x_0}{t - t_j}\right)\right\} \;:\; x_0 + v_j(t - t_j) \leq x \leq x_0 + v_f(t - t_j) \\ \left\{Q(k), k \in \partial\_R\left(\dfrac{x_{n_{ini}} - x_0}{t - t_{j+1}}\right)\right\} \;:\; x_0 \leq x \leq x_0 + v_j(t - t_{j+1}) \end{cases} \quad (9)$$

which can be rewritten as: $\partial\_N_{c_{up}{}^j}(x_{n_{ini}}, t) = Q(k_j(t))$ where:

$$k_j(t) = \begin{cases} \rho_j \;:\; x_0 + v_j(t - t_{j+1}) \le x \le x_0 + v_j(t - t_j) \\ \partial\_R\left(\frac{x_{n_{ini}} - x_0}{t - t_j}\right) \;:\; x_0 + v_j(t - t_j) \le x \le x_0 + v_f(t - t_j) \\ \partial\_R\left(\frac{x_{n_{ini}} - x_0}{t - t_{j+1}}\right) \;:\; x_0 \le x \le x_0 + v_j(t - t_{j+1}) \end{cases} \tag{10}$$

It is straightforward to verify from both the above expression and Equation 15 in Theorem 1 that $k_j(t) \le k_i(t)$ for all $t > t_j + \frac{x_{n_{ini}} - x_0}{v_f}$. This results again from the convexity of $R(\cdot)$, which implies that its subderivative is increasing.

Hence, we have that $\partial\_N^j_{c_{up}}(x_{n_{ini}}, t) \le \partial\_N^i_{c_{ini}}(x_{n_{ini}}, t)$ for all times $t > t_j + \frac{x_{n_{ini}} - x_0}{v_f}$, and thus in particular for $t > t'$. Therefore, given that $N_{c^i_{ini}}(x_{n_{ini}}, t') \ge N_{c^j_{up}}(x_{n_{ini}}, t')$, we have that $\forall t > t'$, $N_{c^i_{ini}}(x_{n_{ini}}, t') \ge N_{c^j_{up}}(x_{n_{ini}}, t')$.

Theorem 3: Let a set of upstream boundary conditions be defined as in Eq. 3.14. Let us assume that $N_{c^j_{up}}(x_{n_{ini}}, t') \le N_{c^i_{up}}(x_{n_{ini}}, t')$ for some, for some $i < j$, for some time $t' > t_j + \frac{x_{n_{ini}} - x_0}{v_f}$. We have that $\forall t > t'$, $N_{c^j_{up}}(x_{n_{ini}}, t') \le N_{c^i_{up}}(x_{n_{ini}}, t')$.

Proof: The proof follows directly from the structure of the subderivative Eq. 9 and Eq. 10, remarking that if $i < j$, and $t > t_j + \frac{x_{n_{ini}} - x_0}{v_f}$, then $k_j(t) < k_i(t)$, and thus, $\partial\_N^j_{c_{up}}(x_{n_{ini}}, t) \le \partial\_N^i_{c_{up}}(x_{n_{ini}}, t)$, which implies that $\forall t > t'$, $N_{c^j_{up}}(x_{n_{ini}}, t') \le N_{c^i_{up}}(x_{n_{ini}}, t')$.

Equivalent properties can be derived for $x = x_0$ (upstream boundary), leading to the following theorems, which can be proved in a similar way as theorems 1, 2 and 3. For compactness we omit the proofs of these results, which are similar to the proofs outlined above.

Theorem 4: Let set of n_{ini} initial conditions be defined as in (1). Let us further assume that $N_{c_{ini}^{i}}(x_0, t') \leq N_{c_{ini}^{j}}(x_0, t')$ for a time $t' \geq \frac{x_i - x_0}{w}$, with $j < i$. Then:
$\forall\ t \geq t', N_{c_{ini}^{i}}(x_0, t) \leq N_{c_{ini}^{j}}(x_0, t)$

Theorem 5: Let set of n_{ini} initial conditions be defined as in (1). Let a set of downstream boundary conditions be defined as in Eq. 3.15. Let us assume that $N_{c_{ini}^{i}}(x_0, t') \geq N_{c_{down}^{j}}(x_0, t')$ for some $i \in [1, n_{ini}]$, for some time $t' > t_j + \frac{x_{n_{ini}} - x_0}{w}$. We have that $\forall t > t'$, $N_{c_{ini}^{i}}(x_0, t') \geq N_{c_{down}^{j}}(x_0, t')$.

Theorem 6: Let a set of downstream boundary conditions be defined as in Eq. 3.15. Let us assume that $N_{c_{up}^{j}}(x_0, t') \leq N_{c_{up}^{i}}(x_0, t')$ for some, for some $i < j$, for some time $t' > t_j + \frac{x_{n_{ini}} - x_0}{w}$. We have that $\forall t > t'$, $N_{c_{up}^{j}}(x_0, t') \leq N_{c_{up}^{i}}(x_0, t')$.

The Fast Lax-Hopf algorithm leverages the outlined theorems to reduce the number of calculations required to determine the solutions at a given boundary (upstream or downstream) of the domain. The Fast Lax-Hopf algorithm is summarized in Figure 2 below, for the computation of the downstream demand over time, over a single road link.

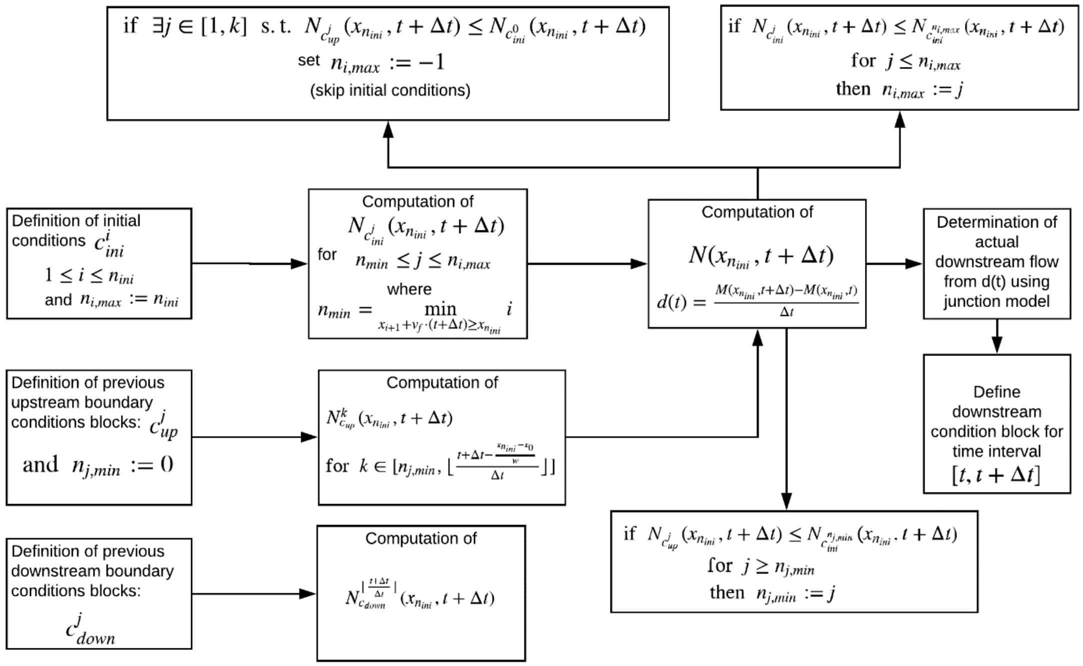


Figure 31: required operations to determine the exiting flow (downstream) over the time interval [t,+Δt] using the Fast Lax-Hopf algorithm

Given its similar structure as the Lax-Hopf algorithm (only with less operations), the FLH algorithm has a complexity that is upper bounded by that of the Lax-Hopf algorithm, while still retaining the exactness of the former for single link problems with piecewise constant demand and supply functions. Note that exactness is lost (as with all other algorithms available, except possibly wave-front tracking) on network problems since boundary demand and supply functions are not piecewise constant in general.

FAST LAX-HOPF ALGORITHM FOR TRIANGULAR FUNDAMENTAL DIAGRAMS

In this section, the Fast Lax-Hopf Algorithm formulation for triangular fundamental diagrams (FDs) is presented. A more specific formulation is derived for particular situations where initial conditions have constant size and the time step satisfies the CFL condition.

Specific formulation of triangular FDs

In the specific case of a triangular fundamental diagram, the convex transform $R(\cdot)$ is affine:

$$\forall u \in [-w, v], \qquad R(u) = k_c(v - u) \tag{11}$$

and the solutions to affine initial, upstream or downstream boundary conditions are piecewise linear, as shown in Mazare et al. (2011), and can be written explicitly. In particular, the solution at any arbitrary point (t, x) depends only upon at one specific (predictable) upstream boundary condition block, and one downstream boundary condition block, leading to the following:

$$N(x,t) = \min(min_{i \le j \le n_{ini}} N_{c_{ini}^{j}}(x,t), N_{c_{down}}^{\left\lfloor \frac{t}{\Delta t} - \frac{x_{n_{ini}} - x_0}{w\,\Delta t} \right\rfloor}(x,t), N_{c_{up}}^{\left\lfloor \frac{t}{\Delta t} - \frac{x_{n_{ini}} - x_0}{v_f\,\Delta t} \right\rfloor}(x,t)) \tag{12}$$

Furthermore, the number of required operations required to compute the solution at an arbitrary point (t, x) of the computational domain can also be reduced as follows:

Corollary 1: Let a set of n_{ini} initial conditions be defined as in (8), with Lipschitz continuity constraints (2) and (3). Let us further assume that $N_{c_{ini}^{j}}(x, t_s) \le N_{c_{ini}^{i}}(x, t_s)$ for a time $t_s \ge \frac{x_{i+1} - x}{w}$, with $i < j$. Then:

$$\forall\, t \ge s, N_{c_{ini}^{j}}(x,t) \le N_{c_{ini}^{i}}(x,t) \tag{13}$$

Proof: using the structure of the solutions $N_{c_{ini}^{j}}(x,t)$, we have that $N_{c_{ini}^{j}}(x,t) \le N_{c_{ini}^{j}}(x,t_s) + (t_s - t)v\, k_c$ if $t_s \ge \frac{x_{i+1} - x}{w}$ and $i < j$, irrespective of the value of k_j. We also have that $N_{c_{ini}^{i}}(x,t) = N_{c_{ini}^{i}}(x,t_s) + (t_s - t)v\, k_c$. Since $N_{c_{ini}^{i}}(x,t_s) \le N_{c_{ini}^{j}}(x,t_s)$, we have that $\forall\, t \ge t_s, N_{c_{ini}^{j}}(x,t) \le N_{c_{ini}^{i}}(x,t)$.

This theorem implies that inside the computational domain, if the solution associated to a particular initial condition piece j is lower than the solution associated with another initial condition piece i (with $i < j$), for a location x and time t_s such that $t_s \geq \frac{x_{i+1}-x}{w}$, then the solution associated with piece i cannot influence the solution (at the same location) at subsequent times.

Corollary 2: Let a set of n_{ini} initial conditions be defined as in (8), with Lipschitz continuity constraints (2) and (3). Let us further assume that $N_{c_{ini}^j}(x, t_V) \leq N_{c_{ini}^i}(x, t_V)$ for some $t_V \geq \frac{x-x_i}{v_f}$, with $i > j$. Then:

$$\forall\, t \geq t_V, N_{c_{ini}^j}(x_0, t) \leq N_{c_{ini}^i}(x_0, t) \qquad (14)$$

Proof: using the structure of the solutions $N_{c_{ini}^j}(x, t)$, we have that $N_{c_{ini}^i}(x, t) = N_{c_{ini}^j}(x, t_V) + (t_V - t)v\, k_c$ if $t_V \geq \frac{x-x_i}{v}$ and $i > j$, irrespective of the value of k_j. We also have that $N_{c_{ini}^j}(x, t) \leq N_{c_{ini}^j}(x, t_V) + (t_V - t)v\, k_c$. Hence, we have that $\forall\, t \geq t_V, N_{c_{ini}^j}(x, t) \leq N_{c_{ini}^i}(x, t)$.

This result similarly allows us to exclude a priori some terms from (12), and can be used to speed up computations inside the computational domain. Hence, with the above rules, the computation of the solution at any point of the computational domain can be further simplified as:

$$N(x, t) = \min(min_{j \in S(x,t)}\, N_{c_{ini}^j}(x, t), N_{c_{down}}^{\left\lfloor \frac{t}{\Delta t} - \frac{x_{n_{ini}} - x_0}{w\,\Delta t} \right\rfloor}(x, t), N_{c_{up}}^{\left\lfloor \frac{t}{\Delta t} - \frac{x_{n_{ini}} - x_0}{v_f\,\Delta t} \right\rfloor}(x, t)) \qquad (15)$$

where $S(x, t)$ is the set of initial conditions indices used for the computation $N(x, t)$, which is updated using Corollary 1 and Corollary 2.

Note that $S(x,t)$ depends on the structure of the initial conditions, and is difficult to compute a-priori, though it can be iteratively computed on a computer using Corollary 1 and Corollary 2. If, in addition, the solution is computed at the boundaries of the domain, and the discretization of the initial conditions follows a CFL-type condition, $S(x,t)$ can be computed straightforwardly.

FORMULATION FOR SPECIFIC SPATIO-TEMPORAL DISCRETIZATIONS

In this section, we further assume that the domains of the initial condition satisfy $x_i = x_0 + i\Delta x$ (where $i \in N$), that is, that the initial conditions are piecewise constant on domains of constant size Δx. We also assume that the space and time steps satisfy a CFL-type condition: $\Delta t \leq \frac{\Delta x}{v}$. In this situation, we can prove the two following results (for the upstream boundary, the downstream boundary case being similar), which further simplify the computation of the solution at the upstream and downstream boundaries:

Corollary 3: Let a set of n_{ini} initial conditions be defined as in (1), with Lipschitz continuity constraints (2) and (3). Let us further assume that $x_i = x_0 + i\Delta x$ and $\Delta t \leq \frac{\Delta x}{v}$. For any discrete time $t = i \cdot \Delta t,\ i \in N$ we have that:

$$N(x_0,t) = \begin{cases} \min\left(N_{c_{ini}^{l}}(x_0,t), N_{c_{ini}^{l-1}}(x_0,t), N_{{c_{up}}^{j}}(x_0,(i-1)\Delta t) + v \cdot k_c \cdot \Delta t\right) & if\ t \leq \frac{x_{n_{ini}} - x_0}{w} \\ \min\left(N_{{c_{up}}^{j}}(x_0,(i-1)\Delta t) + v \cdot k_c \cdot \Delta t, {N_{down}}^{k}(x_0,t)\right) & otherwise \end{cases}$$

(16)

where $j = i - 1, k = \left\lfloor \frac{t - \frac{x_{n_{ini}} - x_0}{w}}{\Delta t} \right\rfloor, l = \left\lfloor \frac{wt}{\Delta x} \right\rfloor$

Proof: The first case corresponds to the situation where only initial components and upstream boundary condition components can influence the upstream condition ($t \leq \frac{x_{n_{ini}}-x_0}{w}$). In this situation, we have that $N_{c_{ini}^k}(x_0, t) = +\infty$ if $k > l$. Hence, we can write that $N(x_0, t) =$ $\min\left(N_{c_{ini}^0}(x_0, t), \dots, N_{c_{ini}^{l-1}}(x_0, t), N_{c_{ini}^l}(x_0, t), N_{c_{up}{}^j}(x_0, (i-1)\Delta t) + v \cdot k_c \cdot \Delta t\right)$. However, by the structure of the initial condition solution components (12), we have that for any $k \in [0, l-2]$, $N_{c_{ini}^k}(x_0, t) = N_{c_{ini}^k}(x_0, (i-1)\Delta t) + v k_c (t-(i-1)\Delta t)$. By the inf-morphism property $N_{c_{ini}^k}(x_0, (i-1)\Delta t) \geq N(x_0, (i-1)\Delta t)$, and thus, since $N(x_0, t) \leq N(x_0, (i-1)\Delta t) + k_c v(t-(i-1)\Delta t)$, we have that $N(x_0, t) \leq N_{c_{ini}^k}(x_0, t)$ for any $k \in \{0, \dots, l-2\}$, which shows that only $N_{c_{ini}^{l-1}}$ or $N_{c_{ini}^l}$ can influence the solution in (x_0, t). The proof of the second case is similar.

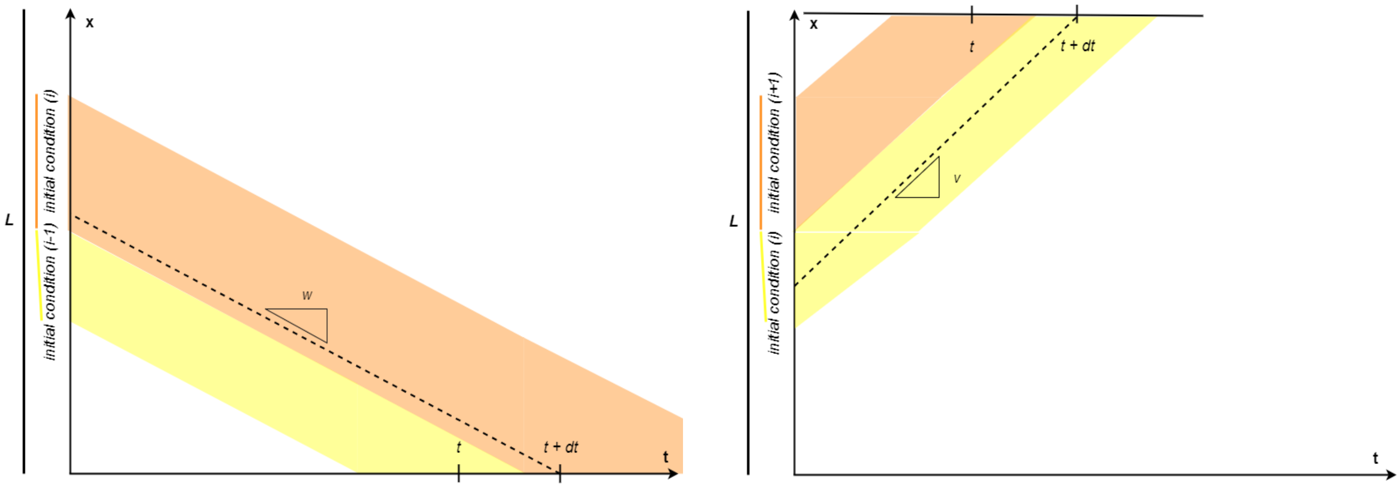
Corollary 4: Let a set of n_{ini} initial conditions be defined as in (8), with Lipschitz continuity constraints (2) and (3). Let us further assume that $x_i = x_0 + i\Delta x$ and $\Delta t \leq \frac{\Delta x}{v}$. For any discrete time $t = i \cdot \Delta t$ ($i \in N$) we have that:

$$N\left(x_{n_{ini}}, t\right) = \begin{cases} \min\left(N_{c_{ini}^l}\left(x_{n_{ini}}, t\right), N_{c_{ini}^{l+1}}\left(x_{n_{ini}}, t\right), N_{c_{down}{}^j}\left(x_{n_{ini}}, (i-1)\Delta t\right) + v \cdot k_c \cdot \Delta t\right) & if\ t \leq \dfrac{x_{n_{ini}} - x_0}{v} \\ \min\left(N_{c_{down}{}^j}\left(x_{n_{ini}}, (i-1)\Delta t\right) + v \cdot k_c \cdot \Delta t, N_{up}{}^k\left(x_{n_{ini}}, t\right)\right) & otherwise \end{cases} \quad (17)$$

where $j = i - 1, k = \left\lfloor \frac{t - \frac{x_{n_{ini}} - x_0}{v}}{\Delta t} \right\rfloor, l = \left\lfloor \frac{vt}{\Delta x} \right\rfloor$

Proof: The first case corresponds to the situation where only initial components and upstream boundary condition components can influence the upstream condition ($t \leq \frac{x_{n_{ini}}-x_0}{v}$). In this situation, we have that $N_{c_{ini}^k}\left(x_{n_{ini}}, t\right) = +\infty$ if $k > l$. Hence, we can write that $N\left(x_{n_{ini}}, t\right) =$ $\min\left(N_{c_{ini}^0}\left(x_{n_{ini}}, t\right), \ldots, N_{c_{ini}^{l-1}}\left(x_{n_{ini}}, t\right), N_{c_{ini}^l}\left(x_{n_{ini}}, t\right), N_{c_{up}{}^j}\left(x_{n_{ini}}, (i-1)\Delta t\right) + v \cdot k_c \cdot \Delta t\right)$. However, by the structure of the initial condition solution components (4), we have that for any $k \in [0, l-2]$, $N_{c_{ini}^k}\left(x_{n_{ini}}, t\right) = N_{c_{ini}^k}\left(x_{n_{ini}}, (i-1)\Delta t\right) + vk_c(t-(i-1)\Delta t)$. By the inf-morphism property $N_{c_{ini}^k}\left(x_{n_{ini}}, (i-1)\Delta t\right) \geq N(x_{n_{ini}}, (i-1)\Delta t)$, and thus, since $N\left(x_{n_{ini}}, t\right) \leq$ $N\left(x_{n_{ini}}, (i-1)\Delta t\right) + k_c v(t-(i-1)\Delta t)$, we have that $N\left(x_{n_{ini}}, t\right) \leq N_{c_{ini}^k}\left(x_{n_{ini}}, t\right)$ for any $k \in$ $\{0, \ldots, l-2\}$, which shows that only $N_{c_{ini}^{l+1}}$ or $N_{c_{ini}^l}$ can influence the solution in $(x_{n_{ini}}, t)$. The proof of the second case is similar.

The above results (and their downstream boundary condition counterparts) imply that, when computing the upstream and downstream conditions in the initial phase of the computation, the associated solutions can be computed on just two consecutive blocks (Figure 3a-b). Furthermore subsequent computations of the solutions at the upstream and downstream boundaries (outside of the area of influence of the initial conditions) can be reduced to those in the classical LTM formulation. The FLH scheme thus computes the boundary conditions with a slightly higher computational cost as the LTM during the initial phase of the simulation (in the domain of influence of the initial condition), requiring two operations to account for the initial conditions instead of one. For subsequent times both formulations (LTM and FLH) are identical, and thus have the same computational cost.



(a) **(b)**

Figure 32: Initial conditions considered for computation of flows upstream (a) and downstream (b) according to Theorem 5 and Theorem 6

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