An agent-based simulation assessment of freight parking demand management strategies for large urban freight generators

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A R T I C L E   I N F O

A B S T R A C T

A growing body of research looks specifically at freight vehicle parking choices for purposes of deliveries to street retail, and choice impacts on travel time/uncertainty, congestion, and emissions. However, little attention was given to large urban freight traffic generators, e.g., shopping malls and commercial buildings with offices and retail. These pose different challenges to manage freight vehicle parking demand, due to the limited parking options. To study these, we propose an agent-based simulation approach which integrates data-driven parking-choice models and a demand/supply simulation model. A case study compares demand management strategies (DMS), influencing parking choices, and their impact in reducing freight vehicle parking externalities, such as traffic congestion. DMS include changes to parking capacity, availability, and pricing as well as services (centralized receiving) and technology-based solutions (directed parking). The case study for a commercial region in Singapore shows DMS can improve travel time, parking costs, emission levels and reducing the queuing. This study contributes with a generalizable method, and to local understanding of technology and policy potential. The latter can be of value for managers of large traffic generators and public authorities as a way to understand to select suitable DMS.

1. Introduction

Large urban freight traffic generators (LTGs) can be defined as buildings containing one or more businesses that product/attract a comparatively large number of freight vehicles (Jaller, Wang, & Holguín-Veras, 2015). The concept is particularly applicable to high-rise buildings with residential, business, or mixed uses (Thompson & Flores, 2016) but can also be applicable to low-rise buildings, inclusive of retail areas or shopping malls. In the case of a shopping mall, each retail store might generate a small amount of freight deliveries, but the building as a whole can generate a significant amount of freight traffic and being even considered as a small urban center (Thompson & Flores, 2016). Parking is an intrinsic activity in urban freight distribution, repeatedly performed by freight vehicle drivers. Parking choice has been

defined as the search and choice process for a parking spot, which rely on linked decisions based on updated knowledge and past experience (Thompson & Richardson, 1998). A high demand for commercial vehicles parking for pickup and delivery purposes at LTGs prompts for the use of Demand Management Systems (DMS). DMS aim to influence parking choices by changing the cost in time or money or effort associated with each choice. DMS can range from loading bay capacity or pricing adjustments but can also rely on technologies such as information provision, booking systems or guidance. The lack of a unified method to model the impact of DMS motivated us to integrate behavioral models into an agent-based simulation to explore the applicability of the framework and quantify DMS benefits. Agent-based simulations rely on explicitly representations of relevant actors (i.e. "agents") and their decision-making abilities, often interacting with other agents and

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their choices.

Freight vehicles have different parking needs compared to passenger vehicles: (a) they need more space since they are larger vehicles and workers need of extra space to access the cargo and unload goods; (b) drivers have a lower threshold for walking since they often carry heavy loads; (c) they have limited access to parking lots if using vehicles with a comparatively higher height and commercial vehicles often cannot use car parks reserved for passenger vehicles; (d) they have shorter parking duration; and (e) they have a limited flexibility in adjusting schedule or travel mode; (f) they are often more willing to park in unauthorized locations (Nourinejad, Wenneman, Habib, & Roorda, 2014), e.g., on street (Demir, Huang, Scholts, & Van Woensel, 2015). Therefore, some urban areas and buildings have been equipped with loading bays for loading/unloading goods. They are designed for short-term use for facilitating deliveries without causing an impact on crossing traffic. Existing loading bay systems are commonly reported as: a) unsuitable for current demand, either due to their location and/or size (Alho, de Abreu e Silva, Pinho de Sousa, & Blanco, 2018; Dezi, Dondi, & Sangiorgi, 2010) or b) incorrectly used by freight and passenger vehicle drivers (Alho & de Abreu e Silva, 2014). However, while logistics coordination might exist among different branches of the same business, typically there is limited coordination in the ordering process between businesses located in the same LTG (Jaller et al., 2015). Therefore, the carriers often have to compete for the limited loading bay capacity. Further, the drivers often have to take the goods to the receiver located inside the LTG building(s), which increases the required parking duration. Thus, the main issue associated with freight vehicle parking at LTG is a mismatch between supply and demand, which leads to queueing/parking practices that cause externalities.

Externalities derived from supply/demand mismatches could be significant, comprising of environmental (e.g., air pollution), economic (e.g., delivery delays and thus loss of delivery reliability and higher delivery costs) and social problems (e.g., noise pollution, road traffic congestion due to spill overs, illegal parking, drivers and pedestrians' safety). In the case of a large shopping malls (the focus of the case study analyzed in this paper) commercial vehicle parking externalities include: (a) unauthorized parking on-street, potentially blocking traffic and creating unsafe conditions for pedestrians and other drivers, (b) higher delivery cost due to loading bay congestion, with several commercial vehicles having to queue and wait to park and perform their deliveries and pick-ups, (c) longer parking duration due to the drivers having to walk inside buildings and search for final delivery destination. Dalla Chiara and Cheah (2017) measured an average of 7.7 min of waiting time to access a loading bay at an observed mall in Singapore. Fig. 1 illustrates a queue of commercial vehicles waiting to access a loading bay in a shopping mall in Singapore. Queuing is costly for the freight carriers, with a truck driver's value of time has been estimated to range from US$20 to US$30 per hour (Weisbrod, Vary, & Treyz, 2001).

Moreover, vehicles generate emissions while idling in the queue, and if the queue it spills over to the road network, can cause delays and nuisance to the passing traffic.

Despite some similarities between parking problems arising from deliveries to LTGs and those to street retail, these are hypothesized as different problems due to (a) scale and concentration of demand, and (b) range of applicable DMS. Examples of DMS include loading bay capacity or pricing adjustments but can also rely on technologies such as information provision, booking systems or guidance.

To evaluate the effect of DMS in reducing the negative externalities of freight deliveries and pickups, we propose a simulation-based approach, in which a set of parking demand management strategies are considered as alternative scenarios. The objective is to evaluate the impacts of DMS using an agent-based mobility simulator; for this evaluation, we integrated a parking choice and duration model into the agent-based mobility and freight simulator – SimMobility.

This method relies on unique contributions to the integration of a data-driven econometric parking-choice model and a supply simulation considering various infrastructures and traffic impacts of queuing. A case study is used to illustrate its application to a commercial zone in Singapore with multiple shopping malls. In the following section, we provide a literature review covering freight parking models and simulations of thereof, as well as applicable DMS. Following, we detail the models of parking demand, parking choice, dwell time, supply interactions and performance metrics. This section concludes with the case-study details. Then, results are explored for the multiple DMS, suggested settings and achieved externalities reduction. We finish the paper with discussion and conclusion sections. Here, respectively, we elaborate on the connection between the case-study results and prior literature, and how the results can be put to practice as well as next steps. We put forward that this effort should be of value for mall operators and public authorities as a way to understand behavior and better manage existing freight parking infrastructure.

In summary we acknowledge this study's contributions as threefold. First, we propose a method to model parking choices in the context of an agent-based demand/supply simulator. Then, we demonstrate the applicability of the method using a case-study for a relatively large study area. Finally, we compare demand management scenarios to shed light on their relative performance for the case at hand.

2. Literature review

We structure this literature review in three main sections which contributed to our research design: (a) parking demand management strategies and expected effects, (b) simulations of parking choice targeted at evaluating demand management strategies and (c) parking choice and duration models.

Fig. 1. Illustration of queue to loading bay at a mall in Singapore with spill over to service and main road.

2.1. Parking demand management strategies

There is a wide body of research exploring the impact of different parking DMS, with our focus being on demand management relevant to parking operations only. In this literature review we focus on the following alternatives: loading bay location/size, pricing, assistance, coordination/guidance.

2.1.1. Location and sizing

Providing freight-centric parking locations where needed and with adequate availability ensure that these locations are considered as viable options by the drivers. Thus, a strong body of research focused on street-level loading bay location and size (Dezi et al., 2010, Kladeftiras & Antoniou, 2013, Gardrat & Serouge, 2016, Tamayo, Gaudron, & de La Fortelle, 2017, Alho et al., 2018), for which there is no agreed upon method that is widely applied. Regulatory agencies often set some guidelines on loading bay provision which might or not be adequate and/or based on a sound method (Gardrat & Serouge, 2016; Muñuzuri, Cuberos, Abaurrea, & Escudero, 2017). The same authors highlight the example of the "CERTU method" (CERTU, 2009), where average weekly deliveries are divided by 90 to determine the number of bays needed. Muñuzuri et al. (2017) elaborate on the alternative options to estimate demand, such as average demand, peak demand and coincident demand. In Singapore, the Land Transport Authority specify minimum parking provisions depending on the land-use and activity of the building (LTA, 2011). However, these guidelines do not account for food and beverages retailers, which can lead to an underestimation of parking demand needs.

2.1.2. Pricing

Pricing can target loading bays or to alternatives considered by the drivers. There are several research contributions related to finding the optimal curbside (on-street) parking price for passenger vehicles, while little is found targeting freight, and more specifically loading bays at LTGs. Inci (2015) highlights the need for more research on illegal/informal parking as well as on parking enforcement. Dalla Chiara, Cheah, Azevedo, and Ben-Akiva (2020) has explored several parking pricing policies for loading bays, car parks and illegal parking for two malls in Singapore, which found the price increases or decreases to isolated system elements do not lead to significant financial or environmental benefits through a discrete-event simulation. It is particularly useful to note that even if heavy fines are imposed on double parking, unless there is adequate parking availability, some carriers might bear the fines. This can lead to "higher user service costs and potentially lower social welfare" (Nourinejad, 2017). Carriers unable to bear the fines might add to congestion by cruising for parking, i.e., to 'circle around' until they find somewhere suitable to park.

2.1.3. Delivery assistance

One example of a strategy aiming to assist drivers is Centralized Receiving (CR). CR involves a logistics operator (e.g., third-party) being available to receive goods from the drivers at the LTG's loading bay and to perform the deliveries inside the LTG on the carrier's behalf. The main effect of the policy is to reduce vehicles parking duration, since a driver using the CR service needs only to unload the goods at the Loading Bay (LB) and does not have to carry them to the stores. Shorter parking duration can result in a higher LB utilization and shorter queuing times. It also introduces some level of buffer storage between the carrier and the receiver, although that is not the focus of this research. The concept has been modelled by Allen et al. (2003) demonstrating cost reductions for carriers. Dalla Chiara, Cheah, Guerrero-Ayala, and Courcoubetis (2017) demonstrated that, albeit promising, CR receiving policies might lead to counter-intuitive effects, by making LBs more appealing, which might not be compensated for by decrease in handling time. Singapore has piloted CR (Kwang, 2016) as well as Japan (Taniguchi & Qureshi, 2014) with pilots being too specific to generalize the conclusions.

2.1.4. Guidance

Regarding parking guidance, it is typically associated with the provision of information relying on digital technologies. There are several examples of this strategy for passenger parking, especially in shopping malls where capacity and availability by level and row are often provided to those who seek an open parking slot (Hanzl, 2020). Given the existence of parking alternatives, such as a car park which can provide reasonable access to shops by delivery staff, one option is to direct freight vehicles to the passenger car park. Such parking guidance might be helpful in reducing queuing and illegal parking. Practically, it can be implemented as a sign-based messaging board, or a smartphone application. No real-world application was found of such system, which we aim to test in these experiments.

2.1.5. Coordination

An example of coordination are booking systems. Booking systems consist in software or app-driven interfaces that allows carriers/drivers to book in advance a parking slot based on expected arrival time and duration of parking activity. The concept is introduced by Teodorović and Lučić (2006) in the context of passenger vehicle parking but it allows staggering deliveries and thus achieve a more uniform use of the loading bay throughout the day. Guaranteeing a parking slot through booking eliminates the need to search and choose parking on-the-fly. Simulation studies were performed by McLeod and Cherrett (2011) and Comi et al. (2017, 2018a). McLeod and Cherrett (2011) highlighted that the results critically depend on the selection of assumptions regarding the system's setting. This is mainly because there is considerable uncertainty regarding the driver's arrival time, which can be earlier/later than expected. Patier, David, Chalon, and Deslandres (2014) have presented an architecture for the implementation of such systems that allows for dynamic adjustments. Roca-Riu, Fernandez, and Estrada (2015) propose and evaluate several optimization models aiming to satisfy all (or a maximum of) parking requests within their time windows, as to avoid illegal parking. There have been real-world demonstrations in Australia (Bestrane, 2016), as well as in Spain and France (Gonzalez-Feliu et al., 2013), Germany and Switzerland (Lucietti, 2003) Austria (Chloupek & Zajicek, 2013), and Italy (Comi, Schiraldi, & Buttarazz, 2018b). Given coordination systems are not evaluated in this study we refer the readers to the studies listed for further information.

2.2. Freight parking simulations

This research is relevant to the domain of simulation models that are used to evaluate parking-related policies, particularly those that leverage behavioral models to replicate drivers' actions and specific to freight vehicles. Early research on this domain was pioneered from 2000 to ~2010 by Muñuzuri, Racero, and Larraneta (2002), Aiura and Taniguchi (2006), Benenson, Martens, and Birfir (2008), Dieussaert, Aerts, Therese, Maeirivoet, and Spitaels (2009), or Delaître and Routhier (2010) who either developed or adapted tools to study parking behavior and policy impact. From 2010 onwards, the research sophistication started leveraging microsimulation tools, and increasing in design complexity. A critical challenge to be overcome when designing and applying simulation models, highlighted by Waraich and Axhausen (2012), is to achieve an adequate level of abstraction, being representative of the drivers' behavior while computationally practical. We assume as relevant behaviors: (a) parking search, also known as cruising, (b) parking choice (Waraich & Axhausen, 2012 in Horni et al., 2016; Nourinejad et al. 2017), (c) dwell time representation (Gardrat & Serouge, 2016, Dalla Chiara & Cheah, 2017) and (d) impact of obstructions in passing traffic, such as double-parked vehicles (McLeod & Cherrett, 2011) and associated impacts (Alho et al., 2018; Gao & Ozbay, 2016; Kladeftiras & Antoniou, 2013) queue spillovers. The last three are the most relevant as, in LTGs, it is assumed that suitable infrastructures will be concentrated around the building. Microsimulations are adequate tools to be used in this context, as adopted by several

researchers. While there are multiple papers on the topic, there is no standard approach to model parking behavior with studies focusing on different dimensions. Still, only the work of Dalla Chiara et al. (2017, 2020) was found addressing parking in LTGs, in this case shopping malls, where the suitable infrastructures are concentrated in the surrounding of a building, and which does not rely so heavily on the need to replicate cruising behavior. To note that the authors acknowledge the importance of doing so when studying on-street parking as highlighted by Bischoff and Nagel (2017).

2.3. Freight parking choice and duration models

Most disaggregate parking choice/duration models proposed in the literature focused on passenger vehicle drivers, with a detailed review provided in Dalla Chiara and Cheah (2017) and Dalla Chiara et al. (2020). One exception is the work of Marcucci, Gatta, and Scaccia (2015) provide an in-depth analysis of transport providers (i.e., carriers) preferences regarding parking and pricing policies. Data is collected for a limited traffic zone for the city of Rome, and the study evaluates different combinations of number of bays, entrance fees and probability of finding them free. The authors conclude there are non-negligible heterogeneous preferences, depending, e.g., on the commodities carried and frequency of access to the area, with implications towards policy analysis and recommendations.

There are several potentially relevant factors influencing parking choice. Compiled from Axhausen and Polak (1991), Teknomo and Hokao (1997), Waraich and Axhausen (2012), and Nourinejad et al. (2014), examples are: access time, trip purpose, age, gender, search time, queue time, availability, fees, ability to support fine costs, walking time, security and comfort. A model of parking choice for commercial vehicles is estimated by Dalla Chiara et al. (2020) taking into account explanatory variables such as the cost of alternatives (inclusive of expected fines), the total delivery staff, volume to be handled and expected access time. The current study builds upon the latter study combining the behavioral model for commercial vehicle parking choice with a simulation model and applying it to a busy commercial area in Singapore.

Regarding parking duration, its typically hypothesized that parking location has a direct influence on the duration delivery operations. While this is a research gap on freight, Nurul Habib, Khandker, Morency, and Trépanier (2012) and Kobus, Gutierrez Puigarnau, Rietveld, and Van Ommeren (2013) explored the endogenic relationship between passenger vehicle parking choice and, respectively, activity scheduling and parking duration. There are a series of factors that can be thought to have an influence on parking duration, but this is a largely unexplored field due to the challenges of obtaining disaggregate data. Such factors can be related to the type and quantity of goods, use of auxiliary equipment and helpers, distance to the destination, and the waiting time to park the vehicle. In this domain, Zou et al. (2016) used disaggregate data obtained from surveying freight vehicles' drivers that parked on-street in New York to derive a Cox proportional-hazard model of parking duration, using as explanatory variables the arrival time, commodity handled, type of vehicle and parking location. Dalla Chiara and Cheah (2017) explored parking duration for different infrastructures in malls and estimated a regression model for parking duration using as explanatory variables vehicle time, time spent queuing, quantity handled by worked, whether a pickup was performed, and the percentage of vehicle capacity occupied upon arrival. Schmid et al. (2018) estimated a parametric survival model to predict parking duration based on several characteristics of a parked freight vehicle, further justifying the conclusions of Dalla Chiara and Cheah (2017) that parking duration appears related to parking choice.

3. Methods

The methods section is structured as follows. First, we present an

overview of the analytical framework. Then, details of the demand (3.2) and supply (3.3) models and their integration (3.4) After we detail the range of selected DMS (3.5), i.e., the scenarios, and the metrics used to evaluate them (3.6). Lastly, we cover the details of the case study application (3.7). In the experimental framework (Fig. 2), we configure the scenario inputs (pricing, capacity, availability, technologies, etc.) according to either the baseline or DMS. Each scenario is simulated multiple times to overcome the stochastic nature of microscopic simulation. Then, the scenario simulations are assessed according to a set of evaluation criteria which will be detailed.

The analytical framework leverages SimMobility, a multimodal microscopic traffic simulator. SimMobility explicitly models the interaction between the demand and supply of urban transportation. The microscopic simulator includes models of driving behaviors (car-following, lane-changing, route-choice, etc.). Demand (for freight and passengers) is simulated using an activity-based demand model (Sakai et al., 2020, Adnan et al., 2016). Readers can refer to Azevedo et al. (2017) for details on the supply simulator architecture. For this study, we have incorporated the parking demand and supply models in the simulation framework, a process elaborated in the following sections. Note that while it is possible to further expand the behavioral complexities captured in these models, given the challenges in calibrating and validating them holistically, we developed a (deemed) sufficient set of features to the proposed study (Simon, 1990).

It is worth highlighting that while the models are generally applicable to any urban context, they have been calibrated to a specific region. Demand and supply models are calibrated to data available for the City-State of Singapore, and the parking choice models to data collected in the specific case-study area. Singapore was selected based on convenience. Given an extensive presence of the research group laboratory in the region, with several projects collaborating with local authorities, this allowed for large scale data collection and model development. The selection for the latter is justified in this *Methods* section.

Finally, we stress the study is focused on the parking of freight vehicles which does not compete with passenger vehicle parking, except when parking in the passenger car park. However, given their dimension magnitude of demand, this is assumed ignorable.

3.1. Agents, actions and their interactions

For purposes of this paper, the relevant agents, their actions and interactions are:

- Passenger vehicle drivers: being driven by individuals who have chosen specific destinations to perform specific activities. There are no extraordinary actions for this particular study but they interact with freight vehicle drivers that are parked or waiting in the road to access parking facilities. These will obstruct their flow impacting their travel time.
- Freight vehicle drivers are the focus of this study. Having a defined tour (a sequence of stops and purposes to be fulfilled), these drivers make a parking choice before arriving at each destination. They impact other freight vehicle drivers with their parking choices, which change parking availability, and are impacted by passenger vehicles who co-define the congestion level.
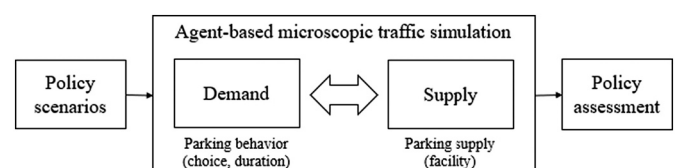- Business establishments can have one or more roles:

Fig. 2. Analytical framework.

- Shipper role: have a set of shipments that required being picked up by freight vehicle drivers.
- Receiver role: expect a set of shipments that required delivery by freight vehicle drivers
- Carrier role: own freight vehicles and define their tours for purpose of pickup-deliveries.

Other relevant entities - represented elements with specific attributes but without decision-making behavior - are:

- Vehicles: transporting freight and passengers,
- Buildings: representing initial departure and arrival nodes for vehicles,
- Parking facilities: representing the final departure and arrival nodes for vehicles,
- Traffic lights: impacting the traffic flow by allowing/blocking circulation,
- Road network: defining the networking connecting the buildings and parking facilities.

3.2. Demand models

Note the details of the freight (commodity and trip) demand models are covered in Sakai et al. (2020). Fig. 3 describes the stages of a parking operation performed by a commercial vehicle driver when delivering to an LTG. *Queueing time* is defined as the time a driver waits before being able to park the vehicle if the driver chooses to park at a loading bay (Activity 1). The vehicle is then immobilized for purposes of delivering (activity 2). The *parking duration* is the time a vehicle remains parked (activity 3). During this time interval, the driver, and any helper perform several activities according to the planned tasks (e.g., deliver goods, perform delivery-related activities) or non-planned activities (e.g., waiting for the receiver to be available). The total time incurred between the entry and the exit to the service road (SR) is defined as *dwell time*. In the rest of the section, we describe the parking choice model, the parking duration model, the traffic simulation model, and how all these models are integrated.

3.2.1. Parking choice model

Upon arrival nearby an LTG, a vehicle driver chooses where to park the vehicle while performing the delivery/pick-up. We define parking choice as the decision to select a parking alternative given a set of alternatives available to the driver and attributes of each alternative. The aggregation of parking choices by multiple drivers determines the distribution of the congestion at and around an LTG. In this study we chose to apply a Random Utility Model (RUM) to predict parking choices. A RUM is selected assuming the underlying hypothesis that choice is conditioned on preferences but also by random factors not captured in the model. The estimated model for a freight vehicle driver's parking choice is derived in Dalla Chiara et al. (2020). In the rest of the section, we summarize the key features of the model. For more details on the modeling and data used to estimate the model we refer to Dalla Chiara et al. (2017, 2020).

The parking choice model assumes three main types of parking infrastructure:

- *Loading bays (LB)*: a parking area reserved for deliveries, commonly off-street and adjacent to the LTG. It provides direct and facilitated access for goods handling to a building through dedicated logistics infrastructures (freight elevators, elevated platforms etc.). Other services might be provided: presence of guards, CCTV (Closed-circuit Television), elevated platforms etc. but these are not explicitly modelled. The LB is characterized by a limited capacity which, when reached, leads to vehicles waiting in queue before being able to park. A LB can be free of charge or have a gantry where payment is required, e.g., according to a price per unit of parking duration. Often, LB are reachable from a "service road", which is a secondary road that only leads to the parking facility; other times the facility is directly accessible from a main road.
- *Carpark (CRP)*: a parking area primarily dedicated for passenger vehicles and characterized by a larger capacity than the LB. When off-street (inside a building), it is usually associated with a vehicle height limit, such that only cars and smaller commercial vans can access it. Pricing can be a function of the parking duration although in some regions a large share of malls' car parks are free (International Council of Shopping Centers, 2003). Although the number of vehicles inside the CRP is usually unobservable, an experienced driver might be aware of the periods of the day where congestion occurs, and therefore expect a longer time spent cruising inside CRP during peak hours. Some malls are equipped with road-side displays showing the number of available parking lots inside the carpark.
- *On-street parking (STR)*: composed of multiple alternative parking locations, such as curbside, in-lane parking, double parking and parking in areas reserved for other vehicles (e.g., taxi stands and bus stops). These are generally considered forms of unauthorized parking, involving the risk of being fined if "caught" by patrolling officers.

We assume that drivers choose among the different parking locations which can physically accommodate the vehicle. A commercial vehicle driver is always free to choose to park on-street or inside the LB, if they are available, while it is possible to park in a car park only if it is small enough.

Moreover, the following attributes have been considered as inputs to the parking choice model:

- Tour-level attributes, represented by vehicle type and number of workers in the vehicle;
- Activity-level attributes, describing the type of activity to be performed at a given stop by its parking duration and shipment volume. We assume parking duration as exogenous and define it as the time that the driver expects to take to perform the delivery operation excluding the queuing element, i.e., after the vehicle is parked. This variable is assumed predictable, and further detailed in a subsequent section.
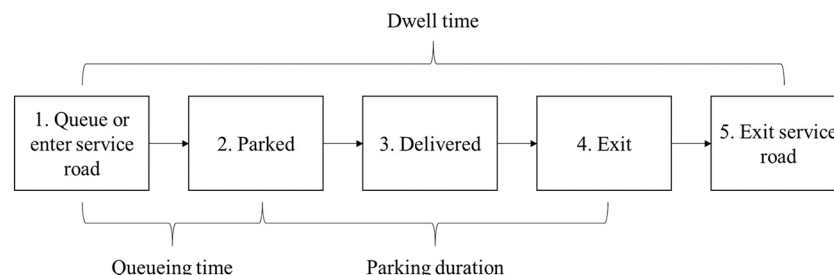

Fig. 3. Stages of parking operation performed by a commercial vehicle at a receiver location.

- Infrastructure-level attributes, describing the static features, such as capacity, cost, fines and patrolling frequency; and the dynamic attributes such as congestion of the alternative parking locations, i.e., queue length. The probability of being fined is modelled as a function of the vehicle parking duration and assumed frequency of enforcement (λ) as a Poisson distribution:

$$p(fine) = 1 - e^{-\lambda d_n}$$

The utility for each alternative is computed using the coefficient estimates in Appendix 1. Note that vehicles above a certain height face a choice only between LB and STR, as they cannot enter the CRP, meaning the probability of CRP is fixed at 0 and only probabilities for LB and STR parking are computed. Finally, we assume that drivers have homologous behaviors, meaning we disregard individual cost and time sensitivities.

3.2.2. Parking duration model

A key determinant in the choice of parking facility is the parking duration, as it affects both the total parking fee paid at the LB and CRP as well as the expectation of receiving a parking ticket if parked in alternative STR. More generally, in aggregate the parking duration determines the parking turnover, and therefore the amount of congestion of a parking facility. There is a myriad of influences to parking duration, which we decompose into a predictable component and an unpredictable component. The predictable component is hypothesized to be predominantly influenced by observable factors at the point of parking such as:

- attributes of the vehicle (vehicle type, vehicle loading, number of helpers),
- attributes of the activity to be performed (stop purpose, commodity type, volume of goods handled), and
- parking location.

Empirical delivery data allows inferring STR parking is associated with a shorter duration, hypothesized due to the risk aversion of the driver in being fined. This relation between the parking choice and parking duration arguably prompts for the need of simultaneously estimate both the parking location choice and the parking duration. An alternative method is used to capture this relationship while remaining compatible with the current agent-based simulation framework. In our simulation framework, the carriers plan for their operations in advance. Here, parking choice is assumed in the LB and a parking duration is estimated. A linear regression model is used to estimate the parking duration based on the following variables: delivery volume handled per worker, load factor of vehicle upon arrival, whether a pickup is performed, vehicle type, arrival time. When the traffic simulation is ongoing, and the parking choice takes place, the same parking duration model is applied, estimated but allowing the influence of other infrastructure specific constants (STR, CRP) in its output.

3.3. Supply models

The supply framework was designed to capture the impacts of queue spill over to the main road as well as of double parking in a microscopic simulation. It also aimed to remain general beyond the cases of freight parking at LTGs. The parking infrastructure is represented by its location in the road network, a capacity, and other relevant attributes (e.g., cost). Its location defines a virtual split of the road segment, resulting in a virtual node (Fig. 4). In case DBL capacity is defined based on the capacity of the outermost lane segment to accommodate double parked vehicles. The limit to double parked vehicles is to avoid crossing, and hence blocking, a prior intersection. Also, in this case spill over capacity and service road capacity are equal to zero.

Vehicles will flow through the sequence of available infrastructure subject to capacity. If a service road is present and the parking infrastructure is full, the queue of waiting vehicles will first block the service road, and only after will spill over the main road link, potentially creating traffic blockages. In that case, the vehicle switches states to "Queuing", blocking incoming vehicles on that lane. A description of vehicle states is provided later in this section. Lane selection in the road segments ensures that traffic flows through other lanes if one is blocked. It is assumed queues only take place is in the outer-most lane. Since lane widths are not explicitly modelled, and wide lanes can allow for queuing/double parking with minor impacts on passing traffic, particularly for one-lane roads, in specific cases additional lanes are added for realism of traffic conditions. This is performing using local knowledge of the network and traffic conditions.

STR is modelled as a parking infrastructure with no capacity available and no service road. The vehicle starts to queue at the entrance point of segment and changes her state from "Queuing" to "double-parked" and delivery time counter starts. Once the delivery time ends, the vehicle is moved to the next segment, proceeding to the next stop.

3.4. Model integration

Regarding the integration of the parking choice and dwell time models with the supply simulation, assumptions were required to operationalize the presented framework:

- In situations where there are more than one LTG at the same network-level node, with multiple parking infrastructures of the same type (e.g., LB), either LTG is chosen first, with subsequent parking choices leading to a routing to the new parking location.
- If a parking choice is not realized for a given reason, the delivery is considered failed. Then, the vehicle follows to its next destination node.

The overall flow of the parking model is illustrated in Fig. 5, with a detailed description following. Note the following acronyms:

- Service road (SR),
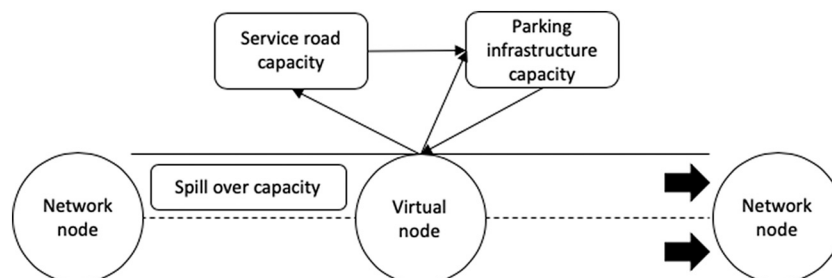- CRP and LB are referred jointly as Parking (P),

Fig. 4. Schematic diagram of parking supply flow, applicable to all infrastructure.
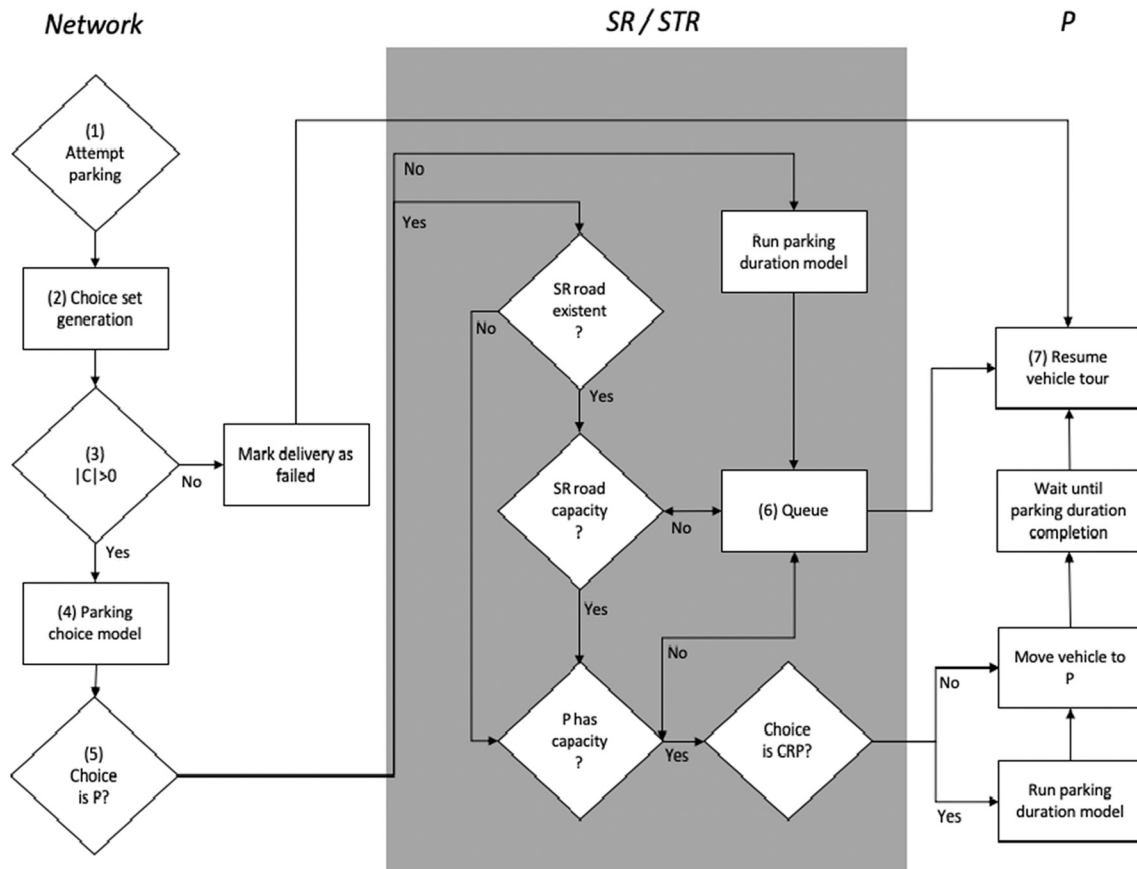
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Fig. 5. Vehicle parking activity flow.

- Universal choice set (C).

  The vehicle is initially set with a "NONE" status.

- Three conditions must be met such that parking is attempted: (1) Vehicle has a set of eligible establishments to deliver to in a destination node, in this case specified as LTG; (2) Vehicle is in route to the activity, and (3) vehicle has entered the last segment before a node to access the LB. It is assumed the vehicle always heads to the LB first, when departing from the prior destination.
- The choice set is generated based on available infrastructure at the destination and subject to vehicle type as prior mentioned. It is assumed that when the choice set is evaluated the driver has full visibility of the parking conditions (queue, capacity) at the destination.
- If capacity is not available in any alternative the delivery is marked as failed and the vehicle follows to the "main" destination node as prior described, i.e., the node to which the LTG is assigned.
- Parking choice performed as per choice model output. Vehicle status is changed to "CHOSEN" with the vehicle in transit towards choice.
- Triggering of parking duration model for purposes of adjusting parking duration to CRP or STR.
- Vehicle state and following steps is dependent on parking choice:
  - If waiting on main road for SR availability, vehicle behaves as per a typical queue-based model, and upon capacity made available vehicle is moved into SR, where, if a queue exists, leads to a change of status to "WAIT_TO_PARK_SR (Queuing on service road), until parked when it switches to "PARKED".
  - If parking in STR, vehicle state is changed to "PARKED_DP" until dwell time completion, after which the vehicle proceeds to the next stop.

- Change vehicle status to "DONE", move vehicle to following segment and proceed to next stop.

3.5. Demand management strategies (scenarios)

A set of DMS are considered as alternative scenarios to the base case where demand and supply are a close representation of reality. Undoubtedly, DMSs could be considered in a complementary fashion, out of scope of the research herein presented. It is assumed strategies are adopted by all LTGs in the case-study area. Associated implementation and running costs are not considered in this analysis, assumed absorbed by the LTG. This illustrates a policy perspective of internalizing externalities, and of minimizing the freight footprint caused the activities intrinsic to the LTG. Similar perspectives have been discussed by Holguín-Veras and Sánchez-Díaz (2016) regarding receiver-led consolidation initiatives. Despite evidence of small-scale pilots, the researchers did not gain access to information on their outputs, nor were able to confirm the current operationally of any of the DMSs being herein studied.

The following strategies are explored, and further detailed regarding their implementation assumptions:

- **Increasing LB Parking Capacity (*Increase Capacity*)**: Increasing LB capacity has the potential to reduce the queue length. Practically, we expect this to increase the relative attractiveness of LB compared to STR and CRP. We size the loading bay at each LTG as 1 bay per 4000 square meters, using as inputs the total gross floor area (GFA) for retail inclusive of food and beverage outlets and entertainment venues, similar to guidelines issued in 1995 (Singapore Government, 1995). The guidelines are not necessarily followed in the baseline resulting in an increase of LB sizes for 6 LTG.

- **Pricing (*Free Car Park, No Double Parking*):** Pricing of the parking infrastructure can be used to achieve reductions of negative externalities. Prior research showed changing pricing of one alternative is unlikely to be a relevant solution (Dalla Chiara et al., 2020). Increases in expected prices in LB would lead to more vehicles in CRP and STR. Decreases in the costs of CRP and STR can reduce queues to LB but more vehicles park on-street and reduce the CRP capacity. Further, depending on the location, queues related to one alternative might be more desirable. For example, vehicles double parked in a secondary road might result in smaller traffic impacts when compared with vehicles queueing for LB in a main road with more traffic. Lastly, prior research emphasizes carriers as a sector typically operating in tight margins, subject to receivers' set time-windows and with limited abilities to transfer incurred costs to the receivers, depending on the policy design (Holguín-Veras, 2011). The base case charges are based on the actual cost table determined by the mall operator (collected from LTA, 2020). Conceptually the prices follow Fig. 6. Pricing scenarios are
  - **Free Car Park:** CRP usage is free, which will make the CRP more appealing especially for longer parking duration versus the LB and CRP alternatives.
  - **No Double Parking:** no use of DBL, i.e., double parking is prohibited, assuming some form of unavoidable fines, such as via the use of CCTV systems with plate recognition, physical barriers or human enforcement.

- **Delivery Assistance (*Centralized Receiving*):** Centralized receiving is explored from a perspective of dwell time reductions. Other effects such as the possibility to introduce a buffer between the carriers and the receivers inside the mall, extending the time-window within which a driver can perform the activity, e.g., up to nighttime deliveries, are not captured in this case study. Thus, the main policy parameter is the efficiency of the CR service, i.e., by how much the parking duration can be reduced. The parking duration is composed both unloading and delivery time. The expectation is that the latter is predominantly affected since the vehicle is still required to unload. The first might or not be affected dependent on the existence of staff to assist this process. We assume a maximum delivery duration of 5 min. This reduction is expected to increase the appeal of the LB versus CRP and DLB, all else equal, given the faster turnover of vehicles which would clear its queue.
- **Guidance (*Directed Parking*)** Directed parking replicates a guidance system that is available to the drivers via, e.g., sign boards. Once there is no capacity at the loading bay, if the vehicle (i.e., LGV) is dimension-wise suitable to enter the carpark, the vehicle is re-routed
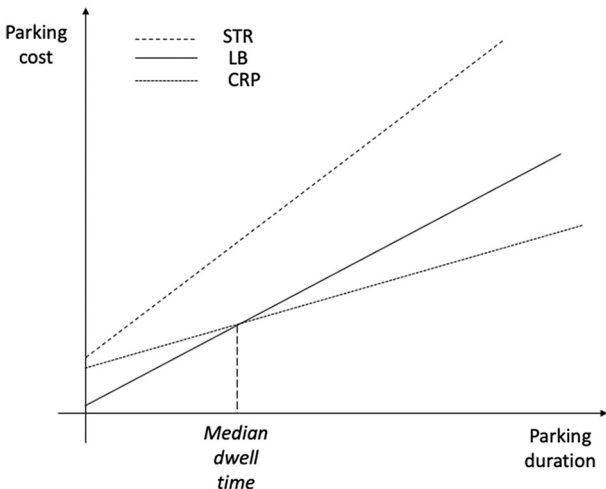
to the CRP alternative. Practically this does not allow the creation of a queue unless there is no alternative. This reduces the queues at LB and can decrease the appeal to DBL.

3.6. Evaluation criteria

The evaluation metrics are structured according to the key stakeholders (the LTG operator, carrier, driver, and traffic authority). It is also structure in two parts: (i) queueing analysis, (ii) cost analysis., with the first contributing to the latter. First, the queueing analysis part illustrates parking activity. It is derived from the sequence of events at the LTG's facility level: *Arrival* at the facility area (*A*), *Park* at the facility (*P*), *Depart* from the facility (*D*). Based on the cumulative count (*N*) on each event, we capture the total queue lengths (*L*) and total delays for parking (*W*) over the LTG ($m \in M$) and time intervals ($t \in T$) of a specific scenario ($SC = \{Base, DBL, DP, PR\}$) which is an important variable from the drivers' perspective (Eq.1, Eq.2).

$$L_{SC} = \sum_{m=1}^{M} \sum_{t=1}^{T} (A_m(t) - P_m(t)) \tag{1}$$

$$W_{SC} = \sum_{m=1}^{M} \sum_{t=1}^{T} (P_m(N) - A_m(N)) \tag{2}$$

SimMobility Short-term provides the detailed trajectory of individual vehicles ($i \in I$) at every 0.1 s and captures the travel time from origin to destination (tt_i) as well as the waiting time near parking facility (wt_i). These variables enable us to perform cost analysis by estimating the travel and waiting time cost (*C*) of drivers with an assumed value-of-time (*VoT*). The measures are aggregated as:

$$C_{SC} = \sum_{i=1}^{I} (tt_i * VoT_{tt} + wt_i * VoT_{wt}) \tag{3}$$

Note that the commercial vehicles are labeled as per size groups used in Singapore: Light-, Heavy, Very Heavy Goods Vehicle (LGV <3.5ton, HGV ≥3.5ton & <16ton, VHGV ≥ 16ton, respectively). In which, *VoT* of en-route travel-time, VoT_{tt} has been assumed as 27.26(S\$/h), 33.68(S\$/h), 41.87(S\$/h) for LGV, HGV, VHGV respectively. Also, *VoT* of waiting in the queue, VoT_{wt} is assumed as 19.57(S\$/h), 24.17(S\$/h), 30.06(S\$/h) for those vehicle types (Weisbrod et al., 2001).

We also have measured the monetary cost (*R*) that each driver paid for the parking fee which is equivalent with the revenue of mall operator (Eq. 4).

$$R_{SC} = \sum_{i=1}^{I} (r_k + \alpha_k * d_i) \tag{4}$$

In which, r_k includes the entrance fee and initial parking price and α_k is the hourly rate per unit time (i.e., 15 min) charged by each parking facility ($k \in K$) for the parking duration of individual (d_i).

To evaluate the environmental impacts of strategies, we estimate the emissions of commercial freight vehicles as well as regular passenger vehicles (*E*, unit: kg). This measure considers two vehicle states: *"driving"* or *"idle"* as:

$$E_{SC} = E_{driving} + E_{idle} \tag{5}$$

In which, $E_{driving} = \sum_{i=1}^{I} \{(0.063 * TD_i * 10^{-3})\}$ where TD is travel distance of vehicles *i*; $E_{idle} = \sum_{i=1}^{I} \{(0.0097 * wt_i * 60 * 10^{-6})\}$ (OECD ITF, 2017).

3.7. Case-study

The current methods are applied to a case study area in Orchard Road in Singapore, a major shopping belt concentrated along a 2.2 km road. We have identified 212 large malls in the main island of Singapore, hosting approximately 25,000 business establishments. The selected

Fig. 6. Conceptual representation of price definition for alternatives at LTG.

case study area includes approximately 10% of all the malls in Singapore, 26 malls, hosting 2500 business establishments. For each mall in the study area, the available real parking infrastructure, the respective parking capacities and prices, and the location of the parking facilities are collected and represented in the simulation network. Fig. 7 shows the location of each mall in the road network, while Table 1 describes the available facilities at each mall. There are 19 on-street parking locations (STR), 18 carparks (CRP), and 21 loading bays (LB) Current guidelines specify one LB slot per 4000 square meters. Around 1/3 of the malls meet or exceed the minimum requirements.

4. Results

4.1. Base case

Passenger and freight travel and parking demand were simulated using SimMobility for passenger (Adnan et al., 2016) and freight (Sakai et al., 2020) demand and supply models. Model calibration targeted nation-wide flows (Hara, Sakai, & Alho, 2021). The count data is available to capture the traffic flow as well as the arrivals of trucks at the loading bays. The parking demand, in terms of total expected arrivals, is kept fixed across all experiments. Traffic demand has been calibrated using the weighted discrete SPSA (Simultaneous Perturbation Stochastic Approximation) algorithm against count data from loop sensors. Parking demand was validated against parking counts. For the study area, the discrepancy between the simulation and observation loop sensor counts has been reduced to 0.3 RMSN (Root Mean Squared Error) after performing multiple iterations where demand model parameters are adjusted. For more details on the calibration method, readers can refer to Oh et al. (2019). The simulation period was defined from 06:00 to 12:00 (noon). In this period the model simulates 1800 freight trips along with 11,400 trips by passenger cars (Fig. 8a). 570 freight parking instances were simulated (Fig. 8b).

Overall parking activity for each facility, per hour, is shown in Fig. 9a. It shows the large portion of parking trips ended at the LB, while less than 10% of trips in CRP and STR respectively. Fig. 9b shows the distribution of parking duration varying by parking type: 16.6 min, 16.7 min, and 8.4 min on average for CRP, LB, and STR respectively. Particularly, the duration of STR shows significantly smaller deviations compared with the case of LB and CRP. Parking durations were compared with empirical distributions and deemed suitable for purposes of the study.

To understand the dynamics at system level, Fig. 10a shows the cumulative number of parking trips with three curves on *Arrivals* (A),

requirements.

Fig. 7. Network of study area (malls are highlighted with index).

Table 1
List of malls assumed as LTG and specified prices/capacities.

LTG ID	LB			CRP			STR
	Capacity (pcu)	Initial fee (r_k)	Rate (α_k)	Capacity (pcu)	Initial fee (r_k)	Rate (α_k)	
1	14	2.5	2	320	2	1.5	V
2	12	0	0	N/A			V
3	N/A			67	1.5	1.5	V
4	10	0	0	496	0	0	V
5	N/A			N/A			V
6	7	0	2.14	304	2.67	1.28	V
7	N/A			1000	1.39	1.39	V
8	5	0	0	230	2	1.5	V
9	5	0	0	379	1.5	1	V
10	0	0	0	N/A			V
11	12	0	0	129	1.5	1.5	V
12	13	0	0	295	2.9	1.5	N/A
13	10	1.07	4.28	506	1.93	1.28	N/A
14	10	0	0	N/A			V
15	6	0	0	N/A			N/A
16	20	0	0	N/A			N/A
17	3	3	1.93	N/A			N/A
18	6	0	0	365	2.5	1.2	V
19	9	3	1.5	185	3	1.5	V
20	N/A			148	1.5	1.5	V
21	11	2.4	1.2	138	2.4	1.2	V
22	6	0	0	N/A			N/A
23	7	1.07	4.28	228	3	1.28	V
24	N/A			279	2.14	1.07	V
25	5	0	0	303	1.4	1.4	V
26	14	3.5	3.1	300	0	0	N/A

Parked (P), *Departures* (D). As parking demand increases, the total delays increase until 11 AM (Fig. 10b). The total delay (W_{Base}) during the simulation period yields around 1461 min for base case which results around 2.6 min for all freight drivers (Note that the average queueing time of individual who experienced queue is around 19.7 min). The total queue length (L_{Base}) across was 60 vehicles, for multiple LTG with the maximum length increased up to 27 vehicles by the time-of-day (average is estimated as around 2.2 vehicles). These measures point out the large parking delay and queue formed by the discrepancy between the parking demand and supply level of LB. Considering the parking capacity, around 10% of LBs are fully utilized (100% in peak), while other types (CRP, STR) remained empty. Fig. 10c presents an example of the queue at a specific location that may result the spill-over to the main road.

The delay and queue may cause significant cost increases for freight drivers/carriers. We measured travel time (C_{Base}) and monetary cost (R_{Base}) as described in the previous section. The marginal costs for each individual ($\overline{C}_{Base}$, $\overline{R}_{Base}$) are presented by facility type (Fig. 11). It shows that, on average, LB users were charged less (S\$2.37) versus those of CRP (S\$3) but incurred in more costs in travel and waiting time (S\$5.41, S\$2.45 for LB and CRP users respectively). However, this does not account for extra time spent in the CRP which is not explicitly modelled. Considering most of parking trips (~86%) ended up in LB, the difference of total costs incurred at each facility becomes much larger (C_{Base} yields S\$1888 (LB), S\$145 (CRP), and S\$318 (STR)). We estimated vehicle emissions (NO_x) equal to emissions 0.1049 kg (E_{Base}) during the 6 h for the study area.
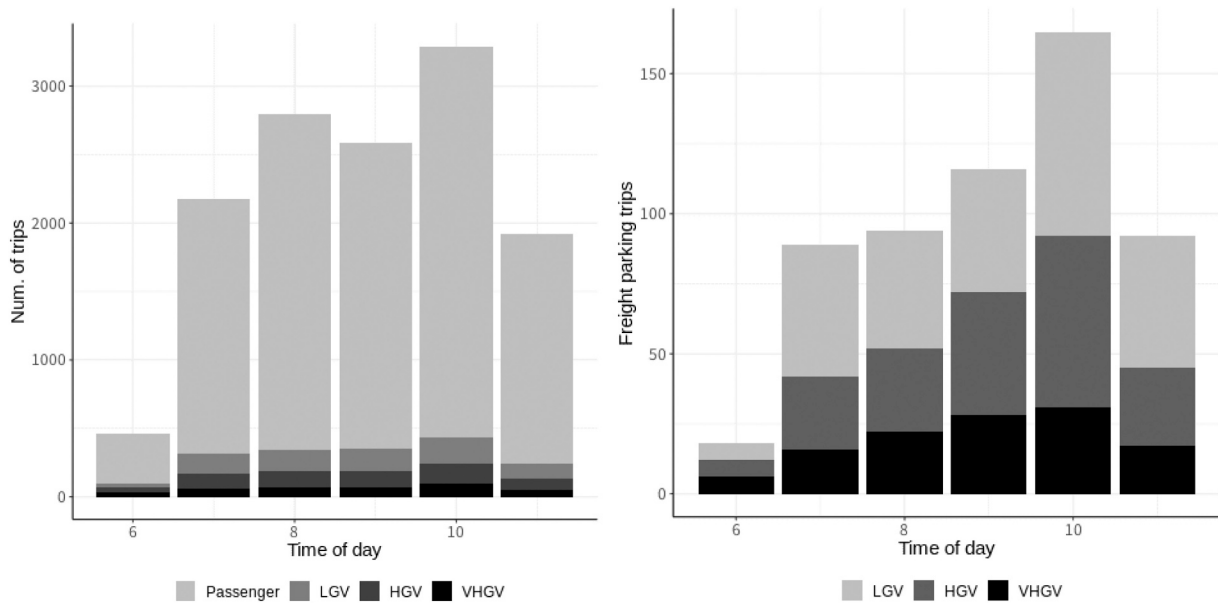
Fig. 8. Demand distribution during the simulation period: (a) Overall traffic demand by mode, (b) Freight vehicle parking demand.
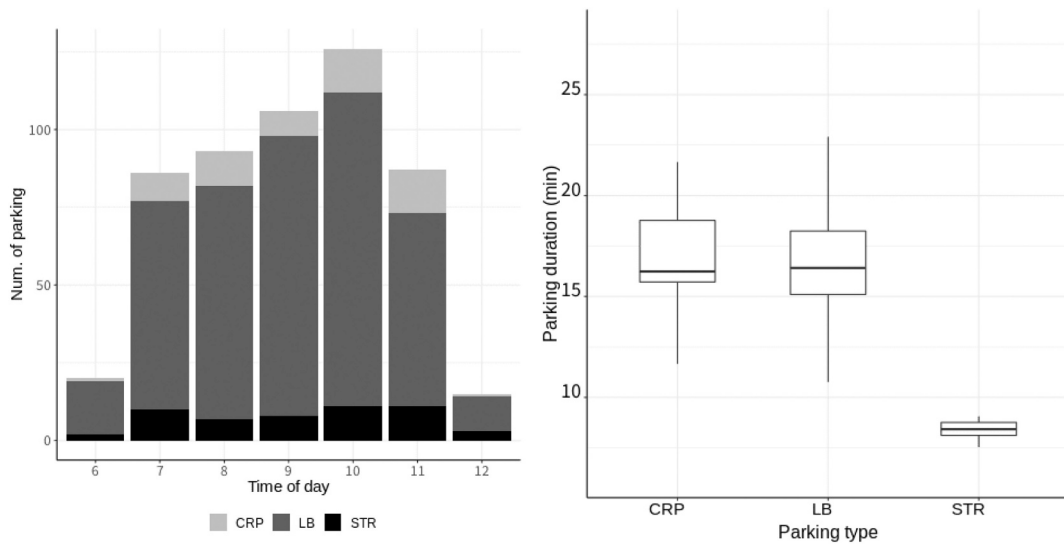

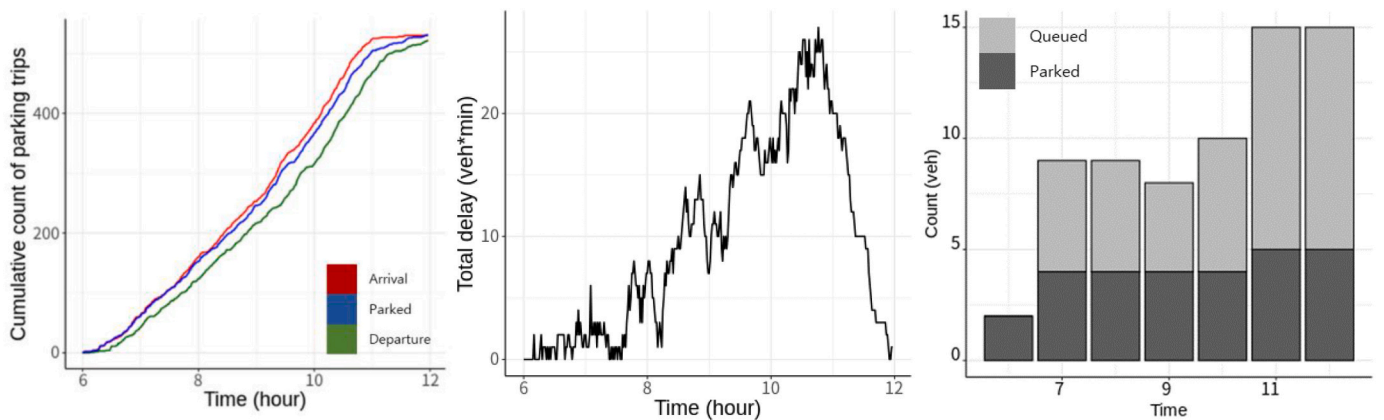**Fig. 9.** (a) Parking activity by facility type and (b) parking duration by facility type.

Fig. 10. Queueing analysis: (a) Cumulative plot (b) Total delay (c) Queue length (selected LB).
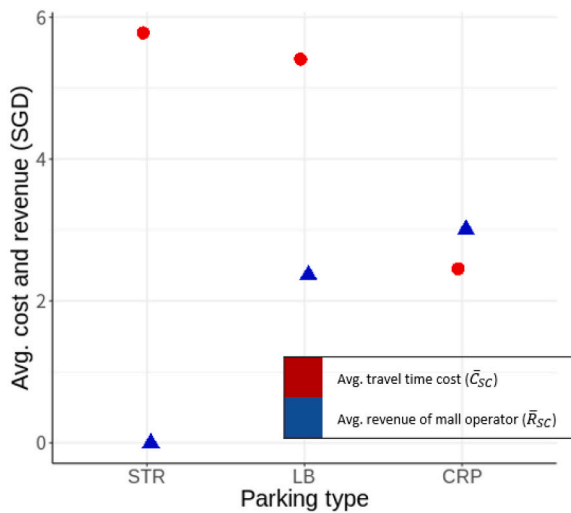
Fig. 11. Average costs and revenue.

4.2. Scenario analysis

The technologies/policies introduced can have an impact on the relative usage of the facilities (Fig. 12). Comparing with the baseline, the number of trips to the LB has been reduced in all but the scenario *Increased Capacity*. Pricing also affected the drivers' choices as, in the scenario *Free Car Park*, the usage of CRP increased to 13% from 10% in the base case. As we eliminated the double-parking option from the choice set in *No Double Parking* scenario, more vehicles tend to choose LB than CRP based on the parking fee. Increasing LB capacity attracts more vehicles to park at LB due to less queues to enter the facility.

These changes in parking usage can result different patterns in parking queue and delay. Table 2 summarizes the performance metrics of each scenario and Fig. 13 shows an example LB across the scenarios. The total queue length and delay (L_{SC}, W_{SC}) decreased for *Directed Parking*, *Free Car Park*, and *Increase Capacity* versus the baseline (L_{Base}, W_{Base}). This means the *Directed Parking* policy results less parking usage and this alleviates the overall congestion level at LB. Note that in *Directed Parking* only LGV (1pcu) may have the option to direct to neighboring CRP, while other types (HGV, VHGV which take 2 ~ 3pcu) must wait and park at LB. Regarding the *Increase Capacity* scenario, both
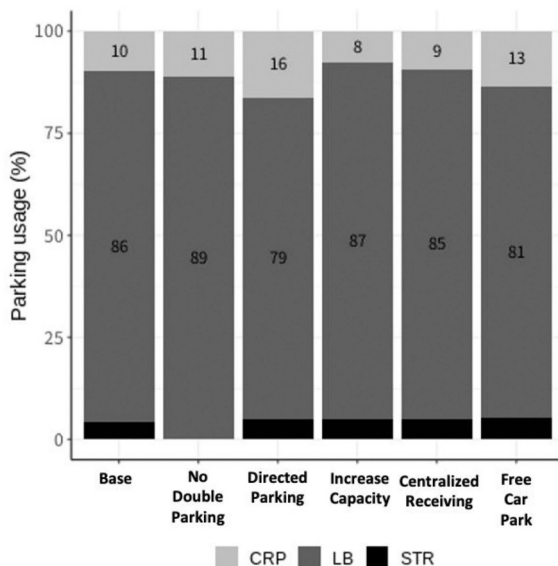

Fig. 12. Parking usage for each facility type by scenarios.

Table 2
Summary of performance metrics.

Scenario	Queuing analysis		Cost analysis		
	L_{SC} (veh)	W_{SC} (min)	C_{SC} (S$)	R_{SC} (S$)	E_{SC} (kg)
Base	60	1461	2320	1232	0.7851
			1773	1247	0.7913
No double parking	61	1422	(−21%)	(1.175%)	(<1%)
			1690	1319	0.7531
Directed parking	37	802	(−30%)	(7.01%)	(−4.1%)
			758	1203	0.7631
Increase capacity	5	9.70	(−75%)	(−2.38%)	(−2.8%)
Centralized			1914	1194	0.773
receiving	63	1795	(−10%)	(−3.14%)	(−1.6%)
			2302	1228	0.7894
Free car park	58	1168	(−4.5%)	(−0.31%)	(<1%)

delay and queue length have been significantly reduced, which is intuitive. Similar pattern has been replicated with *Free Car Park*. However, the impacts of *Centralized Receiving* and *No Double Parking* are minimal in this case.

To quantifying the scale impacts of the scenarios, we leverage travel/waiting time (C_{SC}), monetary cost/revenue (R_{SC}), and emissions (E_{SC}). Fig. 14 shows C_{SC} and R_{SC} by scenarios. First, with *No Double Parking*, C_{SC} has been reduced by 21% while (slightly) increasing R_{SC} (1.175%). Preventing lane-capacity reduction caused by double parking, *No Double Parking* scenario improves the overall travel times (which reduces C_{SC}) with a small increase of revenue of mall operators (R_{SC}). Similarly, the *Directed Parking* scenario generates more revenue to the mall operator (with more trips to CRP which charges more than LB) and reduces travel costs by 7% and 30%, respectively. Both travel time cost and revenue have been decreased in both *Free Car Park* (by 3–75%) and *Centralized Receiving* (by 3–10%). In *Free Car Park* scenario, C_{SC} has been reduced by 4.5%. Introducing CRP as a 'free' alternative seems to cannibalise the parking demand from LB and improve the queueing time (W_{SC}).

We have plotted the scenarios in an "impact diagram". This diagram characterizes the scenarios into four categories (Fig. 15a). It evaluates the financial aspects (changes in R_{SC}) as well as user experience (changes in C_{SC}). Also, we highlighted the "*green*" policies which produce less emissions (E_{SC}) to address the transport authority's interest. Accordingly, three scenarios are considered *optimal* scenarios as the outcome is less cost in travel time and parking fee. These are *Increase Capacity*, *Centralized Receiving*, and *Free Car Park*. Moreover, *Increase Capacity* shows a positive impact on environmental aspect with less emission (−2.76%). *No Double Parking* and *Directed Parking* which fall into *time-saving* by reducing the time of drivers and charging more parking cost to the carrier. *No Double Parking* has been marked as the *greenest* policy as it reduced the total emission from both passenger and freight vehicles by 4% from the base case.

5. Discussion

The results demonstrate that with the exception of lifting the charges for freight vehicles in the car park, all other DMSs can provide benefits with regards to freight drivers time-usage. However, eliminating the option to double park or directing the drivers to use the car park can increase their costs. Centralized Receiving also requires an analysis of associated costs to the mall operator or to the driver if there is an increase to the loading bay usage fee. The relative benefits might be worth the cost to the drivers, but that would require a follow up assessment. The most promising solution is resizing the LB. While arguably changes to LB in an existing building are challenging, with real estate at a premium, the quantified benefits can inspire the design and enforcement of associated guidelines.

The conclusions on the limited impacts of pricing were aligned with past findings by Dalla Chiara et al. (2020). The benefits from changing
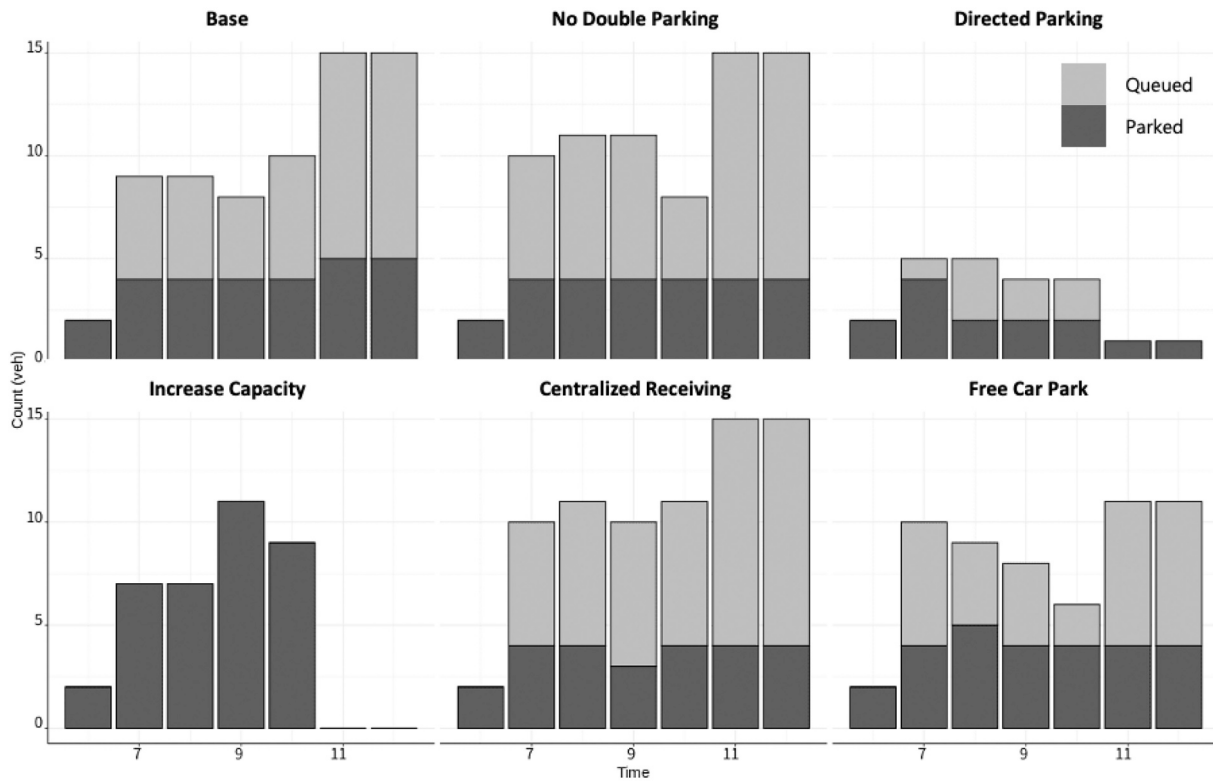
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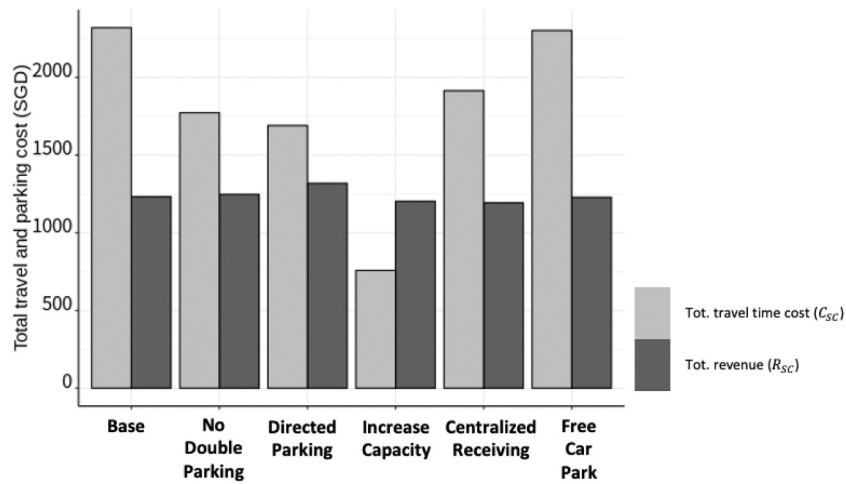**Fig. 13.** Queue length by time-of-day (LB at mall OD23).

Fig. 14. Total costs incurred by freight drivers by scenarios.

LB size, preventing double parking or providing delivery assistance through Centralized Receiving were also aligned with prior studies concluding there are overall benefits in traffic performance. Contrary to Dalla Chiara et al. (2017) we did not observe counter-effects from the Centralized Receiving technology, meaning that increased adoption lead to performance decreases.

Our recommendation, which can only be supported for the case-study area, is to revise and enforce minimum parking guidelines for new buildings, low-cost solutions to prevent double parking and pilots of Centralized Receiving and Directed Parking to evaluate running costs against benefits. We cannot recommend free car park use for freight vehicles given the limited impact and likely challenges to deliveries from the car park without adaptation.

It is important to mention the extremely complex challenge of validating a model of this kind, such as queue lengths and double-parking impacts on traffic flow. Although all models in this study are calibrated with real world data, a holistic validation is limited to traffic counts and road-based speeds. Any subsequent enhancements to model realism of the models, such as search for on-street parking (cruising) or off-street parking (within a parking lot) would add to the challenge. Although it is tempting to leverage computing power to do so, we opted to implement only the minimum set of features required to study what we set for, the impact of certain policies and technologies in parking choices and associated traffic flow. The claims over changes due to the policies-technologies applied in each scenario should also be considered as the best available given current knowledge and tools.
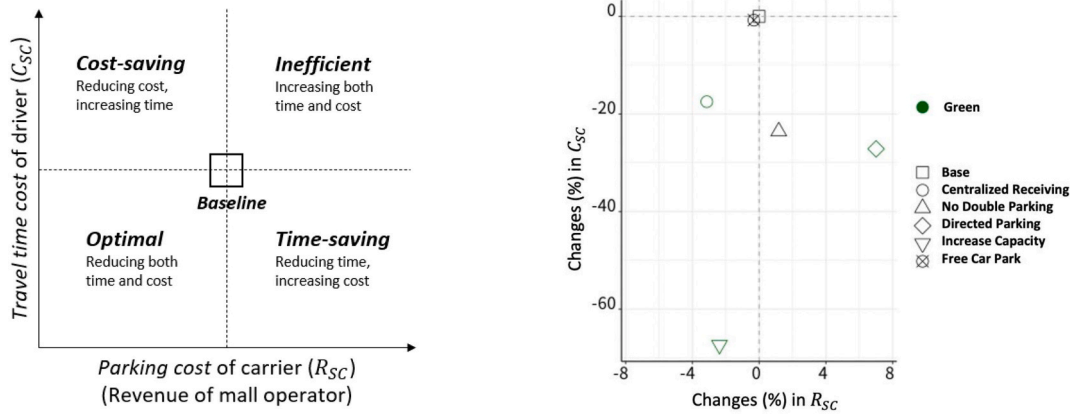
Fig. 15. Policy scenario impacts (a) Impacts Diagram (b) Simulation Results.

6. Conclusions

We identified a research gap regarding the analysis of freight vehicle parking DMS applied to LTGs to lessen the impacts of freight parking demand/supply mismatches on passing traffic. Thus, we proposed and developed behavioral models for demand, parking choice and dwell time predictions, and integrated them in a high-resolution agent-based microscopic traffic simulation. We narrowed down a set of DMS that can be suitably studied with the model system. Particularly, we explore parking capacity, pricing and assistive technologies (unloading and selecting parking). The case-study illustrated the practical applicability of the modeling system and generated several key findings. Anecdotal and observed evidence of queueing and congestion due to mismatches between parking demand and LB capacity have been validated with the microsimulation model. Through the scenario simulations, we can differentiate and quantify the policy scenario impacts. We have clustered the changes into two groups. The first set, termed optimal for freight agents reduces time and cost of operations, and it comprises of Centralized Receiving and increasing the capacity of the loading bays. These solutions however, come at an investment compromise for the mall operator. The second group reduces time spent in parking operation but increases costs, with these being the elimination of the double parking option and the directed parking strategy where upon reaching full capacity the freight vehicles are directed to the passenger car park. It is worth noting that, albeit omitted, we noticed differences in solution performance for several LTG. This is due to their passenger/freight demand profiles, characteristics of current parking infrastructure and street layout surrounding the building. These results are expected, and the omission was intentional, as we do not intend to make specific recommendations for a given LTG. Still, we emphasise that the aggregated impact of these policies cannot be interpreted as a *one-for-all* solution.

Moreover, further research is recommended into how models of this kind can be holistically validated. The various model components we brought together are transitioning from state-of-the-art to state-of-the-practice, and this brings weight to this research question. Specifically, there are agent-based demand models for passenger travel influencing the majority of passing traffic. This is the bulk contributor to whom gets affected by double parked and queued vehicles. Then, there are agent-based freight demand models influencing freight vehicle passing traffic and the demand that is subject to the parking choice models. Finally, a supply simulation model couples together their interactions, in a business-as-usual and alternative scenarios. Given data collected to calibrate and validate the models is often done at different time periods, and not necessarily in a coordinated way, some level of uncertainty remains on the aggregated results. Thus, we only go as far as expecting that studies of this nature provide us results that are directionally (positive/negative influences) and magnitude-wise correct. In addition to this limitation - and also a suggestion for future research - the set of considered parking DMS was relatively limited. For simplicity sake, each DMS was considered as an exclusive alternative to the base case, while they could be considered in a complementary fashion. Further, the DMS set can also be expanded to include other technology-based solutions such as a booking system, and target passenger vehicle parking choices. The latter would increase the realism of occupancy levels for the passenger car park, at the cost of increased complexity of model calibration/validation.

Appendix 1. Parking choice model coefficients

ID	Coeff. name	Input var.	Alt.	Coeff. value
1	Queue	$((((QUEUE/N\_SERVERS) + 1)^{delta})-1)/delta$	LB	−10.5756
2	Cost LB	COST_LB	LB	−1.01366
3	Volume	(VOLUME/N_WORKERS)	LB	0.602112

(*continued*)

ID	Coeff. name	Input var.	Alt.	Coeff. value
4	CRP (ASC)	1	CRP	−3.638925
5	Cost CRP	COST_CRP	CRP	−0.964774
6	STR(ASC)	1	STR	−4.165678
7	Expected Fine	EXPFINE	STR	−1.40715
8	Expected Fine (HGV+)	EXPFINE*(LGV==0)	STR	0.773932
9	Workers in vehicle	WORKERS	STR	1.348070

Note:
- delta $= -3.84706$
- WORKERS is a dummy variable taking value 1 if there are more than 1 worker (hence whenever the driver has helpers) and is calculated as follows: WORKERS $= 1$ if N_WORKERS>1, 0 otherwise.
- EXPFINE is the expected fine for on-street parking, and is calculated as follows: EXPFINE $=$ FINE*$(1-\exp(-(\text{PATROL\_FREQ}/(24*60))*\text{DURATION}))$
- PATROL_FREQ $= 2$
- ASC stands for alternative-specific constants.

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