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Predicting freight demand for planning loading docks

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Abstract

With a greater focus on placemaking in urban centres, the provision of loading docks can make a significant contribution to traffic management in urban centres This paper describes a Decision Support System (DSS) to forecast the generated freight task of a development and determine the optimal provision of on-site loading docks in new major developments. A predictive model to estimate parking demand and vehicle movements by freight and service vehicles in loading docks is described.

The model processes various parking surveys collected by Transport for NSW (TfNSW) from buildings in Sydney for different land uses across a three-weekday period. The output of the model is presented in two interactive templates. The first one is the 'Optimisation Solver' template that determines the recommended dock configuration for the building under consideration by calculating the optimal number of parking spaces. The goal is to minimise the parking area while keeping the dock's effectiveness (ability to accommodate incoming vehicle demand) to a user configurable service level. The second template is the 'Dashboard' which displays valuable insights about the parking demand, vehicle movements and utilisation of the dock. The Dashboard is an interactive and transferrable template that various stakeholders could use in different locations to input the parameters and generate results and outputs. The overall model development approach ensures a mathematically robust process to ensure the outputs' validity based on the observed datasets.

The model has several applications and provides various stakeholders including transport authorities, city planners and property developers, with a user-friendly tool to assess the requirements in advance during the planning and approval process of new developments. Model applications include space proofing, supporting planning applications, enhancing the overall logistics delivery and service operations of a development, and streamlining traffic flows in and around the development, making it more attractive to tenants and end-users.

1. Introduction

Large buildings in urban centres generate significant freight tasks. Vehicular access for deliveries and servicing is essential to achieve efficient and productive distribution systems. However, the arrangement and provision of loading dock capacity during the design and planning processes and development approval is often contentious. In the city centres of many major cities where land values are high, servicing capacity is often a cause of disagreement between planning authorities and developers.

Large buildings (e.g., office towers, residential towers and hotels) have a on-site loading dock to allow freight and service vehicles to park and perform their activities within the building. This loading dock is part of the building and maybe located underground in the building or on the ground floor. It is accessible only to freight and service vehicles, such as mail deliveries, food deliveries, electricians, trash collection, or construction services. Freight and service vehicles generally access and park in the loading dock at buildings free of charge. The objective of planning authorities is typically that the building has capacity to be self sufficient.

Current processes for arrangement and provision of loading docks demonstrate a limited understanding by various stakeholders on the number of goods and services traffic a building generates as well as the contribution that an adequate loading dock makes to a successful place outcome. There is also a low confidence in current guidelines used in planning processes that rely on very outdated data and inadequate articulation of all the considerations needed to provide suitable facilities which support existing processes.

Given the above, there is a need to improve current forecasting models and develop a robust approach for the provision of loading docks in large developments so that they are suitable for wider use by transportation planners involved in permitting processes for new buildings. Ultimately, planning and transportation agencies can use the models to provide a new and improved process that provides greater insight, understanding and assistance in evaluating new developments and their loading dock provision. This is achieved by identifying a process to ensure the approach is mathematically robust to ensure the validity of the outputs as well as to enable the easy addition of new data sets. Such an approach will lead to greater trust among stakeholders within the Development Approval process and better outcomes for our cities.

Many building owners consider loading dock facilities to be secondary to maximising valuable retail space in new buildings. The result can be inadequate facilities that detract from the amenity surrounding a building and create other negative externalities. A building with an inadequate design and loading bay capacity relies on roadside space adjacent to the building. If off-street loading space capacity is not provided to make a building self-sufficient, and roadside space is not available, buildings become challenging to serve, inefficient for deliveries, and less attractive to customers, resulting in impacts on the urban environment.

2. Review

Currently, the method for determining the size of loading docks typically relies on transportation and planning authorities either providing quantities and formulae in their Development Control Plans (DCPs) or requiring a property developer to refer to traffic and building guidelines issued by local authorities. Models and methods that support the process of freight and service vehicles demand estimates are generally outdated and poorly applied.

The size of a loading dock depends on several key building characteristics, such as the size of the building and its primary use and local planning ordinances. Factors influencing the loading dock requirement, include the size of the development, it’s primary land use, zoning and local regulations, vehicle type mix, operational practices, peak hour volumes, average dwell time and characteristics of the loading dock.

In NSW, loading rates in the DCPs are based on regulations issued by the Roads and Traffic Authority (RTA) in 2002, which were produced using driveway counts carried out in the early 1970s, leading some developers to claim that they are outdated and unreliable. Hence, the planning and approval process for the size and capacity of a loading dock goes through several rounds of negotiation between authorities and developers until both parties reach a consensus.

Given the importance of effective freight management to large developments, local governments have made several regulations to reduce the reliance on on-street parking for freight and service activities. One such approach is necessitating off-street parking in large developments where in Freight and Service (F&S) vehicles do not overload the heavily utilised on-street parking facilities, and instead utilise specially designated areas in a loading dock inside the buildings (Holguín-Veras et al., 2018). On-site loading docks need to be designed appropriately to avoid any mismatch between the requirements of the vehicle and the parking space and to accommodate the geometric needs of current and future freight vehicles. The delivery characteristics of vehicles including type, size, schedule, type of cargo and the loading equipment should be considered in such facilities (Butrina et al., 2017).

The planning and provision for on-site loading docks in new developments are defined in local land-use zoning codes that are regulated by local planning and transport authorities (Chen et al., 2017). These building codes provide guidelines for the capacity of a loading dock. The recommended number of loading spaces is determined for a land-use type by multiplying its relevant parking provision rate by the scale of the development, number of dwellings in a residential tower or Gross Floor Area (GFA) in a commercial tower. However, the performance approach adopted in these codes provides flexibility to enable a proposal to be supported where the proponent can demonstrate to the satisfaction of local authorities that the objectives can be met either by provision of a lesser on-site rate or by utilising spare capacity in publicly available on-street or off-site parking. Parking provision rates were mostly based on historical studies and unreliable vehicle generation estimates that are outdated and do not reflect current operational requirements and practices of last mile delivery (Holguín-Veras et al., 2018).

Further, local authorities often overlook freight demand by receiving establishments and incorrectly apply minimum requirements for passenger car parking spaces in the provision of loading spaces in commercial or retail uses (Shoup, 2011). This results in developers looking only at how they can supply the number of spaces and ignoring the efficiency of the loading dock. In some cities such as New York, the focus is mainly on commercial developments while no loading requirement exists for residential buildings. Most planning regulations do not specifically discuss how on-site docks should be set or managed to facilitate efficient loading infrastructure for F&S vehicles. Supply is further constrained by lack of freight elevators that increase delivery times to large establishments and lead to higher average parking times for vehicles and lower rates of parking turnover. Having access to a freight lift can reduce delivery service times (Jaller et al., 2013 and Bassok et al, 2013). However, it was noted that there are no requirements for freight elevators in many US cities, including New York.

Relevant literature ranges from evaluation of commercial parking availability and demand-to-supply ratio at different times of day to simulation models of urban commercial parking behaviour. Three major approaches applied for evaluation and selection of loading infrastructure for F&S vehicles are econometric models and freight generation approach, optimisation models and facility location problem approach, and traffic simulation approach.

In econometric models, the primary consideration is that the choice of parking space or freight generation is influenced by social, economic and environmental factors such as number of parking spaces available, parking price, accessibility, seeking time, and multiple other parameters related to the driver (Parmar et al., 2020). This approach models parking or freight generation as a function of average turnover rate, parking lot occupancy, parking price impact coefficient, level of service of parking facility, motor vehicle growth, differences in land uses (Jaller et al, 2013; Dalla Chiara and Cheah, 2017; Chiara et al, 2020). These works are in search for efficient models that can estimate the number of freight vehicle trips attracted and produced by urban establishments. Some publications define the parking demand rate as a freight trip generation rate multiplied by the average parking time. The freight trip generation rate has been traditionally estimated as a function of the number of employees, type of industry, establishment area or land use. Parking supply is defined as the number of parking spaces. A large number of these studies applied disaggregate data-driven models to capture freight drivers' parking behaviour. Modelling of such systems usually involves regression based methods (Sánchez-Díaz, 2017). The aim is to build a predictive model that uses data and statistics via mathematical and computational methods to forecast outcomes with data models. Parameters help explain how model inputs influence the outcome. Predictive modelling is often performed using curve and surface fitting, time series regression, or machine learning.

The second optimisation modelling approach relies more on data driven complex mathematical methods to find a feasible solution for the optimal location or configuration of the loading facility (Aira and Taniguchi, 2006; Muñuzuri et al., 2012; Figliozzi and Tipagornwong, 2017). Techniques such as genetic algorithms are often employed in such an approach using very complex datasets. However, these models require a high level of computational approaches by software solvers and are not easily transferrable to a real-life context. The final approach considered by researchers is based on traffic simulation and is in general, less explored than the other two approaches discussed in literature. This more holistic approach considers various aspects of freight management such as the preliminary phase, planning requirements, management aspects, and control as parts of a single integrated system to accurately represent transportation networks and loading zones, generate commercial vehicle trips and their parking times and estimate delays for commercial vehicles (Nourinejad et al., 2014; Comi et al., 2018).

3. Data Collection

To develop a prediction model, a comprehensive data collection effort was conducted by TfNSW to survey buildings of varying sizes, anticipated vehicle types, and land use types. The project team collected detailed parking surveys “driveway counts” of 17 different buildings for the parking activities of freight and service vehicles that used the on-site loading docks in these buildings to park their vehicles. The parking activities were collected from 12 different commercial buildings and five residential towers. Additionally, the sample included a diverse range of building characteristics “commercial area, retail area and/or residential area” in order to ensure a representative sample of the most common buildings in central business district of Sydney. For instance, the size of commercial buildings ranges from smallest building having 15,000 m^2 of commercial area, while the largest building has 57,000 m^2 of commercial area with 42 floors. Moreover, residential towers range from a building with 14,000 m^2 residential area with 211 apartments on 17 floors to the largest tower having 38,000 m^2 residential area with 292 apartments on 50 floors. The surveys were conducted over a three-weekday period, "Tuesday, Wednesday and Thursday" during different weeks in November and December 2020. These weekdays were selected because they represent the busiest weekdays for freight and service vehicle visits in Sydney CBD based on TfNSW traffic counts. Loading docks were observed throughout the 24 hours, and each parking event was recorded. The surveys also captured where the F&S vehicle parked on the street close to the building.

The template contained variables for three main categories: building information, loading dock characteristics and parking events of each unique F&S vehicle as shown in the template in the Appendix (Figure 5). Data captured for buildings included the land-use types, areas, and number of floors. Loading dock characteristics collected included operational hours, number and size of loading bays and number of loading elevators. Details recorded for each parking event included date and arrival time, vehicle type, activity type and exit time.

Due to the ongoing pandemic (COVID -19), the sample size was somewhat smaller than expected. This was also due to specific privacy issues. Thus, the model and analysis are based on the observations and data collected from 17 buildings. A robust assessment of the raw data was conducted to understand the various patterns associated with vehicle arrivals, types, durations and relationship to land use. Figure 1 shows sample charts that were produced by the descriptive analytics of the raw data obtained in the parking surveys.

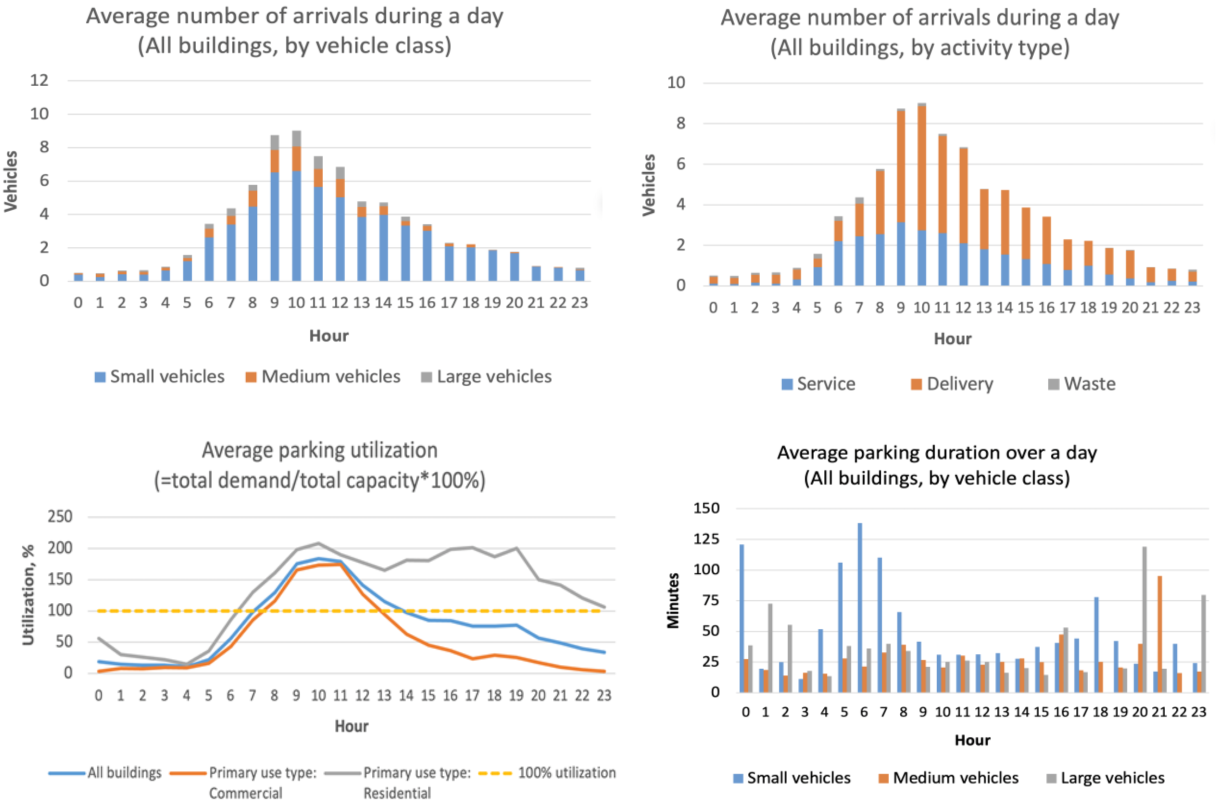


Figure 1. Snapshot of the analysis conducted into assessed buildings

4. Model Development

The model's main aim is to develop a decision-support system using a predictive model to estimate the levels and types of freight and servicing activity and hence the parking demand and recommend the optimal dock configuration for the planned building.

The following objectives were defined to achieve the overall aim:

(i) estimate the vehicle movements, i.e. total number of daily movements of freight and service vehicles that a proposed building will typically generate,
(ii) estimate parking demand based on vehicle movements and building characteristics,
(iii) develop an optimal dock configuration, i.e. determine the recommended number of parking spaces (small, medium, and large spaces) in a loading dock in the proposed building to efficiently accommodate the estimated vehicles,
(iv) assess the efficacy of the recommended dock configuration, and
(v) facilitate a flexible and scalable approach for model inputs to add future datasets efficiently.

The decision-support tool was developed using a predictive modelling approach that incorporates Regression Analysis with a Clustering technique. The selection of the mathematic approach to building the DSS using predictive modelling was based on several factors:

(i) systematically promoting a versatile and scalable method for model inputs, allowing different datasets and new variables to be used (e.g. new land-use types or vehicle types),
(ii) being ideal for typical land-use styles and building sizes,
(iii) externalisation and sharing of the model and its outputs to external stakeholders were made possible by the modelling environment transferability. Using freely available analytics platforms, the model could be shared as an interactive tool (e.g. MS Excel), and

(iv) prescriptive analytics may be used to assist decision-makers in deciding on a course of action and providing appropriate suggestions based on future predictions and inferred observations and trends in datasets.

The model uses data collected from the surveys conducted at 17 different buildings, including:

(i) Building Information capturing the relevant characteristics for each of the buildings,
(ii) Loading Dock Characteristics, capturing the parameters for the loading docks, and
(iii) Parking events of each unique F&S vehicle accessing the loading dock, capturing the vehicle activities with each data point representing a different unique parking event for an individual F&S vehicle that is parked in a loading dock during that specific day.

Model constraints includes vehicle types, activity types (delivery, pickup, service & maintenance, waste, construction), variable dwell time per vehicle class, operating capacity of the loading space per hour across the day, estimated vehicle movements and allocation of loading space types. The mathematical approach (regularised general linear model with clustering) allows relatively effortless updating of results when new surveys become available. The approach involved data entry, demand inference and computing peak demand. For each of the 17 buildings, vehicle records were captured over three working days. Data was used to generate descriptive statistics. Demand was calculated for each time point *t* (minute) of each of three days for each building for small, medium and large vehicles. The peak demand for each vehicle class for each building over the three days was corrected for outliers. As minimum and maximum are unbounded - there can be very unusual values that are not informative. We used the 99th percentile of peak demand instead of the absolute maximum so that extremely unusual demand situations occurring less than 1% of the time are neglected to exclude sporadic demand. This approach is standard in empirical research and is known as 1% winsorisation (Wilcox, 2005).

The peak demand was modelled by creating three models: one for each vehicle class, based on 17 observations (1 per building). This model was intended to predict peak demand for each vehicle class for a given building, using residential area, number of apartments, commercial and retail area, and availability of a dedicated elevator as inputs. The potential pool of predictors was based on the conceptual model, which considered moderating effects of the number of floors, presence of a dedicated elevator, and primary use type on the relationship between residential, commercial, and retail space peak demand.

The estimation procedure was selected according to several criteria that allow the inclusion of nonlinearities (such as log-linear relationships instead of linear ones) and interactions to account for the possibility of a differential effect of one variable on the outcome depending on the value of another variable. The model should be able to work with many predictors when the sample size is small. Regularised generalised linear regression models appeared to meet the above criteria. Regularisation essentially means eliminating irrelevant predictors. The LASSO and the stepwise variable selection minimisation technique selection techniques were used.

Separate relationships were estimated for the demand for small, medium and large vehicles based on the amount of retail and commercial area as well as based on the number of residential apartments and the number of dedicated elevators. The model implies that having dedicated freight elevator results in a faster turnaround of vehicles in the commercial's building dock.

Despite the natural presence of some unexplained heterogeneity in peak demand across buildings, the resulting set of three models was shown to fit data reasonably well. Predicted demand values and actual demand across the 17 buildings are strongly correlated as Pearson's correlation coefficient of 0.89 represents a high (strong) correlation. The mean absolute error (MAE) is two vehicles, which is a good result considering that the total demand varies across

17 buildings from 5 to 21 with a mean of 9.4 and standard deviation of 5. The R^2 of the predictive model is 0.79, which indicates a reliably accurate model prediction for the demand. Although peak demand “maximum parking demand throughout the whole day” varies depending on the building's size and other factors, intra-day trends of relative demand (percentage of peak demand) were found to be consistent across buildings of the same primary use category. Simply, the demand patterns based on relative demand is more accurate than values of demand, i.e. more accurate to predict that 45% of peak demand in a building happens at 9:35AM than predicting three small spaces are specifically occupied at 9:35 AM.

Buildings were clustered using all 18 variables produced using the six time periods and three vehicle classes present in the model to reveal common shapes of intra-day dynamics of relative demand (for example, average relative parking demand for small vehicles from 6 am to 9 am and so on). Two distinct clusters were discovered using a model-based clustering technique. Cluster one is distinguished by a distinct peak between 9 am and 12 pm. Cluster 2 lacks a consistent peak and has a more evenly distributed parking demand during the day. It was discovered that revealed clusters are linked to the primary use sort. Cluster membership prediction is rational and straightforward since all primarily commercial buildings belong to cluster 1 and all primarily residential buildings belong to cluster 2.

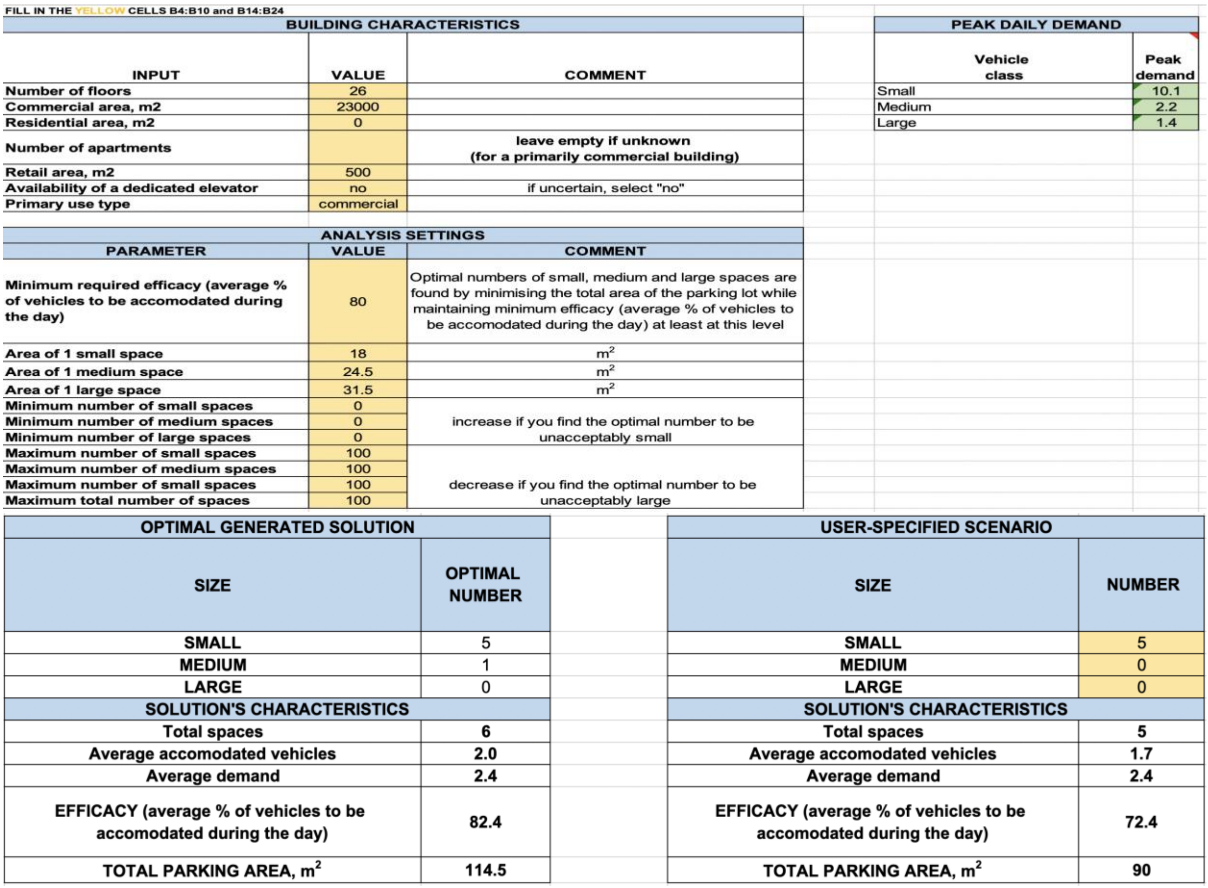
The model outputs have been summarised in the below list:

(i) Characterisation of the freight and service (F&S) vehicle movements, including arrivals volume, profiles, distribution, and parking duration at any given time for each vehicle class and activity type category.
(ii) Estimation of the parking demand for the three most popular vehicle groups (van/ute, SRV, and MRV/HRV) at various time intervals during the day.
(iii) Recommendation for the number and distribution of the three types of loading spaces that should be used (small, medium and large) in a loading dock.
(iv) Capacity evaluation and use of suggested loading spaces (performance and efficacy evaluation) for the estimated F&S vehicle movements of the three major vehicle groups at various time intervals.

5. Model Application

The two main outputs of applying the predictive modelling approach to create the DSS resulted in two model templates, the Optimisation Solver and the Dashboard (Figure 2). Determining an optimal number of parking spaces while keeping the desired efficacy levels is an optimisation problem. Microsoft Excel's Solver Add-in has been used to generate a solution to this problem as illustrated for the example building shown in Figure 2. The optimisation algorithm searches over various combinations of small, medium and large spaces to find the optimal solution that meets the required efficacy level of meeting a certain threshold of parking demand. Simulated demand for a building with user-specified characteristics is carried out and then assessed to the extent to which a given dock configuration can meet the simulated demand. Peak demand was determined based on the regression coefficient and the input building characteristics. Peak demand (maximum daily demand) was highly dependent on building characteristics. Best-fitting regression models were calculated to allow for peak demand prediction for small, medium, and large vehicles based on building characteristics. Forecasts are strongly associated with real data and make sense from a domain knowledge perspective.

Overall, the optimal dock configuration recommended by the optimisation solver does not only focus on satisfying the estimated parking demand, but also considers minimising the overall area of the dock and other supporting regulations such as specified minimum number of loading spaces for medium and/or large vehicles. Hence, the multi-criteria perspective applied in the decision-support process facilitates considering the various requirements and expectations of the different stakeholders.



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BUILDING CHARACTERISTICS

INPUT	VALUE	COMMENT
Number of floors	26	
Commercial area, m2	23000	
Residential area, m2	0	
Number of apartments		leave empty if unknown (for a primarily commercial building)
Retail area, m2	500	
Availability of a dedicated elevator	no	if uncertain, select "no"
Primary use type	commercial	

PEAK DAILY DEMAND

Vehicle class	Peak demand
Small	10.1
Medium	2.2
Large	1.4

ANALYSIS SETTINGS

PARAMETER	VALUE	COMMENT
Minimum required efficacy (average % of vehicles to be accomodated during the day)	80	Optimal numbers of small, medium and large spaces are found by minimising the total area of the parking lot while maintaining minimum efficacy (average % of vehicles to be accomodated during the day) at least at this level
Area of 1 small space	18	m^2
Area of 1 medium space	24.5	m^2
Area of 1 large space	31.5	m^2
Minimum number of small spaces	0	increase if you find the optimal number to be unacceptably small
Minimum number of medium spaces	0	
Minimum number of large spaces	0	
Maximum number of small spaces	100	decrease if you find the optimal number to be unacceptably large
Maximum number of medium spaces	100	
Maximum number of small spaces	100	
Maximum total number of spaces	100	

OPTIMAL GENERATED SOLUTION

SIZE	OPTIMAL NUMBER
SMALL	5
MEDIUM	1
LARGE	0
SOLUTION'S CHARACTERISTICS	
Total spaces	6
Average accomodated vehicles	2.0
Average demand	2.4
EFFICACY (average % of vehicles to be accomodated during the day)	82.4
TOTAL PARKING AREA, m^2	114.5

USER-SPECIFIED SCENARIO

SIZE	NUMBER
SMALL	5
MEDIUM	0
LARGE	0
SOLUTION'S CHARACTERISTICS	
Total spaces	5
Average accomodated vehicles	1.7
Average demand	2.4
EFFICACY (average % of vehicles to be accomodated during the day)	72.4
TOTAL PARKING AREA, m^2	90

Figure 2. Optimisation Solver outputs

The Dashboard provides additional valuable insights into a building's freight and servicing activity levels and loading dock operations and efficiency through several parking characteristics (Figure 3). This allows users to understand the performance of operations, dock occupancy, peak requirements and parking availability throughout the day. For instance, the efficacy of different dock configurations can be compared with the likely success of the recommended loaded spaces in meeting different parking demand thresholds. Additionally, the highest and lowest hour intervals are identified in terms of highest parking demand, vehicle arrivals by class, activity visits and success and/or failure to accommodate incoming vehicles. Different stakeholders could directly utilise these outputs to optimise further (as an example) any new delivery vehicles could be provided with an appropriate time slot when the overall activity levels are low within the day. These insights provide an ability to develop a booking management system to schedule freight and service vehicle trips.

The Dashboard provides many additional valuable insights into building's freight and servicing activity levels and the loading dock's operations and efficiency through several parking characteristics. This has many use cases to understand the performance of the operations, occupancy of the dock, peak requirements, parking availability at the time of the day. For instance, the efficacy of different dock configurations can be compared in terms of the likely success of the recommended loaded spaces in meeting a different threshold of parking demand. Additionally, the highest and lowest hourly intervals are identified in terms of highest parking demand, vehicle arrivals, vehicle classes and activity visits and success and/or failure to accommodate incoming vehicles.

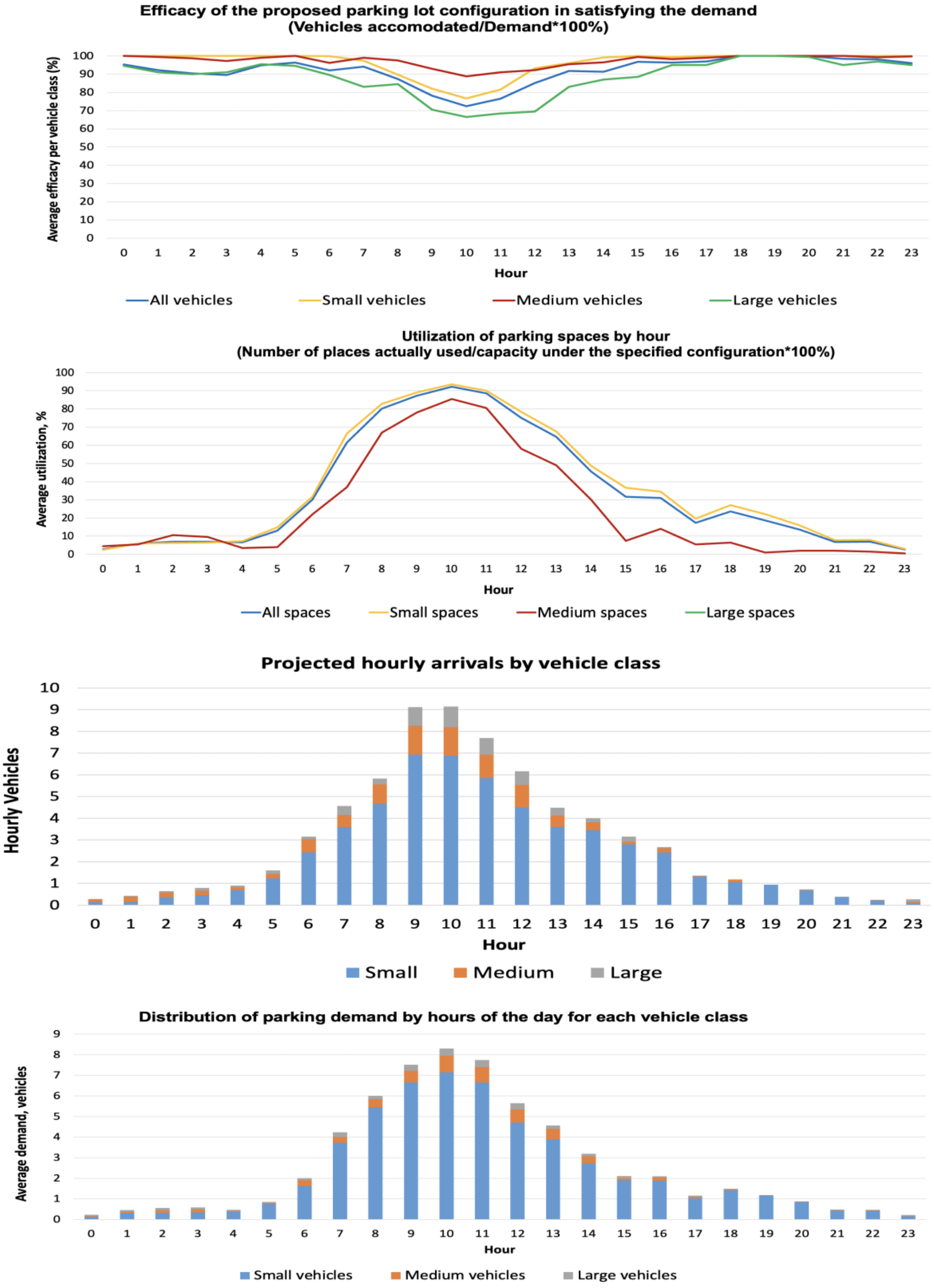


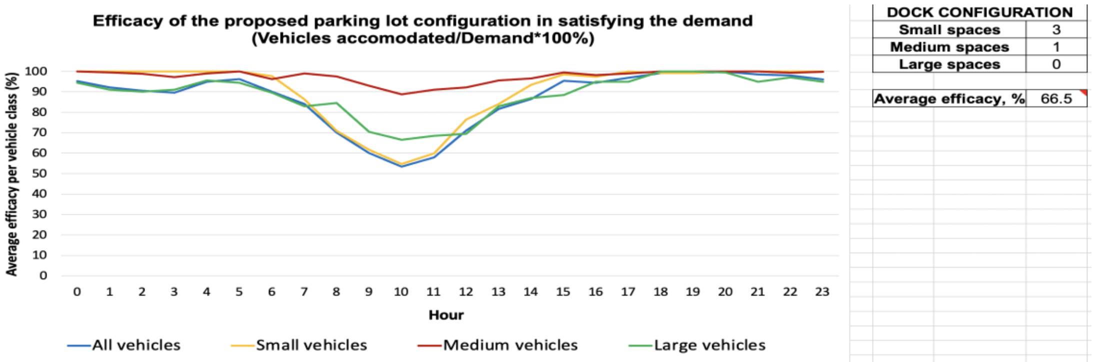
Figure 3. Snapshot of the dashboard outputs

Different stakeholders could directly utilise these outputs to optimise further (as an example, any new delivery vehicles could be provided with an appropriate time slot when the overall activity levels are low in the day). These insights provide an ability to develop a booking management system to schedule freight and service vehicle trips.

6. Discussion and Implications

The model could be shared as an interactive tool using publicly accessible analytics software. Prescriptive analytics can help decision-makers choose a course of action and make recommendations based on potential forecasts, inferred findings, and patterns in datasets.

The acquired knowledge and insights from existing loading docks facilitates an enhanced understanding and depicts an accurate picture of the current utilisation of docks by F&S vehicles. Moreover, the data-adjusted decision-support tool developed overcomes the shortcomings of existing dock provision approaches and provides all the stakeholders involved in new building approval applications with an enhanced understanding and confidence about the optimal configuration of loading docks in new major developments. For instance, the model outputs offer detailed characterisation scenario analysis of the likely efficiency of different dock configurations, as shown for the example building illustrated in Figure 4 below.



DOCK CONFIGURATION	
Small spaces	3
Medium spaces	1
Large spaces	0
Average efficacy, %	66.5

Figure 4. Efficiency of Different Dock Configuration (different combination of loading spaces)

The model templates allow users to compare the suitability and efficacy of different dock configurations in terms of accommodating the estimated parking demand and vehicle arrivals. This will contribute to greater confidence and less contention between different stakeholders within the building planning and approval process. Moreover, the model helps plan an optimal loading dock configuration that keeps a balance between the amount of space required and fulfils the freight and service vehicle demand optimally. Thus, eliminating issues around long queueing times, a large share of vehicles parking illegally, and road safety concerns when the drivers load and unload goods on the street. Urban planners may take a proactive approach to incorporate the derived knowledge on vehicle movements and parking demand in land-use ordinances of on-site loading docks for sustainable integration with sensitive surrounding uses. Additionally, the outputs from the model could allow local authorities to recommend supporting measures and regulations to accommodate vehicles' different operational requirements and practices. For example, off-peak delivery programs could be considered to encourage F&S vehicles to utilise loading docks during off-hours with a broader aim to reduce non-essential traffic from the road network during peak hours. The idea of creating a consolidation centre where the F&S operations of several adjacent but inter-connected developments could be consolidated should be pursued further. These criteria are supported by the model as most activities happen during peak hours, which may be used to explicitly promote the evaluation of such proposals, including testing off-peak delivery schedules.

7. Conclusions and Outlook

Freight and service vehicles need to park close to their customers, and they require an operationally effective loading dock to perform their services in buildings. However, an onsite-loading dock becomes a viable solution only when enough spaces are present.

Regression and clustering analysis techniques used to develop the predictive modelling methodology promotes a versatile and scalable model input system that allows different datasets and variables to be used (e.g. different land-use types and/or vehicle types). Due to its value and applicability, this method is ideal for the most common land use forms and sizes. The predictive model was not intended for a certain form or size of a building. The transferability of the environment/platform modelling will allow the model to be externalised and accessed by relevant external stakeholders. Additionally, the inclusion of a diverse and representative list of buildings with a different mix of land-use types “commercial, residential and retail” in the collected parking surveys and model inputs facilitates producing valid and reliable estimates for most common building types and sizes that are common in CBDs.

In terms of model implementation, stakeholders should be mindful of data quality and coverage. The stronger the input data (in terms of data quality, coverage, survey program size and scale and various building types covering all sizes and activity types), the higher the predicted degree of model robustness. Other variables that may influence data inputs include seasonality, holiday times, and other factors such as demographics of property tenants, which affects the length and demand for service vehicles.

There are a few limitations of this study that include the relatively low number of collected parking surveys, as the relatively low response rate indicates there might be other types of land-use categories that might have been excluded from the analysis. The relevance of the developed decision support system is highly dependent on the relevance and representativeness of the model inputs. However, the difficulty of accessing and observing a larger number of commercial buildings in the highly competitive CBD area could be expected due to the extremely busy and challenging business environment for the various building management business tenants in these buildings that might be reluctant to participate in such surveys.

Hence, there are several future research directions that could be recommended to improve the applicability and usefulness of the developed model. The model will be further enhanced by including new datasets from other building types in future. Further studies can expand the model by applying more effort to create a template that would capture the operational setup of a loading dock and the underlying building regulations and business requirements of building tenants. A future study could focus on incorporating freight demand management initiatives such as off-hour deliveries, consolidated deliveries and booking systems that would reduce the number of delivery vehicles entering loading docks.

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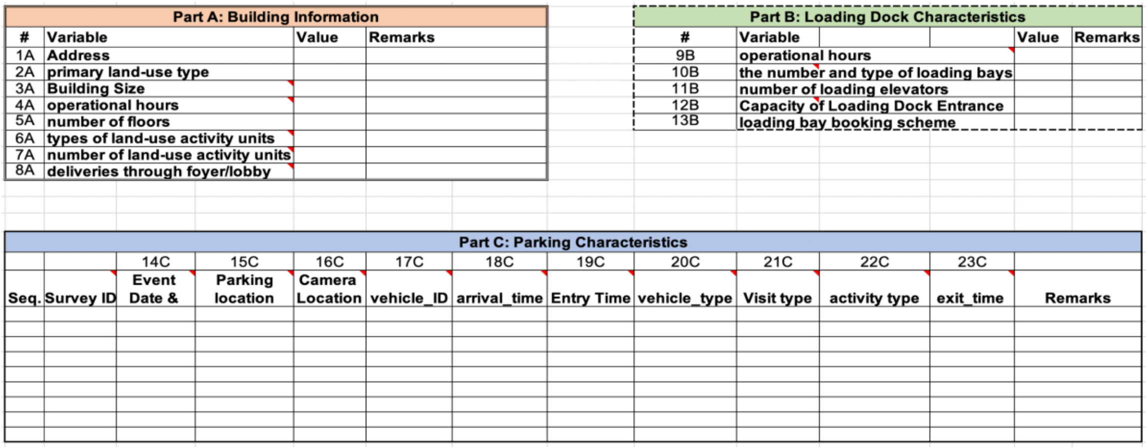
Appendix



Part A: Building Information

#	Variable	Value	Remarks
1A	Address		
2A	primary land-use type		
3A	Building Size		
4A	operational hours		
5A	number of floors		
6A	types of land-use activity units		
7A	number of land-use activity units		
8A	deliveries through foyer/lobby		

Part B: Loading Dock Characteristics

#	Variable	Value	Remarks
9B	operational hours		
10B	the number and type of loading bays		
11B	number of loading elevators		
12B	Capacity of Loading Dock Entrance		
13B	loading bay booking scheme		

Part C: Parking Characteristics

		14C	15C	16C	17C	18C	19C	20C	21C	22C	23C	
Seq.	Survey ID	Event Date &	Parking location	Camera Location	vehicle_ID	arrival_time	Entry Time	vehicle_type	Visit type	activity type	exit_time	Remarks

Figure 5. Parking Survey Template used in the Data Collection Process