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Modeling the competing demands of carriers, building managers, and urban planners to identify balanced solutions for allocating building and parking resources

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ABSTRACT

While the number of deliveries has been increasing rapidly, infrastructure such as parking and building configurations has changed less quickly, given limited space and funds. This may lead to an imbalance between supply and demand, preventing the current resources from meeting the future needs of urban freight activities. The aim of this study was to discover the future delivery rates that would overflow the current delivery systems and find the optimal numbers of resources. To achieve this objective, we introduced a multi-objective, simulation-based optimization model to define the complex freight delivery cost relationships among delivery workers, building managers, and city planners, based on the real-world observations of the final 50 ft of urban freight activities at an office building in downtown Seattle, Washington, U.S.A. Our discrete-event simulation model with increasing delivery arrival rates showed an inverse relationship in costs between delivery workers and building managers, while the cost of city planners decreased up to ten deliveries/h and then increased until 18 deliveries/h, at which point costs increased for all three parties and overflew the current building and parking resources. The optimal numbers of resources that would minimize the costs for all three parties were then explored by a non-dominated sorting genetic algorithm (NSGA-2) and a multi-objective, evolutionary algorithm based on decomposition (MOEA/D). Our study sheds new light on a data-driven approach for determining the best combination of resources that would help the three entities work as a team to better prepare for the future demand for urban goods deliveries.

1. Introduction

Urban freight efficiency has become highly dependent on the successful management of urban infrastructure given rapid urbanization and the explosion of e-commerce. Urban freight transport increases accessibility to resources and trade markets by collecting, transporting, and distributing goods within urban areas. Urban freight transport plays a crucial role in economic growth and the promotion of sustainable and livable cities (He and Haasis, 2020). In recent years, urban freight policy has been challenged by the complexity and cost of last-mile deliveries, as well as increasing congestion and pollutant emissions (Bergmann et al., 2020). To better prepare for future urban logistics, researchers have emphasized the importance of innovation in every aspect of traffic management, urban planning, and urban warehouse design (Browne et al., 2018). As past research has recognized that delivery processes rely on transportation networks and systems, the major focus has been on network optimization in lastmile deliveries (Sakai et al., 2020). This focus has showcased other

activities during the final 50 ft that merit further study, including unloading/loading activities, use of freight elevators, pick-up/delivery operations, and the implications of these activities for building and parking infrastructure design (Kim et al., 2018b).

Delivery process does not end until the package is delivered to the final customer (Kim et al., 2018b). The process time spent outside of the vehicle, including indoor walking time, can be much longer than the driving time, as much as 87% of the entire urban freight delivery process (Allen et al., 2000; Álvarez and De la Calle, 2011). Analyzing the final 50 ft of urban freight delivery is important because excessively long stays by delivery workers could contribute to the lack of curbside space and urban congestion (Rhodes et al., 2012). However, data within the final 50 ft of delivery activities are extremely limited, and building and parking requirements and policies are often developed without substantial supporting data (Shoup, 2020). Although these parking policies can greatly impact architecture and urban designs,

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Fig. 1. Relationships of city planners, building managers, and delivery workers to parking infrastructure.

which can consequently increase the cost of development, the final decisions on parking policies are often influenced by elected officials and other existing parking requirements that are not scientifically grounded (Shoup, 2020). Analysis of delivery activities at the final 50 ft will produce valuable information and assets to help policymakers understand current parking situations and create data-driven parking policies that can meet future demand. Creating efficient parking policies is also important because a lack of curbside space can increase urban congestion. For example, delivery vehicles may be forced to circle city blocks multiple times looking for parking spaces (Rhodes, 2012). In this study, we aimed to close this research gap by providing useful simulation and optimization tools that will better reveal the freight delivery cost dynamics among delivery workers, building managers, and city planners, as well as better estimate adequate numbers of building and parking resources to help policymakers readily prepare for an increasing demand for urban delivery of goods.

This study applied a multi-objective optimization method, combined with a discrete event simulation (DES), also known as simulation-based multi-objective optimization (SMO) (Lidberg et al., 2019). A DES was first used to account for complex delivery movements inside of an office building in downtown Seattle, Washington, U.S.A. Using a DES model that reflected the real-world infrastructure would allow us to understand the impact of freight cost on delivery workers, building managers, and city planners. We then estimated the numbers of building and parking resources that could minimize costs associated with freight deliveries for all three groups.

There were three main objectives in the problem formulation:

- 1. Minimize the costs for delivery workers.
- 2. Minimize the costs for building managers.
- 3. Minimize the costs for city planners.

This model can provide insights into infrastructure design that can benefit both the users (e.g., delivery companies) and planners (e.g., city planners, building managers) of building and parking infrastructure.

Fig. 1 shows the relationships of city planners, building managers, and delivery workers to parking infrastructure as an example.

2. Literature review

Future infrastructure design should consider the evolving nature of people's shopping behaviors and the various delivery methods possible, given advanced technologies.

Although various simulation and optimization tools have been used in transportation research, they have been limited to solving multiple objectives within a single organization, rather than used to understand the complex dynamics among different parties and to maximize benefits for all. This study shed new light onto potential applications of simulation and optimization tools to achieve common transportation goals for multiple organizations.

2.1. Parking and building infrastructure

McDonald and Yuan (2021) extensively reviewed the zoning code requirements for loading zones throughout the United States, emphasizing the lack of a systematic approach to determining the supply of loading zones (McDonald and Yuan, 2021). The current urban planning policies and practices showed that there are significant variations in offstreet loading requirements while on-street loading spaces are designed ad hoc or based on the requests by local businesses (McDonald and Yuan, 2021).

With limited urban spaces and rapid growth in deliveries, many European cities demonstrated efforts on providing regulations on providing loading spaces. For example, the City of Paris Transportation Department required loading and unloading areas for the main freight generators according to their generated freight volumes (City of Paris, 2016). The City of Barcelona required off-street spaces based on the size of the buildings and their land use (City of Barcelona, 1999). On the other hand, Morries (2004) points out that the number of off-street loading bays in New York has been unchanged for several decades, while deliveries to commercial properties have grown exponentially over the past years (Morris, 2004). Morris (2009) also points out the lack of requirements for building infrastructure such as the number of freight elevators in commercial buildings of many American cities, including Atlanta, Boston, Chicago, Dallas, New York, and Seattle (Morris, 2009). McDonald and Quan also implied the slow promotions for such changes in American cities (McDonald and Yuan, 2021).

Potential rationales for this could be a lack of communication between the public and private sectors. Although off-street parking spaces and building infrastructure can be regulated by city officials, they need to be designed with new construction and they are mainly managed by private building managers. Without good communication between the public and private sectors, it is difficult for city planners to understand the building's potential delivery issues at the micro-level. The scarcity between public and private sectors could have contributed to the slow changes in regulations for the off-street parking spaces and building infrastructure in our cities. The City of Seattle Final 50 ft Program of exploring commercial vehicle dwell times (Kim et al., 2021) and parking behaviors (Girón-Valderrama et al., 2019) are good examples of the collaborative efforts between the public and private sectors to improve freight delivery systems. McDonald and Quan also emphasized the importance of engagement from multiple organizations to coordinate actions to improve cities' limited freight loading spaces (McDonald and Yuan, 2021).

As compared to off-street parking, on-street loading zones can be flexibly determined by municipalities. With increased numbers of deliveries, urban cities are making efforts to improve physical spaces for commercial vehicles by increasing and relocating on-street parking spaces. New York City's 'Commercial Vehicle Parking Plan' initiated offering additional curbside spaces for commercial vehicles (U.S. Department of Transportation, 2009). Philadelphia reserved 80 to 100 ft as an all-day loading zone in busy downtown (Calvert, 2019). Washington, D.C.'s 'Downtown Curb-space Management Plan' attempted to improve commercial vehicle loading zones (CVLZs) by relocating to the end of each block face wherever possible to make parking easier for commercial vehicles and extending the loading zones on K Street from 40 ft to 100 ft to increase commercial parking capacity (Jones et al., 2009). However, the efficiency of locating the parking at the end of the block was later questioned by Campbell et al. (2018) who found that it can increase parking time by about 4%, as the parking is farther away from the delivery locations (Campbell et al., 2018). This demonstrates the need for data-driven approaches and complexity in commercial vehicle parking policies.

On-street loading zones are crucial for those buildings without off-street loading spaces, especially older buildings. However, Mcdonald and Quan identified that provision of these spaces is often ad hoc (McDonald and Yuan, 2021). Although cities like Philadelphia offer an application for a new loading zone to local businesses (The Philadelphia Parking Authority, 2011), on-street parking spaces are competed by other transportation use such as bus lanes and passenger load zones. This requires a high degree of coordination across agencies when making changes to on-street loading zones. Our simulations and optimization cost models can be used as a valuable communication tool between key agencies as they can quantify the current and future impacts based on the supply and demand of limited parking and building resources.

Not only providing more spaces for on- and off-street loading spaces, but also assessing utilization of these spaces is important. Brown et al. found that on-street commercial parking spaces in Paris were highly underutilized (47% of the time unused and another 47% of the time misused by passenger vehicles), and only 6% of the time was used for loading spaces legitimately (Browne et al., 2007). In Belo Horizonte, Brazil, De Oliveira and Guerra found that on-street loading and unloading spaces were occupied more by passenger vehicles (57% of the time) than freight vehicles which used the spaces for only 35% of the time (Oliveira and Guerra, 2014). Demands and utilizations for CVLZs by commercial vehicles can be varied by land-use type (Girón-Valderrama et al., 2019), adding complexity to parking management for commercial vehicles. This means that the one-size-fits-all approach is likely to be unsuccessful. To manage commercial vehicle demands for on- and off-street parking spaces, systems such as demand-based pricing (Pierce and Shoup, 2013) and loading bay booking program has been studied (McLeod and Cherrett, 2011). However, the San Francisco County Transportation Authority report emphasizes the unique challenges in managing commercial loading demand because commercial loading demand does not have flexibility like passenger vehicles which can switch travel patterns or modes based on the availability of parking spaces (San Francisco County Transportation Authority, 2015). Regardless of the supply of loading zones, deliveries are made in busy urban areas where there are few alternatives to a truck or other delivery modes.

Delivery systems with increased delivery demands and misused parking spaces could easily result in unauthorized parking behaviors because delivery workers are left with options such as cruising until finding other parking spaces or double-parking in unauthorized areas (Dalla-Chiara and Goodchild, 2020). The capacity of the roadway could be decreased by unauthorized parking which will inevitably contribute to congestion and traffic safety negatively. A survey conducted in Paris in 2006 pointed out that 75% of all deliveries in the city were made with unauthorized parking behaviors (Browne et al., 2007). In New York City Studies, delivery vehicles usually pay \$ 500 to \$ 1000 per truck per month for parking fines (Holguín-Veras et al., 2011). The intention of discouraging unauthorized parking through fines is often voided as delivery companies expect to pay for parking fines and allocate costs for them intentionally (Wenneman et al., 2015). Downtown Seattle also showed that 40 percent of commercial vehicles parked in unauthorized locations including passenger vehicle loading zones (PLZs), the middle of the road, tow-away zones, and no-parking zones (Girón-Valderrama et al., 2019). With increasing challenges created by commercial vehicle parking systems in cities, it is important to understand the impacts of increasing demands on our building and parking infrastructure.

2.2. The future of deliveries

Embracing new technologies, retailers are constantly making efforts to revolutionize shopping experiences for their customers. For an optimal mobile user experience, corporations are adopting technology innovations such as progressive web applications and accelerated mobile pages (Shopify, 2020). Voice assisted devices such as Amazon Alexa and Google Assistant are another way that shopping has been made easier. The artificial intelligence and machine learning technology in these devices allow customers to purchase goods and groceries online with improved customer services (Shankar et al., 2020). Loup Ventures expects that 75 percent of U.S. households will have smart speakers by 2025 (Kinsella, 2019), which may have a ripple effect on increasing online shopping behaviors. Retailers have recently been trying "offline to online" (also called O2O) services, which open up the store for display purposes only, allowing customers to try physical goods offline but complete buying/selling online (Visser et al., 2014). For example, Nike's new physical stores allow users to try exclusive products, customize products onsite, and partake in fitness tests, experiences that online shopping cannot offer (Nike Inc., 2018). In another example, Nordstrom expanded its "Reserve Online and Try in Store" services to nearly 40 stores across the U.S. in 2017 after a successful pilot project in the fall of 2016 (Nordstrom, 2017). With rapidly changing advancement in technologies, customers' expectations for shopping are changing, most likely leading to the demand for goods and services in urban areas to increase.

The COVID-19 pandemic shifted shopping to on-line. More people were also highly dependent on online platforms for food given limited public transportation, reduced store hours, and higher risk of COVID-19 exposure at brick-and-mortar stores.

The rate of e-commerce adoption during the pandemic has longterm impacts (Adobe Analytics, 2020). Gatta et al. (2020) studied the potential acceptability and adoption of "e-grocery" shopping (purchase of groceries online), pointing out that changes in such shopping behavior would substantially impact how goods reach houses, as buying groceries is a recurrent activity for any household (Gatta et al., 2020). While technologies are changing people's shopping experiences faster than ever, most cities' infrastructure designs and policies lack rigorous data collection and scientific approaches. As our simulation and optimization models accounted for real-world observations in the final 50 ft of deliveries, we focused on providing data-driven tools that policymakers can use to better understand the dynamics of current and future urban freight deliveries.

2.3. Methods to optimize resource allocation

2.3.1. Simulation techniques

Simulation techniques are widely used in much operational research to assist in decision making for system analysis and improvements (Uriarte et al., 2015). The simulation approach is popular not only for transportation but also for health care, production lines, and businesses. Simulation models are useful for understanding complex system flows over time. They are also useful for testing "what if" scenarios and predicting system performance before any plans have been implemented. Choosing an appropriate approach among many types of simulations is crucial.

There are many types of computer-based simulations, such as system dynamics (SD), agent-based (AB), and discrete-event simulations (DES) (Brailsford et al., 2009). Borshchev and Filippov (2004) stated that whereas SD deals mostly with continuous processes, DE and AB work mostly in discrete time (i.e., moves from one event to another) (Borshchev and Filippov, 2004). This section explores various types of simulation tools and summarizes our rationale for choosing DES over other types of simulation tools for our study.

SD simulation, which was developed by electrical engineer Jay W Forrester in the 1950s, is defined as "the study of information-feedback characteristics of industrial activity to show how organizational structure, amplification, and time delays (in decisions and actions) interact to influence the success of the enterprise" (Forrester, 1958, 1968). SD represents the real-world process as stocks (e.g., of material, knowledge, people, money), flows between those stocks, and information that determines the value of the flows. Because SD stocks do not have individuality and the SD needs to consider global structural dependencies, SD simulation is best suited for describing system behavior as several interacting feedback loops, balancing or reinforcing them with three to four tools that are very similar to each other (e.g., piston motion) (Borshchev and Filippov, 2004).

AB simulation is often called "bottom-up" modeling (Schieritz and GroBler, 2003) because AB does not have global system behavior up front. Instead, behaviors at an individual level are defined first, and then the complex global behavior emerges as a result of many individuals interacting with each other, living in some environment together (Borshchev and Filippov, 2004). The big advantage of using AB simulation is that models can be constructed without knowledge about global inter-dependencies (Borshchev and Filippov, 2004). Therefore, AB simulation has been a popular tool to model parking behaviors of individual drivers and to study driver's dynamic decision making processes in response to changes of surrounding traffic conditions (Benenson et al., 2008; Zhang et al., 2014; Ni and Sun, 2018). AB simulation approach has also been used for locating parking variable messaging signs as the simulation can be constructed to provide information such as cruising process, parking choice behavior and traffic assignment (Ni and Sun, 2018; Sun et al., 2016).

DES was developed by Geoffrey Gordon, who evolved the idea for the General Purpose Simulation System and introduced IBM implementations (Gordon, 1978). DES models comprise entities that enter a system and travel through multiple steps before leaving the system. Each step represents a discrete timestamp (i.e., event) that alters the state of entities. Each event can be described in terms of resources and their capacity and efficiency. In DES, entities act as a passive element of the system, and therefore, the entity will wait until its turn if the resources are pre-occupied with other entities. In this way, DES incorporates queuing in the model and is able to discover bottlenecks and measure system performance (Lebeau et al., 2013).

The DES model was most suitable for this study, as we could simulate delivery workers (entities) traveling through a building (system), using the building and parking resources (resources). Through DES, we were interested in learning about the utilization of building and parking resources under different "what-if" scenarios. DES requires specific data for on-time distribution for each activity (Layeb et al., 2018). Fortunately, a complex delivery process and detailed activities had been documented in a discrete event flowchart with time distributions for each delivery task during a previous study conducted by Kim et al. (2018b). With this previously obtained empirical data, we built our DES model with realistic complex stochastic distributions.

2.4. Simulation-based optimization approach in transportation research

Although DES can provide the results of specific "what-if" scenarios based on the complex and stochastic flows of delivery workers, the optimal solution is not guaranteed (Uriarte et al., 2015). Therefore, an additional optimization tool was required to find the optimal solution (AlDurgham and Barghash, 2008) even though simulation and optimization have traditionally been considered to be different approaches in the operational research domain (Figueira and Almada-Lobo, 2014). Numerous recent studies have used a combination of optimization and simulation tools and confirmed their effectiveness at making quick decisions about optimal system configurations and complex integrated facilities (Uriarte et al., 2015). As meta-heuristic optimization can quickly identify good quality solutions, it has usually been used in combination with DES (Figueira and Almada-Lobo, 2014). When there are multiple objectives, simulation-based, multiobjective optimization (SMO) can search for trade-offs between several conflicting objectives to find the optimal solutions (Deb, 2011). Several meta-heuristic algorithms have been developed for simulation-based optimization, such as the genetic algorithm, scatter search, pychoclonal algorithm, hybrid algorithm, and nondominated sorting generic algorithm (NSGA II). Among these algorithms, NSGA II is the most commonly used for simulation-based optimization (Avci and Selim, 2017).

The simulation-based optimization approach has been widely used in transportation and logistics studies. Optimizing the costs of deliveries has been one popular topic. Yanchuk et al. (2020) conducted a simulation of cost optimization for package delivery with a combination of carriers for fast (same day or next day) and lazy (not the nearest day or week) deliveries (Yanchuk et al., 2020). Avici and Selim (2017) used SMO to develop a supply chain inventory management system by determining suppliers' flexibility and safety stock levels in terms of inventory holding costs and premium freight (i.e., expedited shipping with high costs such as airways) (Avci and Selim, 2017).

Transportation routing networks have been another area of popular research using simulation-based optimization. Poeting et al. (2019) and Simoni et al. (2020) simulated last-mile delivery routes to optimize them with delivery robots (Poeting et al., 2019; Simoni et al., 2020). Anderluh et al. (2019) utilized SMO to select the best routes given trade-offs between the economic objective of minimizing delivery costs and the social objective of minimizing the negative impacts of delivery vehicles, such as noise and congestion (Anderluh et al., 2019). Similarly but for transit, Schmaranzer et al. (2019) designed a complex urban mass rapid transit system by using SMO to minimize the cost of fleets and maximize service levels (e.g., average waiting time per passenger) (Schmaranzer et al., 2019). Layeb et al. (2018) approached scheduling problems in stochastic, multimodal freight transportation systems with a simulation-based optimization model (Layeb et al., 2018).

Optimization approaches have also been applied in selecting optimal locations of facilities and managing parking systems. Jardas et al. (2020) selected an optimal location for a distribution center that would minimize delivery costs by considering the distance between a start point and the destination (Jardas et al., 2020). Wei (2020) found optimal network nodes and passages of urban underground logistics that would minimize logistic time cost, exhaust emissions, and congestion costs (Wei et al., 2020). To determine advanced parking strategies such as dynamic pricing, Zheng and Geroliminis (2016) applied optimization to reduce congestion and lower the total travel costs of all users (Zheng and Geroliminis, 2016).

Although much research has used simulation-based optimization in the transportation and logistics fields, no study has utilized SMO to optimize building and parking resources. On the other hand, research in the fields of healthcare and production lines has a long history of using simulation-based optimization to determine resource allocations for improving system performance. For example, multiple buffer allocation studies have determined optimal buffer capacities by maximizing throughput rates while minimizing total resource capacities for production lines. Motlagh et al. (2019) produced an extensive literature review on research since 2000 that has used buffer allocation problems (Mosayeb Motlagh et al., 2019). Since the 1990s, the healthcare field has applied SMO to study the optimal number of expensive medical devices in an emergency (or surgical) department that can minimize the costs of medical resources while maximizing service levels for patients (e.g., minimizing waiting time) (Lin et al., 2013; Uriarte et al., 2015; Feng et al., 2017; Chen and Wang, 2016). Similarly, SMO can be applied to optimize a city's parking and building infrastructure, considering not only the city's constraints (e.g., limited parking spaces and costs) but also the costs of delivery workers and building managers. For example, if the city increases the number of on-street parking spaces simply because of increased numbers of deliveries, then delivery queues of deliveries will be transferred to the queues at elevators or receptionists, pushing the costs from delivery workers to building managers. Conversely, if city or building managers decrease the numbers of onand off-street parking spaces without proper analysis, then the costs may be pushed to delivery workers who use the urban infrastructure. SMO can help reveal the complex relationships among different parties and balance such ambiguity in parking and building policies.

In this study, SMO was developed to optimize building and parking resources in order to minimize the costs for three parties: city planners, building management, and delivery workers.

3. Simulation and optimization designs

This research evaluated the impacts of increasing demand for urban goods deliveries on parking and building operations through simulation models. Data collected from an office building in downtown Seattle, Washington, U.S.A., were used to model the final 50 ft of the delivery process in our discrete event simulation model. In a previous study, the data-collection process took place over five business days between January 31 and February 4, 2017, between the hours of 9:00a.m. and 4:00p.m. Trained data collectors shadowed delivery workers (n = 31) at freight-attracting urban buildings and collected data on the time distributions associated with each delivery task by using a customized mobile app (Kim et al., 2018a). Their task time distributions and dwell times (the moment when the vehicle was parked until the vehicle left the site) were used to validate the simulation model. The details of the data collection process can be found in Kim et al. (2018b).

In Python software (version 3.8), the discrete event simulation was built by using a SimPy package (version 4.0.1). Once the simulation had been validated to replicate real parking durations with an observed delivery arrival rate of four deliveries per hour (the baseline scenario), then varied delivery arrival rates were applied as inputs to understand the cost dynamics between different parties (scenarios). After the simulation model showed several scenario results, a possible near-future delivery rate was chosen, and the optimization algorithms (NSGA II and MOEA/D) were utilized through the Pymoo package (version 0.4.1). The optimization can help decision makers determine the optimal numbers of parking and building resources to better prepare adequate numbers of resources at the chosen delivery arrival rate. A value stream map was used to create a computer simulation model and represent essential process delivery steps in the final 50 ft. Five important variables (i.e., numbers of on- and off-street parking spaces, security guards, elevators, and receptionists) were selected as decision variables to calculate the costs for delivery workers, building managers and city planners.

Although the real-world environment involves complex dynamism and uncertainty which affect the formulation of the optimization including input data and constraints, metaheuristic algorithms may solve oversimplified models of real systems with the deterministic inputs and constraints. This may lead to casting doubts on the validity and recommendations from its results alone. Therefore, combining simulation with metaheuristics has been gaining popularity as an effective procedure to deal with complex combinatorial optimization problems (Ferreira, 2013; Chica et al., 2017). Our proposed method of combining metaheuristics and simulation can offer solving large-scale stochastic optimization problems as a natural extension of metaheuristic in transportation logistics. The assumptions in our models are grounded not only in the literature but also on the expertise of industry experts from various logistic companies who participated in the data collection.

3.1. Problem formulation

A multi-objective optimization model was formulated to identify the optimum numbers of parking spaces, staff, and elevators to minimize freight delivery costs for city planners, building managers, and delivery workers. The indices, decision variables, boundaries, input parameters of this model, and cost objective functions are defined in this section. We were interested in exploring the cost impact on the off-street parking separately because the city's off-street parking spaces are designed and managed by the city planners rather than building managers. Therefore, city planners' perspective may focus more on the utilization of off-street parking and unauthorized parking frequencies, separately from the building manager's point of interest. This is reflected in our cost function for city planners.

Indexes:

- i :Index of building staff (i = 1, ..., I) such as security guard, receptionist
- j :Index of building resources (j = 1, ..., J) such as elevator, off-street

parking spaces (e.g., loading bay) for commercial parking

k :Index of on-street parking type such as commercial parking, un-authorized parking (e.g., double parking)

Decision variables:

 X_i : Number of building staff types i

Χ	: Vector of the number of building staff types, $X =$
	$[X_1, \ldots, X_I]$
Y_i	: Number of building resource types j

- Y : Vector of the number of building resource types, $Y = [Y_1, ..., Y_J]$
 - : Number of on-street parking types k
- Z : Vector of the number of on-street parking k, $Z = [Z_1, ..., Z_K]$

Upper and lower boundaries for decision variables:

l_i	: Minimum number of building staff type i
l_i	: Minimum number of building resources type j
$\vec{l_k}$: Minimum number of on-street parking type k
u _i	: Maximum number of building staff type i
u _i	: Maximum number of building resources type j
u_k	: Maximum number of on-street parking type k

 Z_k

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Simulation parameters:

R	: Total simulation replications
r	: Index for simulation replications $(r = 1,, R)$
n	: Index for delivery vehicles
N	: Total delivery vehicles in a building
m	: Index for resources used (can be X_i, Y_i, Z_k, W_o)
Start	: Arrival time of delivery vehicle
End	: Departure time of delivery vehicle
f	: Total number of goods that failed to be delivered
unau	: Total number of unauthorized parking occurrences
c_f	: Failed delivery cost
c_d	: Labor cost for delivery worker n
c_i	: Labor cost for building staff i
c_i	: Operational cost for building resource type j
c_k	: Operational cost for on-street parking type k
cunau	: Environmental cost for unauthorized parking
u_{im}	: Utilization rate of resource m for the building staff
u_{im}	: Utilization rate of resource m for the building
5	resource type j
u_{km}	: Utilization rate of resource m for the on-street parking
	type k

Multi-objective functions:

1. Minimize delivery worker's costs (DC):

$$f_1(X, Y, Z) = \hat{E}[DC(X, Y, Z; \xi)] = \frac{\sum_{r=1}^R DC(X, Y, Z; \xi)_r}{R}$$
(1)

2. Minimize building manager's waste costs (BWC):

$$f_2(X, Y, Z) = \hat{E}[BWC(X, Y, Z; \xi)] = \frac{\sum_{r=1}^R BWC(X, Y, Z; \xi)_r}{R}$$
(2)

3. Minimize city planner's waste costs (CWC):

$$f_{3}(X,Y,Z) = \hat{E}[CWC(X,Y,Z;\xi)] = \frac{\sum_{r=1}^{R} CWC(X,Y,Z;\xi)_{r}}{R}$$
(3)

Cost functions for DC, BWC, CWC:

DC estimator:

$$DC(X, Y, Z; \xi)_r = (\underbrace{\frac{\sum_{n=1}^{N} (End_n - Start_n)}{N}_{\text{Length of stay cost}}}_{\text{Length of stay cost}})_r * c_d + (\underbrace{\frac{\sum_{n=1}^{N} (f)}{N}_{\text{Failed delivery cost}}}_{\text{Failed delivery cost}}$$
(4)

BWC estimator:

 $BWC(X, Y, Z; \xi)_r$

$$= \sum_{i} \sum_{m=1}^{X_{i}} c_{i} * (1 - u_{im}) + \sum_{j} \sum_{m=1}^{Y_{j}} c_{j} * (1 - u_{jm})$$

$$= (\sum_{i} X_{i} * c_{i} + \sum_{j} Y_{j} * c_{j})$$
Resource costs
$$- (\sum_{i} \sum_{m=1}^{X_{i}} c_{i} * u_{im} + \sum_{j} \sum_{m=1}^{Y_{j}} c_{j} * u_{jm})$$
Utilization cost
$$(5)$$

CWC estimator:

 $CWC(X, Y, Z; \xi)_r$

$$= \sum_{i} \sum_{m=1}^{Z_{k}} c_{k} * (1 - u_{km}) + \sum(unau) * c_{unau}$$

$$= (\sum_{k} Z_{k} * c_{k}) - (\sum_{k} \sum_{m=1}^{Z_{k}} c_{k} * u_{km})$$

$$+ \sum_{k} (unau) * c_{unau}$$
(6)

Unauthorized parking cost

Subject to:

$$l_i \leq X_i \leq u_i \quad \forall i \tag{7}$$

$$l_j \leq Y_j \leq u_j \quad \forall j \tag{8}$$

$$l_k \leq Z_k \leq u_k \quad \forall k \tag{9}$$

$$X_i \ge 0 \quad \forall i$$
 (10)

$$Y_j \ge 0 \quad \forall i$$
 (11)

$$Z_k \ge 0 \quad \forall i$$
 (12)

The mathematical models are explained as follows:

Eq. (1) describes the minimal average cost of delivery workers who make deliveries to the building (DC), where ξ indicates the stochastic effect. The minimal average DC includes two parts: (a) minimum length of stay cost, (b) minimum failed delivery cost. Given each simulation replication r, the average DC of all deliveries is estimated according to Eq. (4). Therefore, the average DC ($\hat{E}[DC(X, Y, Z; \xi)]$) across multiple replications is predicted with Eq. (1) and is applied to approximate a true DC performance $f_1(X, Y, Z)$ under a given number of all staff and building and parking resources.

Eq. (2) describes the minimal average building manager's waste costs (BWC), where ξ indicates the stochastic effect. The minimal average BWC includes two parts: (a) minimum building resource costs, (b) maximum utilization costs for building resources. Given each simulation replication r, the average BWC of all deliveries is estimated according to Eq. (5). Minimizing total BWC will result in minimizing resource costs and maximizing the utilization rate for resources simultaneously. Therefore, the average BWC ($\hat{E}[BWC(X,Y,Z;\xi)]$) across multiple replications is predicted with Eq. (2) and is applied to approximate a true BWC performance $f_2(X, Y, Z)$ under a given number of all staff and building and parking resources. It is important to note that our observations were limited to delivery-related activities only (e.g., security guards checking in/out for the delivery workers, receptionists receiving goods, and signing off the packages). In the model, we assumed that building staff (e.g., X_1 : security guard and X_2 : receptionists) were exclusively dedicated to taking delivery-related activities, and all other activities performed were considered idling, resulting in the wasted costs. For future research, the cost function can be expanded to account for the overall costs that includes other activities (e.g., security guards patrolling the building, receptionists answering the calls, etc.) as productive actions of building staff.

Eq. (3) describes the minimal average waste costs for city planners who manage on-street parking and unauthorized parking (CWC), where ξ indicates the stochastic effect. The minimal average CWC includes three parts: (a) minimum on-street parking operational costs, (b) maximum utilization costs for on-street parking spaces, and (c) unauthorized parking costs. Given each simulation replication r, the average CWC of all deliveries is estimated according to Eq. (6). Minimizing total CWC will result in minimizing resource costs and maximizing the utilization rate for resources simultaneously. Additionally, the total unauthorized parking number is multiplied by the environmental costs, as unauthorized parking will affect the surrounding environment (e.g., congestion, noise, etc.). Therefore, the average CWC ($\hat{E}[CWC(X, Y, Z; \xi)]$) across multiple replications is predicted with Eq. (3) and is applied to approximate true CWC performance $f_3(X, Y, Z)$ under a given number of all on-street parking resources.



Fig. 2. Simplified delivery process flow map.



Length of stay at final 50 feet

Fig. 3. Definitions of parking and dwell time.

3.2. Problem description

This study looked at the process flows in the final 50 ft of urban freight deliveries (see Fig. 2). The delivery workers' arrival interval times and service times for each delivery followed specific stochastic distributions based on field observations. Our model presumed that the type of resources such as building staff (e.g., security guard, receptionist) and resources (e.g., parking, elevator) did not change dynamically over time. Under such pre-established conditions, our multi-objective optimization allocation problem was studied. This study aimed to obtain the most viable solutions for allocating adequate amounts of resources to better prepare for increased demands for urban freight deliveries, given restricted building and parking resources. The building and parking resources that were used in this work included the number of building staff (X_1 = security guard, X_2 = receptionist), the number of building resources (Y_1 = off-street parking, Y_2 = elevator), and the number of on-street parking spaces (Z_1 = on-street parking).

3.3. Delivery flow

Delivery workers' out-of-vehicle activities inside urban buildings were simulated based on field observations from an office building in downtown Seattle. Time in the system was categorized into two sections: time associated with parking activities and dwell time. Fig. 3 shows the definitions of parking and dwell time referred to in this paper.

When a delivery worker arrived at the building, on-street and offstreet parking spaces were filled first. Both on- and off-street parking were assumed to have no queue, reflecting real-world commercial vehicle parking behaviors. When both on- and off-parking spaces were full, then delivery workers were assumed to park at unauthorized areas or leave the building, failing to deliver. Because resources such as security check-in and elevators had to be used in each direction when the building was entered and exited, the resources were shared between delivery workers who entered and exited the system. For example, when there were queues at the security booth and elevator, the queues were formed in a first-in-first-out (FIFO) method, containing a mixture of delivery workers entering and exiting the system. Delivery workers' waiting time for using the elevator up and down may only be approximated by using the entire number of floors in the building and the frequency of freight elevator usage. Fig. 2 shows the overall process flow of the simulation model, and the delivery flows are described as follows.

- Arrival: Delivery workers can park either at off-street parking or on-street parking. In case there is no parking lot is available, delivery workers have the option to park at an unauthorized parking area (90 percent of the time) or leave the building, which is considered a failed delivery (10 percent of the time).
 - 1.1. Once parked, delivery workers take time unloading their goods.
 - 1.2. When unauthorized parking occurs, delivery workers spend extra time walking from the vehicle to the building.
 - 1.3. They walk from the vehicle (or building entrance) to a security booth.

- 2. Security check-in: Most delivery workers go through a security check-in to obtain a guest pass to the building. Some bypass security check-in as they perform regular deliveries (e.g., UPS, FedEx, etc.).
 - 2.1. Once checked in, they walk from the security booth to the elevator.
- 3. Elevator up: All delivery workers take an elevator up to their delivery destination. Based on the capacity of the elevator, other delivery workers may be required to wait till others finish using the elevator either up or down.
 - 3.1. They walk from the elevator to a delivery destination.
- 4. Delivery: Delivery workers can deliver goods to a receptionist. If the receptionist has a queue greater than two, delivery workers either drop off without a receptionist (90 percent of the time) or fail to deliver (10 percent of the time).
 - 4.1. They walk from the delivery destination to the elevator.
- 5. Elevator down: All delivery workers take an elevator down. Depending on the capacity of the elevator, other delivery workers may be required to wait till others finish using the elevator up or down.
 - 5.1. They walk from the elevator to the security booth.
- 6. Security check-out: Delivery workers are required to return the guest pass that they obtained when entering the building.
 - 6.1. They walk from the security booth to their vehicle.
 - 6.2. Once returned to their vehicle, delivery workers take time loading their tools (e.g., dollies).
- 7. Departure: Delivery workers leave the site.

Several parameters for the simulation were set up according to the cost parameters in Table 1 and processing time distributions in Table 2. These time distributions (e.g., minimum, mode, maximum processing time) in Table 2 were based on the real-world data collection described by Kim et al. (2018b). Cost parameters shown in Table 1 were based on the Seattle area's average labor costs for each occupation according to the U.S. Bureau of Labor Statistics (U.S. Bureau of Labor Statistics, 2018). Operational cost and costs for failed delivery and unauthorized parking were assumed as shown in Table 1. Table 3 indicates the resource limit parameters, that is, the maximum and minimum amounts of each resource. The numbers of security guards and receptionists were limited to small numbers and increased and decreased from the existing numbers of security guard (n = 1) and receptionists (n = 4). The upper limits for the number of off-street and on-street parking were slightly increased numbers from the existing numbers of parking spaces (n = 7 for off-street parking and n = 11 for on-street parking). Rather than installing a new elevator or removing an elevator, the upper limit of the number of elevators was limited to two elevators because there were two existing freight elevators. In this study, the use of freight elevators could be changed to a passenger elevator if the optimized number of elevators was the lower limit (n = 1).

Using on-street and off-street parking may lead to differences in time spent on walking to the security booth and taking the elevator. However, our model assumes these differences are small and uses the same walking time distribution that covers walking time from on-street and off-street parking spaces. The model can be further improved with different walking time distributions for walking from on-street and offstreet parking spaces specifically. Meanwhile, our model reflects the longer walking time from unauthorized parking spaces as compared to those from on-street and off-street parking spaces.

A past study found that the average construction costs for parking structures in 2015, excluding land costs, were about \$24,000 per space

Table 1

Resource limit paramete	s for each	building and	parking resource.	
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Model resource	Cost (\$)
Labor cost of delivery worker	\$20 per hour
Labor cost of receptionist	\$18 per hour
Labor cost of security guard	\$16 per hour
Cost of failed delivery	\$30
Operational cost of on-street parking	\$1 per hour
Operational cost of off-street parking	\$1 per hour
Operational cost of elevator	\$1 per hour
Cost of unauthorized parking	\$20

for above ground parking and \$34,000 per space for underground parking (Shoup, 2020). Although building new infrastructure option can be explored, utilizing existing infrastructure may be considered as the first option for city planners and building managers due to high development costs. To provide more realistic options, the costs of onand off-street parking spaces and elevators included operational costs only, rather than the costs for building new infrastructure (e.g., constructing new parking spaces or installing a new elevator). This means that our scope of work was limited to the re-allocation of existing infrastructure, rather than building new infrastructure. Therefore, the upper limit for the parking spaces and elevator in the optimized model were set to the current numbers of resources. For example, when the optimized number of parking spaces or elevators is smaller than the current system, city or building managers can decide to transfer the use of parking spaces that were dedicated for commercial vehicles to passenger vehicles or the use of freight elevators to passengers, etc., rather than removing the current infrastructure. Therefore, the model results can be still valuable to policymakers for allocating existing resources as a first step. In a future study, construction costs for parking spaces and elevators can be added to our cost function to further investigate the option of building new infrastructure.

4. Optimization algorithms

Given the large solution space (4*4*9*2*14 = 4032) and multiobjective nature of our model, this study applied two multi -objective evolutionary algorithms: (1) the population-based NSGA II to search non-dominated solutions (Pareto-optimal solutions) and (2) multi-objective evolutionary algorithm based on decomposition (MOEA/D). NSGA II has been used most commonly for multi-objective, simulation-based optimization (Avci and Selim, 2017). Similar multiobjective, simulation optimization algorithms have been used for optimizing resource allocation in emergency departments and healthcare systems (Feng et al., 2017; Huang, 2016). In this section, the basic concepts of the selected algorithms are described, while more detailed descriptions can be found in Deb et al. (2002) for NSGA II and in Zhang and Li (2007) for the MOEA/D algorithm.

4.1. NSGA II

The nondominated sorting genetic algorithm (NSGA II) is a population-based algorithm developed by Deb et al. (2002) to search for multiple non-dominated solutions (Pareto-optimal solutions) through evolutionary processes. Multi-objective optimization problems involve conflicting objectives (e.g., one objective increases while the other decreases). Therefore, there is no global solution but a set of solutions.

The first non-dominated sorting generic algorithm (NSGA) was proposed by Deb et al. (2002), but three main criticisms followed over the years: (1) the high computational complexity of non-dominated sorting, (2) a lack of elitism, and (3) the need to specify the sharing parameter, σ_{share} , when a parameter-less diversity-preservation mechanism is desirable. The NSGA II algorithm overcomes these drawbacks.

Table 2

Processing/Service times (minutes) Triangle distribution (min, mode, max)

Triangle(9, 12, 165)/60 Triangle(12, 12, 67)/60 Triangle(5, 8, 20) Triangle(4, 8, 102)/60

rocessing times of each activity within the simulation model.	
Activity	
On-street parking	
Off-street parking	
Walking from unauthorized parking to building	
Walking from truck (or building entrance) to security booth	
Security booth	
Unloading goods from truck	

Security booth	Triangle(2, 9, 156)/60
Unloading goods from truck	Triangle(20, 30, 300)/60
Elevator	Triangle(4, 35, 635)/60
Walking from elevator to destination	Triangle(10, 20, 200)/60
Receptionist	Triangle(3, 11, 404)/60
Walking from destination to elevator	Triangle(3, 20, 200)/60
Walking from elevator to security	Triangle(3, 18, 97)/60
Loading a tool back to vehicle	Triangle(5, 30, 100)/60

Table 3

Resource limit parameters of each building and parking resource.

1	0 1 0	
	Lower limit (LL)	Upper limit (UL)
Number of security guard	1	4
Number of receptionist	1	4
Number of off-street parking	2	10
Number of elevator	1	2
Number of on-street parking	2	15

NSGA II is a kind of genetic algorithm, which is a heuristic optimization method inspired by natural evolution that produces better and better approximations. A new population is generated through a process of evaluating individuals based on their fitness levels to identify an elite population (Pareto set) with a non-dominated sorting algorithm (Feng et al., 2017). With each generation, the current elite population is selected to generate new offspring through crossover, mutation, and repair operators. The fitness values of the current elite population's new offspring are reevaluated to create a new elite population. This evolution process is repeated until the approximate non-dominated resource allocation solutions are found (the termination condition).

4.1.1. Initialization

The combination of decision variables can be designed as a chromosome or individual. Each chromosome contains segments of decision variables, forming a combination of decision variables. First, the initial population is randomly generated from the minimum and maximum ranges of each decision variable.

4.1.2. Fitness assignment and selection

The initialized population is sorted into each front based on nondomination (elite). A fast non-dominated sorting system partitions all chromosomes into different non-domination fronts. The first front is the completely non-dominant set in the current population, and the second front is dominated by the individuals in the front only. For each front i, all solutions of front (i) always dominate front (i+1). The fitness values are given to each front. For example, the first fronts are assigned fitness values of 1, and the second fronts are given fitness values of 2, and so on. Therefore, the first front is the best level of all fronts among the population.

In addition to fitness value, crowding distance is calculated for each individual as a new parameter. Crowding distance is a measure of Euclidean distance between two individual chromosomes in the same front based on their multi-objective fitness values. Large average crowding distance will result in better diversity in the population. Parents are selected from the population by using binary tournament selection based on rank and crowding distance.

4.1.3. Crossover

The selected population generates offspring with crossover and mutation operators. Crossover is performed to swap parts of a solution with another in chromosomes to provide mixing of the solutions and convergence in a subspace. Crossover occurs on two chromosomes at a time and generates two offspring by combining the features of both chromosomes under a crossover rate, (p_c) . There are many different types of crossover. For example, uniform crossover operates by uniformly selecting genes from either of two chromosomes and copying them to offspring 1, and the remaining genes are copied to offspring 2. By default, NSGA uses the real-coded genetic algorithm simulated binary crossover (SBX) method, which uses a probability density function that simulates the single-point crossover operator of the binary-coded genetic algorithm. The mixture of population that consists of the current population and offspring is sorted again based on non-domination, and only the best N (population size) individuals are selected.

4.1.4. Mutation

As the crossover operator can generate offspring very similar to the parents, the new generation may lack diversity. As a way to solve this issue, the mutation operator randomly changes the value of some feature of the offspring. A random number between 0 and 1 is generated to pick which feature is mutated. If this number is lower than a value called the mutation rate, that variable is flipped. The mutation rate is usually chosen to be 1/m, where m is the number of features. This means we mutate one feature of each individual. For NSGA II, the polynomial mutation is used (further described by Deb and Deb (2012)).

4.2. MOEA/D

The multi-objective evolutionary algorithm based on decomposition (MOEA/D) is an evolutionary algorithm that decomposes multiobjective optimization problems to several single-objective subproblems (Zhang and Li, 2007). MOEA/D attempts to optimize these sub-problems simultaneously. Each sub-problem has its own best solution, which is determined by comparing all solutions found by the algorithm. Among these sub-problems, the neighborhood relations are constructed based on the distances between the aggregation coefficient vectors. Each sub-problem is optimized in MOEA/D by using information from its neighboring sub-problems. The major advantages of MOEA/D over Pareto dominance-based MOEAs (e.g., NSGA II) is that single objective local search techniques can be readily used in MOEA/D (Peng et al., 2009).

5. Simulation results

The simulation period for this study lasted 8 h (480 min). The first 1 h (60 min) of the simulation constituted the transient period, and the remaining 7 h represented the steady period. Experimental data



Fig. 4. Loading bay with seven off-street parking spaces.

were collected during the latter period. The reliability of the simulation results was ensured by applying a sufficient replication number control (n = 100). Four delivery workers per hour were assumed to arrive at the modeled building. The current resource allocations for the building were seven off-street parking spaces (see Fig. 4), eleven on-street parking spaces, one security guard, four receptionists, and two freight elevators. Multiple simulation runs with various arrival rates of delivery workers were performed to understand the impact of increased numbers of deliveries at an urban building. During the simulation phase, the decision variables were held constant at current levels as follows:

- $X_1 = 1$ security guard
- $X_2 = 4$ receptionists
- $Y_1 = 7$ off-street parking spaces
- $Y_2 = 2$ elevators
- $Z_1 = 11$ on-street parking spaces

5.1. Validation and verification of the simulation model

To confirm that the delivery process simulation model is an appropriate model that can accurately reflect and represent the conceptual model, the following validation and verification processes were employed.

- Validation process: The model was developed on the basis of realworld observations of an urban building in Seattle, Washington. Our data collection processes allowed us to obtain very detailed time distributions and delivery task sequences for multiple urban goods deliveries. We also conducted iterative discussions with representatives from industry experts from logistics companies.
- Verification process: To ensure the quality of the model, multiple checking procedures on the behavior of the model were performed by tracing delivery workers' flows step by step through a time-advance mechanism and simulation animation by printing

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BWC

CWC

Table 4

Simulation re	sults regarding	g dwell tim	e and cost	distribution.	
Delivery arr	ival rate (per	hour)	Ave	erage dwell	DW

, , , , , , , , , , , , , , , , , , ,	time (min)	(\$)	(\$)	(\$)
2 (lowest cost for delivery workers)	17.5	5.7	605.2	87.7
4 (current arrival rate: baseline scenario)	17.7	6	602.8	87.5
6	18.4	6.2	600.5	87.2
8	19.2	6.4	598	86.9
10 (lowest cost for city planners)	20.6	7.1	596.5	86.6
12	24.5	8.1	593.7	89
14	28.4	9.5	591.3	105
16 (lowest cost for building manager)	35.7	12.9	586.4	289.3
18 (system overflow- bad for all)	48.1	15.8	587.7	626.1

Note: Holding decision variables constant at current conditions: $X_1 = 1$ security guard, $X_2 = 4$ receptionists, $Y_1 = 7$ off-street parking spaces, $Y_2 = 2$ elevators, $Z_1 = 11$ on-street parking spaces.

customized messages and graphs during the simulation runs. We also confirmed that the dwell time from a simulation run resulted in a very similar time distribution to that of real-world observations under the same constraints.

5.2. Cost distributions with various arrival rates of delivery workers

The simulation results with various arrival rates are summarized in Table 4. Delivery arrival rates were increased and decreased from the current arrival rate (four deliveries per hour). As expected, the lowest cost for delivery workers resulted when the delivery rate decreased to two deliveries per hour. This makes sense, as there were no queues at the resources, resulting in the shortest average dwell time for delivery workers. On the other hand, building costs were the highest because the resources were idling until deliveries arrived at the building. Therefore, the cost for delivery workers increased as the delivery arrival rate increased. Similarly, building manager's costs decreased as resource utilization increased with increased numbers of delivery rates until the system overflowed at the rate of 18 deliveries per hour. A high number of queues concentrated at one location (e.g., the elevator) resulted in idling at other locations (e.g., reception). We observed the lowest cost for city planners at the arrival rate of ten deliveries per hour. This means that the arrival rate of ten deliveries per hour was the point at which on-street parking was highly utilized, with no or minimum instances of unauthorized parking. The CWC increased again at the arrival rate of 12 deliveries per hour, as the instances of unauthorized parking increased.

With an increased number of deliveries, our simulation model allowed us to better understand the cost relationships among delivery workers, building managers, and city planners. The results showed that the current numbers of resources allocated at the urban building were not designed for the current arrival rate of four deliveries per hour. For example, the current building and parking resources were not utilized at 100 percent capacity with the current arrival rate of four deliveries per hour. We can visualize this by exploring the utilization rate of the resources.

5.3. Utilization of resources

At the arrival rate of four deliveries per hour, the resource utilization rates are visualized in Fig. 5. As expected, the current on-street (n = 11) and off-street (n = 7) parking spaces were being used at less than 20 percent of their capacity. Although the security guard (n = 1) was in service at almost 100 percent of capacity, elevators (n = 2) were in service at 60 percent of their capacity, and receptionists (n = 4) were in service at 30 percent of their capacity.

From the simulation, we could also observe the usage of a resource over the simulation run time. The usage of a resource can be represented in cumulative average counts or instantaneous behavior for



Fig. 5. Utilization rate of building and parking resources at the arrival rate of four deliveries per hour.



Fig. 6. On-street parking space usage.

a specific replication. We showed cumulative average counts with a smoothing effect. For example, when two elevators were constantly used (e.g., at 16 deliveries per hour) over 480 min, the cumulative average count for elevators reached close to its capacity of two elevators on the graph. In Figs. 6 and 7, each line represents one simulation run. They show the cumulative average counts of on- and off-street parking spaces over time. As stated before, we assumed that there was no queue for parking resources. The capacity limits are shown in dotted blue in the figures. As expected, usage of parking spaces increased as delivery arrival rates increased. At the current arrival rate of four deliveries per hour, on- and off-street parking spaces were far too many and were underutilized, at far lower than their capacity, meaning that parking spaces were being used at 100 percent over the simulation time frame.

Figs. 8 and 9 show the cumulative average counts of the security booth and elevators in green and queues in red. Although many queues were generated at the security booth over time, the overall formation of queues did not exceed its capacity most of the time. This is probably because delivery workers spent time loading goods before checking in at the security booth between each delivery, leaving some breathing time for the security guard to check in each delivery worker. Also, some delivery workers could bypass the security guard based on their status (e.g., regular delivery workers such as from UPS or FedEx). On the other hand, we can see that the queues at elevators accumulated more than their capacity at the arrival rate of ten deliveries per hour. At 16 deliveries per hour, the average queue length reached up to 20, showing that the elevators were the bottleneck of the current system.

5.4. Failed deliveries and unauthorized parking

Failed deliveries and unauthorized parking occurred when both onand off-street parking spaces were full. In the simulation, failed deliveries set to occur when the queue at the receptionist desk was more than



Fig. 7. Off-street parking space usage.

8 deliveries per hour







two to replicate delivery workers' behavior, as long waits in a queue had led to a failed deliveries during our data collection. Figs. 10 and 11 show the cumulative occurrences of failed deliveries and unauthorized parking. Each red line represents each simulation run. Failed deliveries and unauthorized parking started to occur at the arrival rate of 12 deliveries per hour. As expected, as the delivery arrival rate increased, failed deliveries and unauthorized parking occurrences increased.

4 deliveries per hour

6. Optimization results

This section summarizes the results obtained by the two optimization algorithms, MOEA/D and NSGA II, to minimize costs for delivery workers, building managers, and city planners. Our optimization models used the delivery arrival rate of 12 deliveries per hour (higher than the current arrival rate of four deliveries per hour), given probable growth in urban deliveries in the future. Therefore, our models could





12 deliveries per hour





Fig. 10. Cumulative occurrences of failed deliveries over simulated time.



Fig. 11. Cumulative occurrences of unauthorized parking over simulated time.

be beneficial in developing building and parking designs that could improve current resource allocations in urban cities. Figs. 12 and 13 show Pareto frontiers obtained by using the NSGA II and MOEA/D, respectively. As one can infer from the figures, both algorithms produced results that were similar (a BWC of between \$220 and \$250, a DC of between \$8 and \$10, and a CWC of between \$60 and \$150), although the NSGA II produced extremely high BWC values of between \$400 and \$600. We can see that the MOEA/D provided more targeted ranges for the Pareto frontiers.

Policymakers can choose any point from the Pareto-optimal solutions presented in Figs. 12 and 13 by creating a proper cost distribution strategy. Currently, the exact cost distributions among delivery workers, building managers, and city planners are unknown and very complex, as there is no data-driven approach for implementing regulations for managing building and parking resources in light of the rapidly growing demand for urban deliveries. Our optimization model aims to minimize costs for all three parties, preventing biased policies that could benefit only one or two parties. By comparing the costs of the alternative solutions, policymakers can consider a broad decision spectrum and consequently take the advantage of more flexible decision making.

For example, policymakers may want to reduce a city's costs more than those of building managers and delivery workers. In this case, policymakers can choose the options (one of the dots in the Pareto frontiers) with a lighter gray color, which represents a low CWC in Figs. 12 and 13, while increasing other costs for BWC or DC or both. Our systematic approach to cost distributions can provide flexibility to policymakers because it considers cost distributions under multiple objectives.

Policymakers can decide on the appropriate resource allocations associated with the chosen cost distribution. Each dot in Figs. 12 and 13 represents a certain combination of decision variables. Policymakers

could add, remove, or reallocate the building and parking resources to tailor them to each different Pareto frontier on the basis of their own policy needs. For example, policymakers may choose the specific dot that is located inside of the circle indication in Fig. 13. As shown in Figure, this case is associated with a BWC of \$238.8, a DC of \$8.3, and a CWC of \$71.6 and the model can inform policymakers that this particular cost was the result of the combination of one security guard, two receptionists, four off-street parking spaces, two elevators, and eight on-street parking spaces.

Our model introduced a data-driven approach that can inform policymakers as they consider the efforts of the three entities (delivery workers, building managers, and city planners) working as a team to better prepare for the future demand of urban goods deliveries in urban cities.

7. Conclusion

As the rapid growth of urban freight volumes is expected to continue, policymakers will look for strategies that can balance the supply and demand of parking and building infrastructure to promote efficient deliveries. In this study, we aimed to discover the future delivery rates that would overflow the current delivery systems and find the optimal numbers of resources through a multi-objective, simulation-based optimization framework.

This framework can ultimately aid decision makers in determining the building and parking resource allocations that yield the best cost distributions for delivery workers, building managers, and city planners. The proposed framework was developed with a simulation phase and an optimization phase. In the simulation phase, analysis of current parking and building infrastructure with different delivery arrival rates was conducted to better understand the dynamics of freight delivery cost distributions among delivery workers, building managers, and city planners.



Fig. 12. Pareto frontiers obtained from the NSGA II. (Population size = 100, crossover = 0.9).



Fig. 13. Pareto frontiers obtained from the MOEA/D. (Population size = 100, number of neighbors = 15).

This was achieved by creating a discrete event simulation model that simulated the final 50 ft of urban freight activities at an office building in downtown Seattle, Washington, U.S.A., which consisted of parking and building resources such as a security guard, receptionists, off-street parking spaces, elevators, and on-street parking spaces. With increasing delivery arrival rates, we found that the costs between delivery workers (increasing - lowest cost at two deliveries per hour) and building managers (decreasing - lowest cost at 16 deliveries per hour) were in an inverse relationship. Meanwhile the cost of city planners decreased up to ten deliveries per hour and then increased. At 18 deliveries per hour, these cost relationships ended, as the system became completely blocked by overflowed queues. This resulted in the cost increases for all three parties. We also observed the most concentrated queues at the elevators, which may require the most attention in designing urban infrastructure with increasing numbers of deliveries. Unfortunately, there are currently no or few specific regulations on dedicating certain numbers of elevators to meet future demands for urban deliveries. We also learned that the current numbers of building and parking resources were highly underutilized at the current arrival rate of four deliveries per hour, which was our baseline scenario. This confirms the lack of consideration for delivery demand in designing limited urban infrastructure. This also points out the importance of understanding and analysis of goods deliveries at the final 50 ft.

Once the simulation model with the various delivery rates had been run, a delivery arrival rate of 12 deliveries per hour was chosen as reasonable to meet potential near-future delivery demand for our optimization model. At this fixed delivery rate, we explored the optimal numbers of building and parking resources that would maximize utility for all three parties. In the optimization phase, results obtained with two popular, multi-objective optimization algorithms, NSGA II and MOEA/D, were compared to find the optimized numbers of resources. Aiming to minimize the costs for multiple parties, our optimization model provided optimized number combinations for parking and building resources that were associated with the specific cost distributions among delivery workers, building managers, and city planners.

The change in land use is known to be one of the factors for great difference in trip generation. The freight generators such as commercial and residential land uses are two critical types of land use in high-density city centers (McDonald and Yuan, 2021). Many cities require for minimum off-street loading spaces for such land uses. However, McDonald and Yuan (2021) found that many cities among 20 largest US cities failed to correlate the requirements with freight traffic demand. Despite the differences in freight trip generation in different land use, commercial land uses were assigned with the same numbers of off-street loading zones with very different freight generators in some cities (McDonald and Yuan, 2021). Also, inadequate attention is paid to off-street loading spaces for high-density residential land use. The massive growth in home deliveries with the explosion of online shopping makes residential land use in desperate need of loading spaces. However, loading zones for large apartments are often not required (McDonald and Yuan, 2021).

In contrast, on-street loading zones may response to delivery growth relatively faster because they can reflect the local businesses' needs on-demand. However, city planners must balance those requests with the use by different transportation users such as buses and passenger vehicles, preferences of neighboring residents and business owners and required approvals from multiple city agencies. Hence, sizes and locations of on-street loading zones cannot be guaranteed, resulting in

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a haphazard manner (McDonald and Yuan, 2021). Commercial vehicle parking observations in downtown Seattle found that lengths dedicated to CVLZs are, in fact, different by land use (Girón-Valderrama et al., 2019). Our simulation model can take a varying number of deliveries as an input and provide the corresponding cost impacts based on the utilizations of building and parking resources. In addition, our optimization models can replicate the existing parking infrastructure's varying sizes by resetting the upper limits of resource parameters. The advantage of our models is mainly based on the discrete delivery activities which remain similar between different freight generators, while taking varying parts such as demands and sizes of parking and building infrastructure as input numbers which can be easily altered in the models. Therefore, our models can be used and updated based on the future needs in many organizations.

This study contributed to the policy making process of allocating building and parking resources by considering three key players involved in urban deliveries: delivery workers, building managers, and city planners. First, it developed a complex simulation that reflects complicated final 50 ft of delivery processes and real-world time distributions. From the simulation model, policymakers can learn how cost distributions for different parties are related to increasing numbers of urban deliveries. Second, it applied multi-objective optimization algorithms to provide insights into possible optimal cases that would minimize the costs for all three parties.

The proposed framework can support policymakers in determining the best combination of building and parking resources that can minimize costs. As the proposed framework considers all of the costs for different parties, it enables policymakers to determine the best trade-offs between the objectives related to these resource allocations. Because the multi-objective evaluation provides several alternative solutions, policymakers make decisions within a broad decision spectrum. Additionally, utilization of optimization algorithms ease the computational burden of the simulation phase of the proposed framework.

Our study sheds new light on the opportunities for delivery workers, building managers, and city planners to work together to better prepare for increased demand for urban deliveries. Our research effort will continue to integrate the proposed data-driven approach into policy making procedure. The largest barrier to our research method is to obtain detailed data on task time distributions and dwell times of delivery workers at the final 50 ft of delivery activities to construct and validate a simulation model. The proposed framework can also be improved by normalizing the costs for each party and by applying weights to different parties to account for different priorities. For example, the city may assign higher weights to the city's costs and may want to investigate how the relationships with building managers and delivery workers may change.

CRediT authorship contribution statement

Haena Kim: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. Anne Goodchild: Conceptualization, Methodology, Investigation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition. Linda Ng Boyle: Conceptualization, Methodology, Investigation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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