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Automated Parcel Locker Configuration Using Discrete Event Simulation

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Abstract

Automated parcel lockers (APLs) are transforming urban last-mile delivery by reducing failed distributions, decoupling delivery from recipient availability, optimizing carrier routes, reducing carbon foot-print and mitigating traffic congestion. The paper investigates the optimal design of APLs systems under stochastic demand and operational constraints, formulating the problem as a resource allocation optimization with service-level guarantees. We proposed a data-driven discrete-event simulation (DES) model implemented in ARENA to (i) determine optimal locker configurations that ensure customer satisfaction under stochastic parcel arrivals and dwell times, (ii) examine utilization patterns and spatial allocation to enhance system operational efficiency, and (iii) characterize inventory dynamics of undelivered parcels and evaluate system resilience. The results show that the configuration of locker types significantly influences the system's ability to maintain high customers service levels. While flexibility in locker allocation helps manage excess demand in some configurations, it may also create resource competition among parcel types. The heterogeneity of locker utilization gradients underscores that optimal APLs configurations must balance locker units with their size-dependent functional interdependencies. The Dickey–Fuller GLS test further validates that postponed parcels exhibit stationary inventory dynamics, ensuring scalability for logistics operators. As a theoretical contribution, the paper demonstrates how DES combined with time-series econometrics can address APLs capacity planning in city logistics. For practitioners, the study provides a decision-support framework for locker sizing, emphasizing cost–service trade-offs.

Keywords: automated parcel locker; city logistics; last-mile delivery; batch queueing; capacity optimization; lockers configuration; discrete event simulation; ARENA simulation

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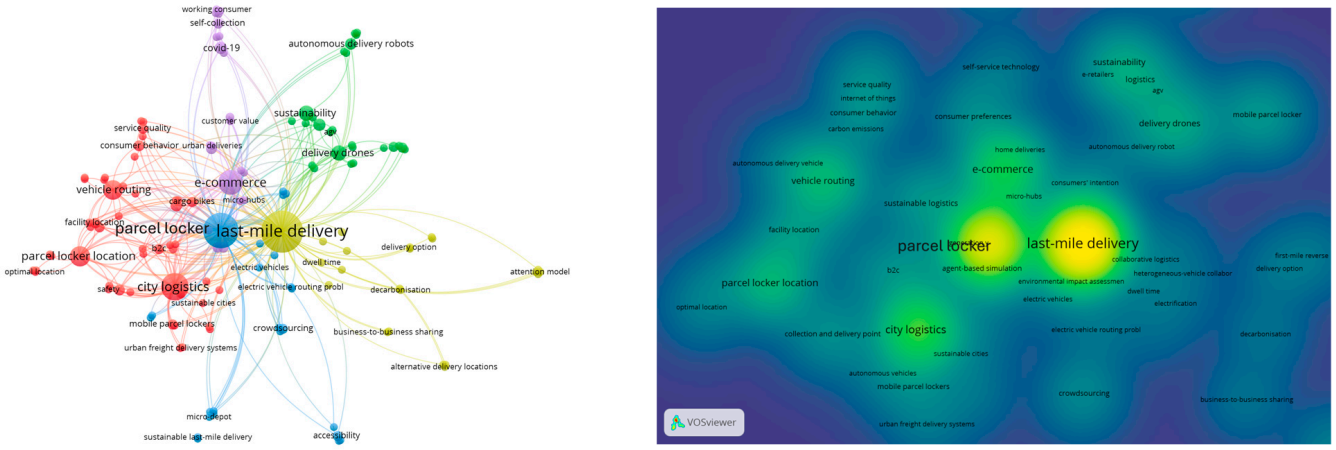
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1. Introduction

Automated parcel lockers (APLs) are self-service kiosks that allow people to pick up and drop off packages at any time. As highlighted by the World Economic Forum [1], APLs have emerged as a globally scalable sustainable solution for last-mile delivery, addressing critical externalities while enhancing operational efficiency. To map the research landscape, a bibliometric analysis was conducted using VOSviewer 1.6 [2], examining 453 publications from MDPI and Scopus scientific databases, published between 2000 and 2025. The literature was filtered using the keywords "parcel locker" OR "urban locker" OR "logistics boxes", revealing five dominant thematic clusters (Figure 1). The first cluster addresses modern city logistics solutions, facility location, vehicle routing, and service quality. The

strategic placement of APLs is paramount for effective urban logistics networks [3–5]. Research demonstrates that optimally located lockers can reduce last-mile delivery distances by 30–50% [6].



(**a**) key-words network (**b**) key-words density

Figure 1. VOSviewer bibliometric analysis on APLs (source: authors).

Placing lockers in the right urban locations is key to making them useful and efficient. Good spots for these lockers include busy areas like shopping centers, transport nodes, and office buildings, where many people pass by daily. Residential neighborhoods also benefit from lockers, as they save delivery trucks from making multiple stops. Other smart locations are near supermarkets, pharmacies, or gas stations, where people already go regularly (Figure 2). Safety is important too, so lockers should be in well-lit, secure areas, possibly with surveillance cameras.



(**a**) besides commercial area (**b**) on street (**c**) in residential area

Figure 2. Different APL sites in urban areas (source: authors).

Geographic information systems and machine learning algorithms enable dynamic capacity planning while maintaining consumer accessibility by analyzing population density, transportation hubs, and commercial infrastructure [7,8]. APLs significantly improve routing efficiency through delivery consolidation. Instead of individual home deliveries,

carriers can service multiple locker locations on optimized routes [9–11]. Studies show this reduces vehicle kilometers traveled by 40–60% and decreases CO_2 emissions by 0.5 kg per parcel [12].

The second cluster is constructed around the integration of APLs in last-mile delivery concepts. Users can collect parcels at their convenience within typically 3–5 days, with 24/7 access at most locations [13]. This flexibility benefits both consumers and carriers by decoupling delivery from recipient availability.

The third cluster highlights the role of e-commerce in driving APL adoption. Modern locker systems employ modular designs to accommodate diverse parcel sizes within compact footprints. Advanced systems dynamically assign compartment sizes, improving space utilization by 30–50% compared to traditional methods [14]. Consumers' attitudes toward innovation are pivotal in the adoption of the newest last-mile delivery solutions and is also an effective mediator of consumers' beliefs towards innovation and turning them from passive to active consumers in the last logistic chain [15]. Wang et al. [16] identify compatibility (alignment with needs), complexity (lifestyle fit), and trialability (ease of testing, values) as key determinants in adopting the new delivery systems.

The fourth cluster encompasses sustainable issues. They contribute to sustainability by reducing vehicle emissions and cutting last-mile trips, lower congestion costs, estimated at EUR 50–150 per ton of CO_2 in urban areas, reduces failed deliveries by 15–25% of total attempts [17–19].

The integration of electric and autonomous vehicles into last-mile delivery systems represents the fifth critical cluster of modern urban logistics solutions. As e-commerce volumes continue to grow globally, these advanced vehicle technologies demonstrate significant potential to reduce the environmental impact of delivery operations while maintaining service efficiency [20,21].

A wide bibliometric investigation on urban last-mile logistics [22] revealed some similar findings. The six thematic clusters explored a diverse range of concepts, including the development of supply chain evaluation tools, the study of parcel lockers and delivery system attributes, the assessment of innovative vehicles and infrastructures such as electric vehicles and urban consolidation centers, the application of technology in logistics, and the proposal of collaborative-based business models. Additionally, three categories of solutions were identified: new vehicles (e.g., drones), operational solutions (e.g., off-peak deliveries), and organizational solutions (e.g., crowdsourced logistics).

Although present among the researchers' interest, simulation is still under-utilized in investigating automated parcel lockers area. Iwan, Kijewska and Lemke [6] used a macroscopic agent-based model for predicting consumer demand and behavior. Double reasons are outlined for the efficiency in using APLs: cost reduction for companies and availability and localization for customers. The most important expectations of users regarding localization include close location to home, on the way to work, and availability of parking spaces. A system dynamics simulation and multi-objective decision support were employed to evaluate the sustainability performance of distribution channel options [23]. The results show that the integration of the players into a distributed network strategy based on a crowd logistics concept is the most viable and sustainable option. Che, Chiang and Luo [24] framed APL localization as a multi-objective optimization problem with three key criteria: coverage maximization, overlap minimization, and total idle capacity minimization. This hybrid approach integrates simulation and optimization to enhance decision-making in urban logistics. While their methodology provides valuable insights, it does not account for uncertain consumer demand or incorporate elastic weighted goals. The study notably emphasizes the importance of establishing minimum utilization thresholds to prevent resource underutilization. Other studies used an agent-based model to estimate

future demand based on socio-economic parameters, and a facility location problem (FLP) optimization model to determine the optimal number and placement of lockers [25,26]. An agent-based model is designed to determine the performance of the APL network and to estimate the future demand based on a few socio-economic parameters. Rabe et al. [27] formulated a multi-period CFLP model to provide the optimal number of APLs to be installed and Monte Carlo simulation was used to estimate the cost and reliability level for different scenarios with random demands. Izco Berastegui et al. [28] used an integrated dynamic simulation to forecast population and e-commerce demand and Pareto Frontier to trade-off between the number of lockers and the desired demand satisfaction of the decision makers. Iannaccone, Marcucci, and Gatta [29] proposed a discrete choice model that allows both to quantify the monetary value of parcel lockers attributes (willingness to pay) and to estimate the potential demand. Using macro-level data, Savik [30] provides an in-depth examination of the potential of automated parcel lockers, capillary distribution, and crowd-shipping as developing solutions to last-mile delivery. Understanding personal values and consumer traits play a significant role in APL success. Utilitarian and hedonic attitudes toward using innovative technologies are determinant through the consumer traits (self-service efficacy) [31]. De Oliveira et al. [32] proved that location, delivery time, information and traceability, cost of transportation, and the willingness to use self-service technologies are determinant factors in estimating the use of APLs. Cieśla [33] found that dedicated application, adjusting the size of the package to the size of the box, placing the parcel in a specific box, security, and parking next to APLs are among attributes that provide customers satisfaction. Lai et al. [34], using the service quality (SERVQUAL) and logistics service quality (LSQ) model showed that timeliness is the strongest predictor that positively impacts customer satisfaction with APLs, followed by reliability, security responsiveness and tangibility.

Existing research on automated parcel lockers predominantly adopts macro- or mezo-scale perspectives, emphasizing network-level optimization, such as facility location, regional/local demand allocation, or system-wide throughput. However, limited attention has been paid to micro-scale operational challenges, particularly on (i) optimal capacity dimensioning (the minimal capacity to handle stochastic parcel arrivals and heterogeneous size distributions), (ii) configuration optimization (strategic selection of locker-type ratios under space and cost constraints), and (iii) dynamic utilization (real-time allocation policies to mitigate capacity shortage during demand fluctuations). This gap is critical, as sub-optimal station-level design directly impacts user satisfaction (e.g., failed deliveries) and operational costs (e.g., overprovisioning, excess inventories). While macro-level studies assume homogeneous demand, at micro-level APLs face nonstationary and stochastic demand patterns—necessitating granular modeling and simulation approaches. Building on the identified gap, this study addresses the following research questions:

1. How can automated parcel locker stations be optimally configured—in terms of the number and mix of locker types (small, medium, large)—to accommodate stochastic demand flows characterized by random arrival rates, heterogeneous parcel size distributions, stochastic dwell time, and operational flexibility (dynamic parcel-to-locker allocation), while maximizing service-level performance (delivery success rate)?
2. Do delivery quality standards (on-time delivery rate) affect the lockers' feasible configuration?
3. How do the key performance metrics for companies (locker utilization rate, variation of undelivered parcels inventory) balance with customers' satisfaction and experience?

The main contributions of this study are as follows:

- It develops a methodological framework and simulation tool to optimize APL configuration.
- It demonstrates how stochastic demand and heterogeneous parcel sizes limit the possible locker configurations while balancing resource capacity and customer satisfaction in terms of on-time successful delivery.
- It integrates discrete event simulation and time-series econometrics to investigate the company's operational performance metrics (including locker utilization rates and fluctuations in undelivered parcel inventory).
- It provides actionable recommendations for improving capacity planning for APL last-mile deliveries.

Section 2 presents a discrete event simulation (DES) model developed in ARENA software, which captures microscopic operational dynamics of APLs. Section 3 completes experimental computation using experimental test data. Section 4 analyzes simulation outcomes. The on-time delivery probability is the key performance measure to assess the system's effectiveness. Results identify feasible APL configurations that maintain on-time delivery probability within target thresholds. Furthermore, time-series analysis of postponed parcel flows confirms stationarity, suggesting that inventory overflow does not critically disrupt operations. Conclusions and recommendations are summarized in the last section.

2. Modelling and Simulation Methodology

Discrete event simulation is a useful technique in transportation and logistics, enabling businesses and governments to optimize operations, reduce costs, and enhance efficiency. By simulating real-world scenarios before implementation, organizations can make smarter decisions and build more resilient systems. It focuses on individual events that occur at specific points in time, making it ideal for modeling dynamic processes such as vehicle movements [35], terminal [36] and warehouse operations [37], supply chain flows [38,39], last-mile delivery [40], and e-commerce logistics [41]. Testing automated parcel lockers through computer simulations before installing them in real life helps cities and delivery companies make smarter decisions. By simulating different capacity options first, cities can install locker systems that work efficiently every day while still managing busy periods—all without wasting space or money. This smart planning leads to the following:

- Preventing overcrowding (predicts how many compartments are necessary at each location, helps avoid full lockers that annoy customers);
- Saving space in busy areas (determines the smallest possible locker size that still meets demand, important for dense urban areas where space is limited);
- Improving delivery efficiency (shows the right balance between small, medium, and large compartments, reduces wasted space from wrong-sized compartments);
- Saving money (prevents buying oversized lockers that are not fully used, avoids the cost of adding more lockers later);
- Matching local needs (customizes capacity based on neighborhood characteristics, residential areas might need different setups than business districts).

The developed simulating model for an automated parcel locker contains four entity types and three resource (server) types (Table 1).

Table 1. Entities and resources in the simulation model.

	Item	Attribute	Type	Description
Entities	Parcel	Serial number	Number	Entity ID.
		Size	Text	The size of the parcel to match the right locker. There are three types of parcels: large, medium, small.
		Creation time	Time stamp	The generation time.
		Dwell time	Number	The time interval a parcel is stored into a locker.
	Delivery person	Delivery moment	Time stamp	The moment the delivery process starts.
Resources	Locker	Size	Text	There are three types of lockers: large, medium, small. The conventional unit locker has the dimensions of a small locker. The medium locker is equivalent to two conventional lockers, and the large locker with four conventional units.
		State	Logical (Empty/Occupied)	Empty lockers are available for parcel storage, and a locker remains occupied for the duration of the parcel's dwell time.

The parcels are passive entities that are generated and placed into lockers, while the delivery person is an active entity that assesses the state of the system (the number of parcels to be delivered, the state of the lockers) and takes actions (deliver the parcel to a specific locker or postpone the delivery). There are three types of lockers, according to their dimensions (Figure 2). Similarly, parcels are classified into three types, with each type fitting into the corresponding locker or a larger one. Large parcels are accommodated solely by large lockers. Medium parcels are prioritized for medium lockers (high priority) but may be placed in available large lockers if necessary (low priority comparing to large parcels). Small parcels are prioritized for small lockers but can be accommodated in both medium or large lockers if available and required (low priority compared to medium and large parcels). Every day, a specific number of parcels are generated, matching client demand. The automated parcel locker acts as a batch queuing system, with deliveries scheduled at a specific time of day (Figure 3). At this designated time, all parcels that fit appropriately within the lockers are deposited simultaneously, and the lockers are subsequently released after an individual dwell time, corresponding to their pickup by customers. The availability of compartments over time depends on the customers' pickup behavior that is stochastic. If a parcel is delivered on the same day as is generated, the delivery is considered on time. Otherwise, undelivered parcels must wait at the central warehouse until the next available delivery opportunity (on subsequent days).

The parcel processing flow-chart is depicted in Figure 3.

The activity of the automated parcel locker model is summarized as follows:

Parameters:

L—the number of conventional lockers;

L_l, L_m, L_s—the number of large/medium/small lockers;

$N_{l,j}$, $N_{m,j}$, $N_{s,j}$—the number of large/medium/small parcels generated on day j ($j \geq 1$);

$n_{l,j}$, $n_{m,j}$, $n_{s,j}$—the number of large/medium/small parcels delivered on day j;

$n_{l,j,k}$, $n_{m,j,k}$, $n_{s,j,k}$—the number of large/medium/small parcels delivered on day j that are picked up after k days (k = 0 picking the day of delivery, k = 1 picking after one day, k = 2 picking after two days from delivery);

$n_{m-l,j}$—the number of medium parcels stored in large lockers on day j;

$n_{s-m,j}$, $n_{s-l,j}$—the number of small parcels stored in medium/large lockers on day j;

$n_{m-l,j,k}$—the number of medium parcels stored in large lockers on day *j* that are picked up after *k* days;

$n_{s-m,j,k}$, $n_{s-l,j,k}$—the number of small parcels stored in medium/large lockers on day *j* that are picked up after *k* days;

$I_{l,j}$, $I_{m,j}$, $I_{s,j}$—the inventory of undelivered large/medium/small parcels at the central warehouse at the end of day *j*;

$L^f_{l,j}$, $L^f_{m,j}$, $L^f_{s,j}$—the number of free large/medium/small lockers at the beginning of day *j*;

$L^f_{m-l,j}$—the number of empty large lockers available for storing medium parcels on day *j*;

$L^f_{s-l,j}$, $L^f_{s-m,j}$—the number of empty large/medium lockers available for storing small parcels on day *j*;

$P(k) = [P(0), P(1), P(2)]$—the probabilities vector for the parcels' dwell time (k = 0 the parcel picked up the same day as the delivery day, k = 1 the parcel is picked up on the subsequent day, k = 2 the parcel is picked up two days after the delivery day).

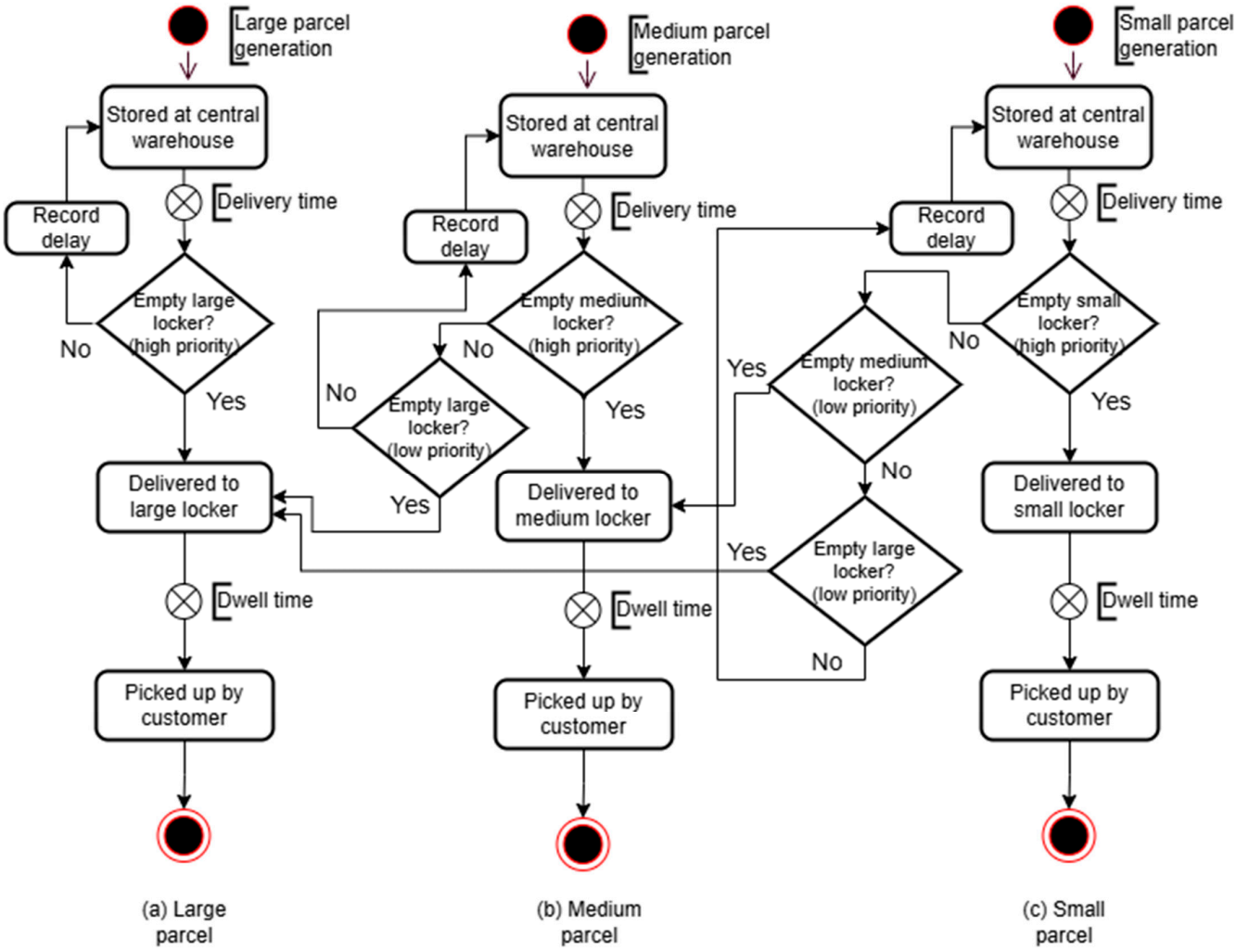


Figure 3. Parcel processing flow-chart (source: authors).

System process equations:

$$n_{l,j} = min\left(I_{l,j-1} + N_{l,j},\ L^f_{l,j}\right) \tag{1}$$

$$L^f_{l,j} = L_l - n_{l,j-1,1} - n_{l,j-1,2} - n_{l,j-2,2} - n_{m-l,j-1,1} - n_{m-l,j-1,2} - n_{m-l,j-2,2} - n_{s-l,j-1,1} - n_{s-l,j-1,2} - n_{s-l,j-2,2} \tag{2}$$

$$I_{l,j} = I_{l,j-1} + N_{l,j} - n_{l,j} \tag{3}$$

$$n_{m,j} = min\left(I_{m,j-1} + N_{m,j},\ L^f_{m,j} + L^f_{m-l,j}\right) \tag{4}$$

$$L^f_{m,j} = L_m - n_{m,j-1,1} - n_{m,j-1,2} - n_{m,j-2,2} - n_{s-m,j-1,1} - n_{s-m,j-1,2} - n_{s-m,j-2,2} \tag{5}$$

$$L^f_{m-l,j} = L^f_{l,j} - n_{l,j} \tag{6}$$

$$n_{m-l,j} = max\left(0, n_{m,j} - L^f_{m,j}\right) \tag{7}$$

$$I_{m,j} = I_{m,j-1} + N_{m,j} - n_{m,j} \tag{8}$$

$$n_{s,j} = min\left(I_{s,j-1} + N_{s,j},\ L^f_{s,j} + L^f_{s-m,j} + L^j_{s-l,j}\right) \tag{9}$$

$$L^f_{s,j} = L_s - n_{s,j-1,1} - n_{s,j-1,2} - n_{s,j-2,2} \tag{10}$$

$$L^f_{s-m,j} = \max\left(0, L^f_{m,j} - n_{m,j}\right) \tag{11}$$

$$L^f_{s-l,j} = L^f_{l,j} - n_{l,j} - n_{m-l.j} \tag{12}$$

$$n_{s-m,j} = min\left(max\left(0, n_{s,j} - L^f_{s,j}\right), L^f_{s-m,j}\right) \tag{13}$$

$$n_{s-l,j} = min\left(max\left(0, n_{s,j} - L^f_{s,j} - L^f_{s-m,j}\right), L^f_{s-l,j}\right) \tag{14}$$

$$I_{s,j} = I_{s,j-1} + N_{s,j} - n_{s,j} \tag{15}$$

$$n_{l,j} = n_{l,j,0} + n_{l,j,1} + n_{l,j,2} \tag{16}$$

$$n_{m,j} = n_{m,j,0} + n_{m,j,1} + n_{m,j,2} \tag{17}$$

$$n_{s,j} = n_{s,j,0} + n_{s,j,1} + n_{s,j,2} \tag{18}$$

$$L = 4L_l + 2L_m + L_s \tag{19}$$

Initial values:

$$I_{l,0} = I_{m,0} = I_{s,0} = 0$$

$$\mathrm{n_{l,j\leq 0,k}} = \mathrm{n_{m,j\leq 0,k}} = \mathrm{n_{s,j\leq 0,k}} = 0\ (\mathrm{k} = 0, 1, 2)$$

Equation (1) determines the quantity of large parcels delivered by calculating the minimum between the sum of the previous day's inventory of large parcels at the central warehouse and the newly arrived large parcels, and the number of available large lockers. The available large lockers (Equation (2)) are calculated by subtracting from the total number of large lockers those currently occupied by large, medium, or small parcels that have not yet been collected (i.e., those with a longer dwell time). Equations (3), (8) and (15) establish the inventory levels of large, medium, and small parcels at the central warehouse at the end of each day, based on the previous day's inventory, the parcels generated daily, and those delivered. Equation (4) calculates the number of medium parcels delivered as the minimum between the available parcels (comprising the previous day's inventory and

newly generated parcels) and the sum of available medium lockers and large lockers that can accommodate medium parcels. The number of available medium lockers is determined by subtracting from the total number of medium lockers those still occupied by uncollected parcels due to their longer dwell time (Equation (5)). The available number of large lockers that can accommodate medium parcels is computed after allocating the large parcels to lockers (Equation (6)). If the number of medium parcels delivered exceeds the number of available medium lockers, the surplus is stored in the available large lockers (Equation (7)). Equation (9) assesses the number of small parcels to be delivered by comparing the existing parcels at the central warehouse with the available small, medium, and large lockers that can accommodate them. The number of small lockers available is the total number of small lockers minus those occupied by parcels that have not yet been collected (Equation (10)). The available number of medium lockers that can accommodate small parcels is derived from the total number of free medium lockers minus those occupied by medium parcels (Equation (11)). Equation (12) calculates the available number of large lockers that can store small parcels as the difference between the number of free large lockers and those used by large and medium parcels. Equations (13) and (14) assess the number of small parcels accommodated by medium and large lockers, respectively. Equations (16)–(18) indicate that the daily delivery of large, medium, and small parcels includes items with different dwell times, as detailed in Table 1. Considering their dimensions, the total number of conventional lockers is equal to the weighted sum of the number of physical lockers (Equation (19)).

The simulation model was developed using ARENA 8.0 simulation software. The model is depicted in Figures 4 and 5.

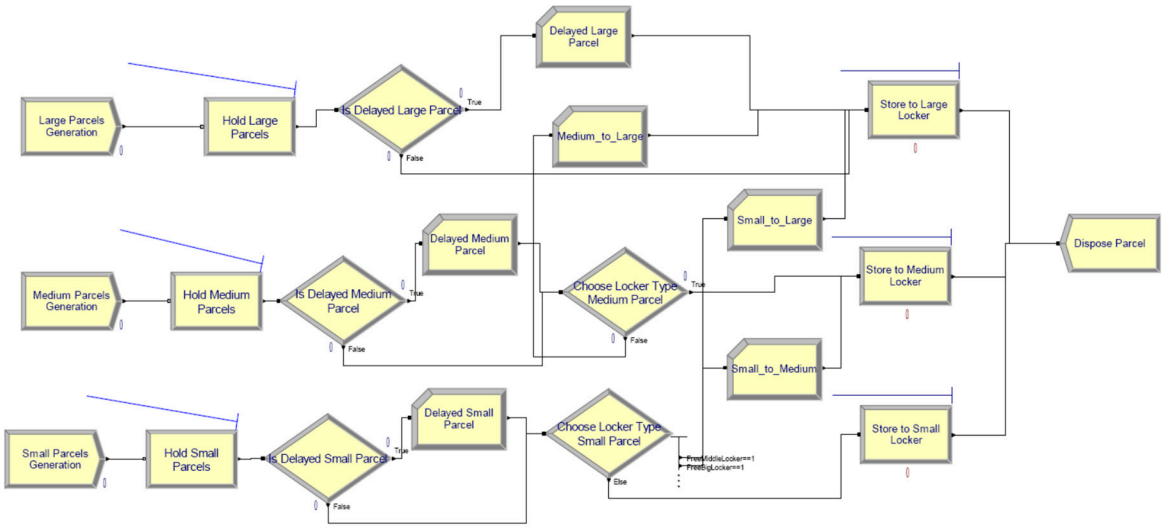


Figure 4. Parcel processing modules (source: authors).

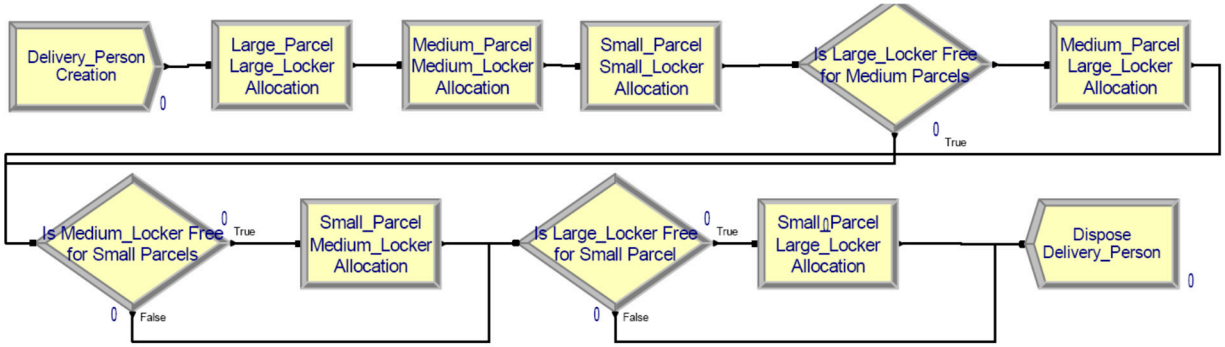


Figure 5. Delivery person acting modules (source: authors).

The modules used in the simulation model are thoroughly described in Table 2.

Table 2. ARENA simulation modules description.

	Module	Type	Role and Parameters
Parcels	Large Parcels Generation	Create	Every day a random number of large parcels ($N_{l,j}$) are generated.
	Medium Parcels Generation	Create	Every day a random number of medium parcels ($N_{m,j}$) are generated.
	Small Parcels Generation	Create	Every day a random number of small parcels ($N_{s,j}$) are generated.
	Hold Large Parcels	Hold	The large parcels are stored at the central warehouse ($I_{l,j-1} + N_{l,j}$) until empty lockers are available. The delivery person controls the parcel releasing process ($n_{l,j}$) by calculating the number of empty large lockers ($L^{f}_{l,j}$).
	Hold Medium Parcels	Hold	The medium parcels are stored at the central warehouse ($I_{m,j-1} + N_{m,j}$) until empty lockers are available. The delivery person controls the parcel releasing process ($n_{m,j}$) by calculating the number of empty medium lockers ($L^{f}_{m,j}$) or remaining empty large lockers ($L^{f}_{m-l,j}$) after the accommodation of large parcels.
	Hold Small Parcels	Hold	The small parcels are stored at the central warehouse ($I_{s,j-1} + N_{s,j}$) until empty lockers are available. The delivery person controls the parcel releasing process ($n_{s,j}$) by calculating the number of empty small lockers ($L^{f}_{s,j}$) or remaining empty medium ($L^{f}_{s-m,j}$) and large lockers ($L^{f}_{s-l,j}$) after the accommodation of large and medium parcels.
	Is Delayed Large Parcel	Decide	It examines whether large parcels are delivered on the day they are generated or if delivery is postponed due to the unavailability of free lockers. It analyzes the time interval between the generation of the parcel and its actual delivery (TNOW–Entity.CreateTime).
	Is Delayed Medium Parcel	Decide	It examines whether medium parcels are delivered on the day they are generated or if delivery is postponed due to the unavailability of free lockers. It analyzes the time interval between the generation of the parcel and its actual delivery (TNOW–Entity.CreateTime).
	Is Delayed Small Parcel	Decide	It examines whether small parcels are delivered on the day they are generated or if delivery is postponed due to the unavailability of free lockers. It analyzes the time interval between the generation of the parcel and its actual delivery (TNOW–Entity.CreateTime).
	Delayed Large Parcel	Record	It records the delayed large parcels by incrementing the counter Delayed_Large_Parcel.
	Delayed Medium Parcel	Record	It records the delayed large parcels by incrementing the counter Delayed_Medium_Parcel.
	Delayed Small Parcel	Record	It records the delayed large parcels by incrementing the counter Delayed_Small_Parcel.
	Choose Locker Type Medium Parcel	Decide	An appropriate locker for the medium parcel is selected based on availability. If an empty medium locker is available, the parcel is stored there (higher priority). Otherwise, the parcel is placed in a free large locker (lower priority competing to large parcels).

Table 2. *Cont.*

	Module	Type	Role and Parameters
Parcels	Choose Locker Type Small Parcel	Decide	An appropriate locker for the small parcel is selected based on availability. If an empty small locker is available, the parcel is stored there (higher priority). Otherwise, the parcel is placed in a free medium or a free large locker (lower priority competing to medium or large parcels).
	Medium to Large	Record	It records the number of medium parcels accommodated in large lockers by incrementing the counter $n_{m-l,j}$.
	Small to Medium	Record	It records the number of small parcels accommodated in medium lockers by incrementing the counter $n_{s-m,j}$.
	Small to Large	Record	It records the number of small parcels accommodated in large lockers by incrementing the counter $n_{s-l,j}$.
	Store to Large Locker	Process	The large locker is seized, and its state becomes occupied until the parcel's dwell time elapses. Following this time, the parcel is picked up by customer and the locker is released.
	Store to Medium Locker	Process	The medium locker is seized, and its state becomes occupied until the parcel's dwell time elapses. Following this time, the parcel is picked up by customer and the locker is released.
	Store to Small Locker	Process	The small locker is seized, and its state becomes occupied until the parcel's dwell time elapses. Following this time, the parcel is picked up by customer and the locker is released.
	Dispose Parcel	Dispose	The parcels are disposed once they are picked up.
Delivery Person	Delivery Person Creation	Create	It creates the delivery person as an entity in the system. The delivery person starts the activity daily at a conventional moment 0.
	Large Parcel Large Locker Allocation	Signal	The large parcels are allowed to be transferred to the large lockers. The signal is transmitted to Hold Large Parcels module and the appropriate number of large parcels are released (see Equation (1)).
	Medium Parcel Medium Locker Allocation	Signal	The medium parcels are allowed to be transferred to the medium lockers. The signal is transmitted to Hold Medium Parcels module and the appropriate number of medium parcels are released (see Equation (4)).
	Small Parcel Small Locker Allocation	Signal	The small parcels are allowed to be transferred to the small lockers. The signal is transmitted to Hold Small Parcels module and the appropriate number of small parcels are released (see Equation (9)).
	Is Large Locker Free for Medium Parcels	Decide	The delivery person checks the availability of unoccupied large lockers ($L^{f}_{m-l,j}$) to determine whether medium parcels can be accommodated.
	Medium Parcel Large Locker Allocation	Signal	If there are free large lockers, a signal is emitted, and the module Hold Medium Parcels releases the adequate number of medium parcels to be delivered into large lockers (see Equation (7)).
	Is Medium Locker Free for Small Parcels	Decide	The delivery person checks the availability of unoccupied medium lockers ($L^{f}_{s-m,j}$) to determine whether small parcels can be accommodated.
	Small Parcel Medium Locker Allocation	Signal	If there are free medium lockers, a signal is emitted, and the module Hold Small Parcels releases the adequate number of medium parcels to be delivered into medium lockers (see Equation (13)).

Table 2. *Cont.*

	Module	Type	Role and Parameters
Delivery Person	Is Large Locker Free for Small Parcels	Decide	The delivery person checks the availability of unoccupied large lockers ($L^{f}_{s-1,j}$) to determine whether small parcels can be accommodated.
	Small Parcel Large Locker Allocation	Signal	If there are free large lockers, a signal is emitted, and the module Hold Small Parcels releases the adequate number of medium parcels to be delivered into large lockers (see Equation (4)).
	Dispose Delivery Person	Dispose	The delivery person is disposed after it completes its activity.

In its daily operations, the automated parcel locker system functions under stochastic conditions. The daily generation of large, medium, and small parcels follows a random distribution, and the dwell time of parcels is likewise a stochastic variable. The system's efficiency is measured by its ability to ensure prompt parcel delivery, prevent overcrowding, and minimize delivery postpones.

An optimal allocation of locker types (large, medium, and small) is essential to efficiently accommodate parcels, reduce wasted space from improperly sized compartments, and avoid unnecessary expansion. Given a fixed capacity of conventional lockers (i.e., the predefined space allocated to the automated parcel locker system), a series of simulation experiments were conducted to determine the optimal proportion of large, medium, and small lockers. The objective was to ensure that the probability of on-time parcel delivery exceeded a specified threshold, thereby maximizing customer satisfaction.

3. Computational Experiments and Results

The simulation experiments were conducted using the data in Table 3.

Table 3. Simulation model input data.

Item	Data	Type	Values/Range of Variation
Large parcel	Daily generation number	Uniform	[0, 4]
	Dwell time	Stochastic discrete distribution	p(k) = [0.80; 0.15; 0.05], k = 0, 1, 2
Medium parcel	Daily generation number	Uniform	[2, 8]
	Dwell time	Stochastic discrete distribution	p(k) = [0.80; 0.15; 0.05], k = 0, 1, 2
Small parcel	Daily generation number	Uniform	[20, 36]
	Dwell time	Stochastic discrete distribution	p(k) = [0.80; 0.15; 0.05], k = 0, 1, 2
Delivery person	Interval between deliveries	Constant	24 h
Conventional lockers	Capacity (number of lockers)	Constant	70

Parcels are generated daily following uniform distributions with varying limits *U[a,b]*. The parcel pick-up probabilities are as follows: 80% of the parcels are collected on the same day as delivery ($p(0) = 0.80$), 15% on the subsequent day ($p(1) = 0.15$), and 5% two days after delivery ($p(2) = 0.05$). The delivery person dispatches parcels once per day (24 h interval between deliveries). The automated locker system has a total capacity equivalent to

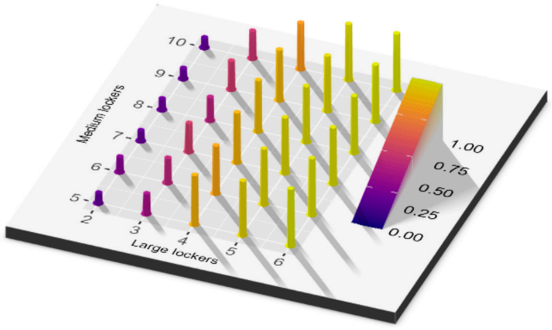
70 conventional lockers, with the number of large, medium, and small lockers constrained by Equation (19):

$$70 = 4L_l + 2L_m + L_s. \tag{19}$$

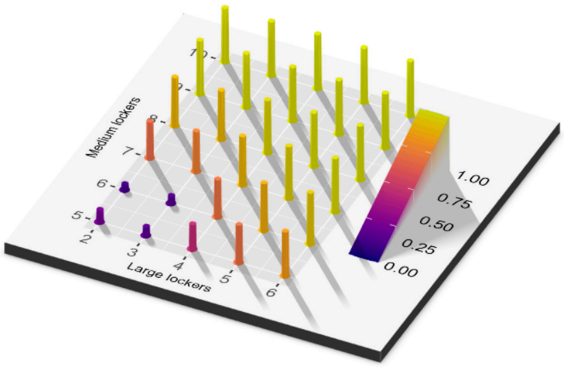
The simulation experiments evaluate the activity of the automated parcel lockers under varying locker-type configurations (i.e., differing proportions of locker sizes). Each simulation runs for a 365-day period. The following outputs are recorded:

- The number of generated parcels per type;
- The parcels' dwell time;
- The number of parcels delivered on-time;
- The undelivered parcel inventory at the end of each day;
- The number of parcels distributed in distinct size lockers.

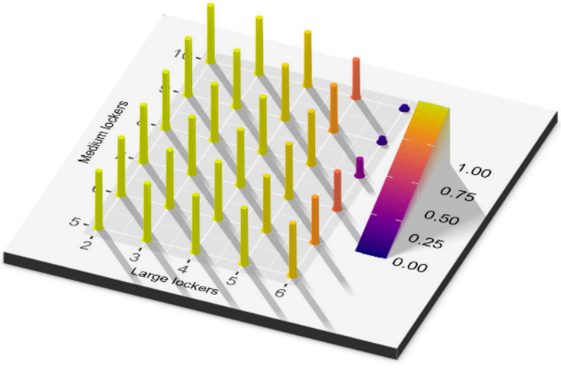
The on-time delivery probability is a key performance measure for both customer satisfaction and company efficiency. Figure 6 illustrates the on-time parcel delivery probabilities across different automated locker configurations $\langle L_l,\ L_m, L_s \rangle$.



(**a**) On-time delivery probability—large parcels



(**b**) On-time delivery probability—medium parcels



(**c**) On-time delivery probability—small parcels

Figure 6. On-time delivery probabilities (source: authors).

The on-time delivery probability for large parcels falls below 0.5 with 2–3 large lockers but improves significantly ($\geq$0.8) when 4 or more large lockers are available (Figure 6a). Medium size parcels can be deposited in both medium and large lockers. For configurations with 2–3 large lockers and 5–6 medium lockers, the on-time delivery probability for medium parcels falls below 0.5 (Figure 6b). However, as the number of available large and medium lockers increases, the on-time delivery probability for medium parcels rises correspondingly. When 6 large lockers and 8–10 medium lockers are available, the on-time delivery probability for small parcels drops below 0.5 (Figure 6c). This probability remains below 0.8 in configurations with either (i) 6 large lockers and 6–7 medium lockers, or (ii) 5 large lockers and 10 medium lockers. In all other analyzed configurations, the probability exceeds 0.8.

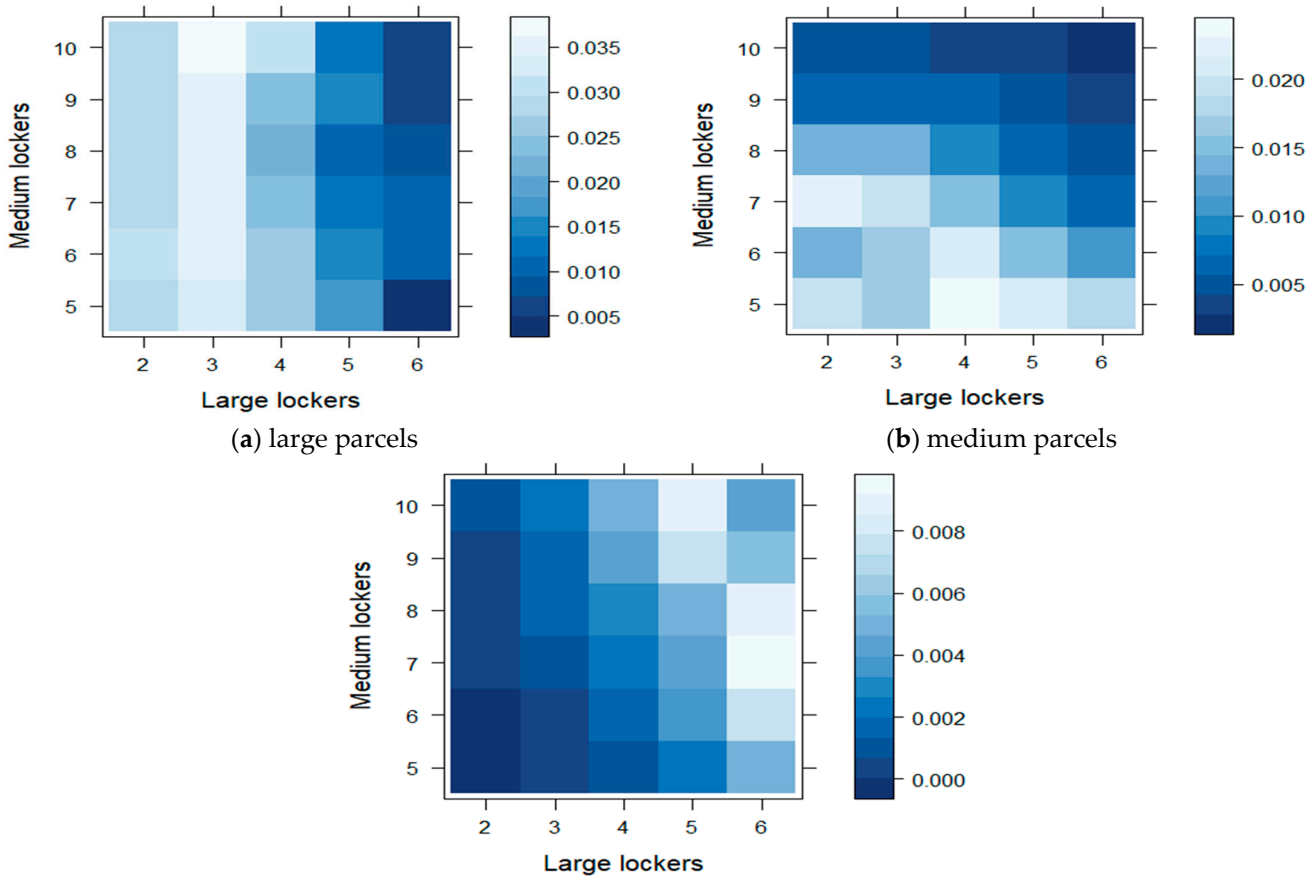
The margins of error for the on-time delivery probabilities are computed based on the sample parcels data are

$$\varepsilon = z * \sqrt{\frac{\hat{p}(1-\hat{p})}{n}} \tag{20}$$

where

ε is the margin of error of the probability;
$\hat{p}$—is the estimated probability for on-time delivery;
n—is the sample size;
z—is the z score ($z = 1.96$ for 95% confidence interval).

Considering the above estimated successful delivery probabilities, the margins of error are depicted in Figure 7.



(**a**) large parcels

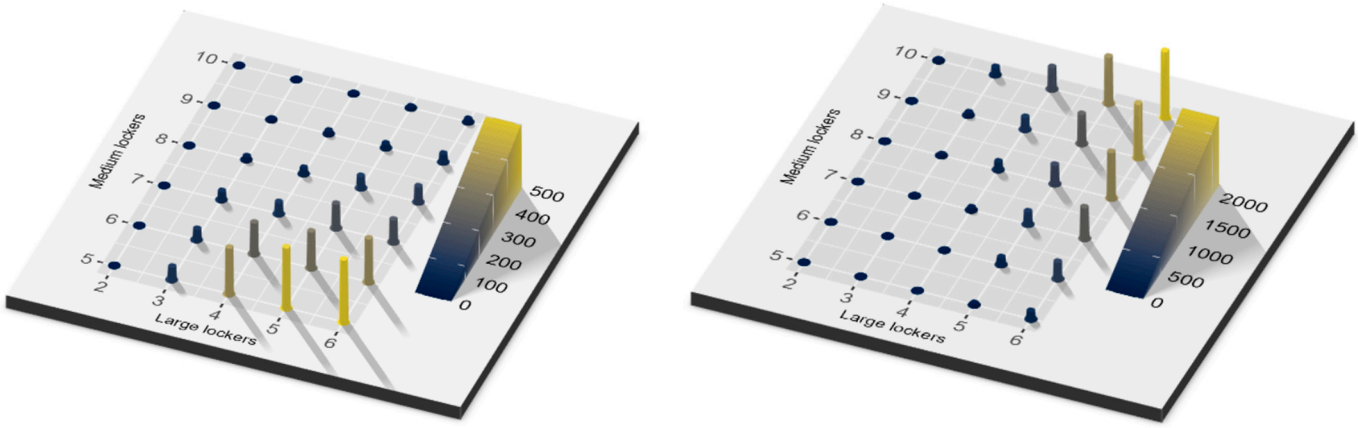
(**b**) medium parcels

(**c**) small parcels

Figure 7. Margins of error for on-time delivery probabilities (source: authors).

Margins of error allow us to accurately assess whether a given APL configuration meets the desired level of successful delivery, accounting for potential fluctuations due to statistical variability. An increase in sample size is associated with a reduction in the margin of error. Specifically, for large parcels, the margin of error typically ranges between 0.5% and 3.5%, whereas for small parcels, it falls below 0.8%. When the successful delivery target falls within the confidence interval of the on-time delivery probability, the decision regarding the feasibility of the configuration becomes inconclusive.

The ability to store parcels in larger lockers enables the system to effectively handle periods of high demand, leading to better utilization of storage capacity and an increased rate of successful deliveries. Figure 8 shows the storage distribution patterns: (a) medium parcels allocated to large lockers, and (b) small parcels distributed across both medium and large lockers. The analysis reveals that configurations with limited medium locker availability (5 units) and substantial large locker capacity (4–6 units) result in over 365 medium parcels being stored in large lockers (Figure 8a). Furthermore, as the number of both medium and large lockers increases, a corresponding rise occurs in the number of small parcels stored across available medium and large lockers (Figure 8b).

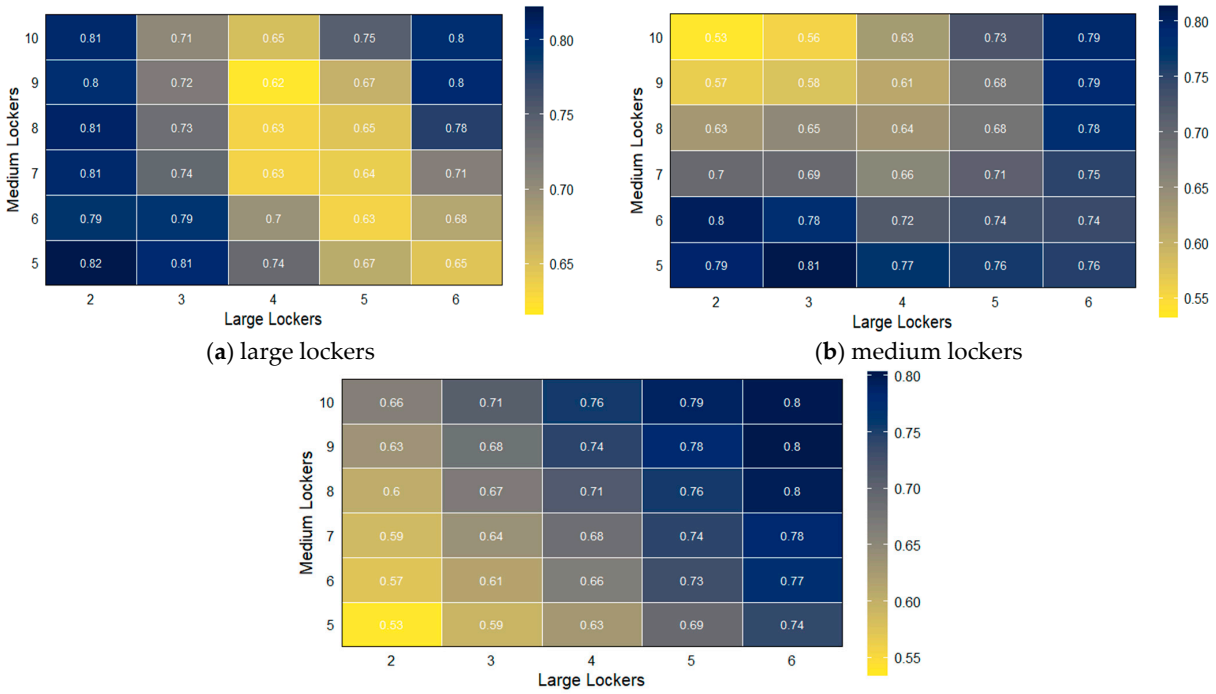


(**a**) medium parcels (**b**) small parcels

Figure 8. Relocated medium and small parcels to bigger-size lockers (source: authors).

From the perspective of the delivery company, system efficiency is determined by locker utilization rates. Low utilization rates indicate system overcapacity, whereas high rates reflect excessive demand pressure. The ability to allocate parcels across different sized lockers enhances the system's adaptability to demand fluctuations. Based on the input variables, Figure 9 presents the corresponding locker utilization rates. The utilization rate gradient for large lockers exhibits a central-to-peripheral orientation, whereas for medium and small lockers, the gradient is oriented bilaterally (along diagonal axes).

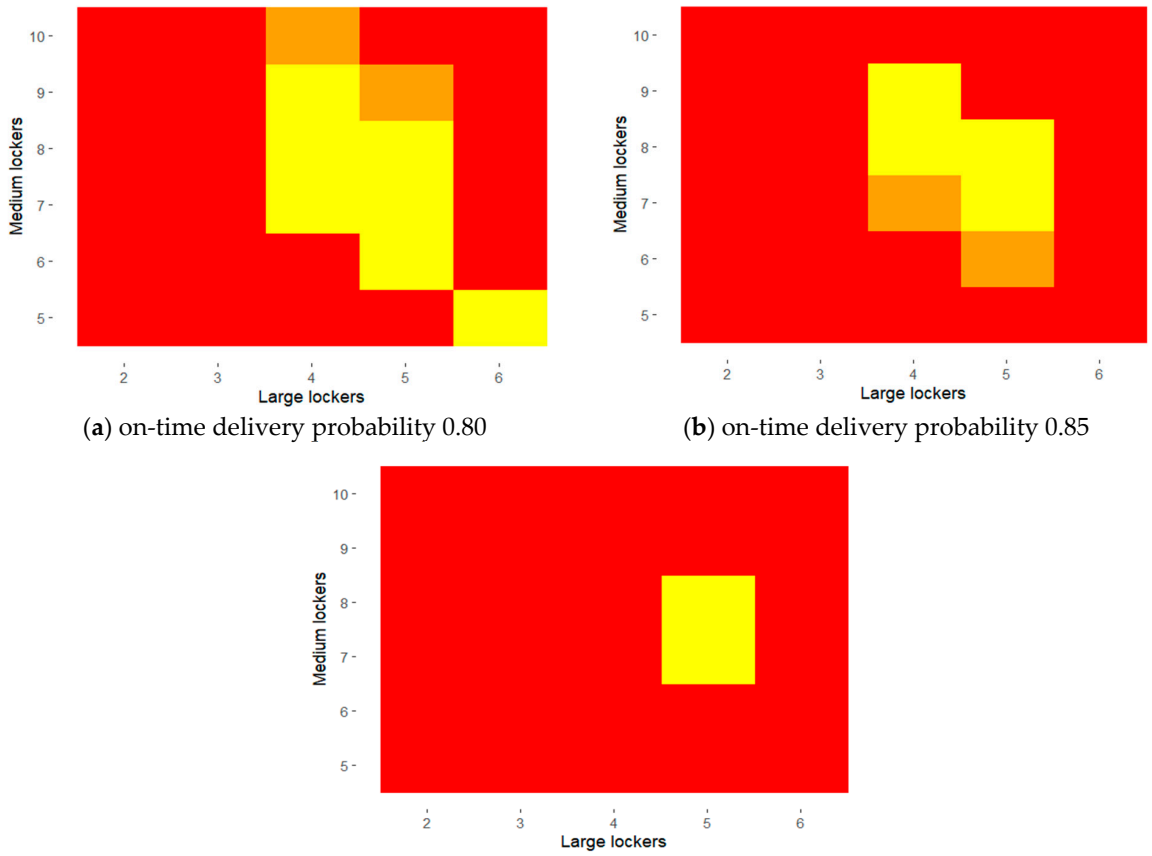
These trends underscore the importance of balanced locker allocation to meet delivery targets, which exhibit flexibility in storage but sensitivity to resource scarcity. By establishing thresholds for on-time delivery probabilities across all parcel types, optimal configurations of automated parcel lockers can be identified (Figure 10). This threshold-based approach enables systematic evaluation of locker system performance under varying operational constraints.



(**a**) large lockers (**b**) medium lockers

(**c**) small lockers

Figure 9. Locker utilization rate by locker size combination (source: authors).



(**a**) on-time delivery probability 0.80 (**b**) on-time delivery probability 0.85

(**c**) on-time delivery probability 0.90

Figure 10. Automated locker configurations for successful delivery (source: authors).

Seven locker configurations satisfy the requirement of ≥80% on-time delivery probability (Figure 10a). When the threshold increases to 85%, only four configurations remain feasible (Figure 10b). For the strictest criterion (≥95% on-time delivery), just two configurations meet the target $\langle L_l,\ L_m, L_s\rangle \epsilon \{\langle 5,7,36\rangle,\ \langle 5,8,34\rangle\}$ (Figure 10c). The fast decline in feasible configurations at higher thresholds highlights the trade-off between delivery reliability and system resource requirements.

Undelivered on-time parcels are temporarily stored at the central warehouse until a new delivery can be scheduled, and sufficient locker space becomes available. The end-of-day inventory of undelivered parcels serves as a key performance indicator, as excessive accumulation may lead to storage capacity constraints. To assess the time-series properties of the inventory data, stationarity was evaluated using the Dickey–Fuller Generalized Least Squares (DF-GLS) test [42–44]. The initial inventory series is detrended (Equation (21)), and the detrended series is then tested for a unit root using an augmented Dickey–Fuller-like regression (Equation (22)):

$$\tilde{I}_{j,x} = I_{j,x} - \beta_0 - \beta_1 j \tag{21}$$

$$\Delta \tilde{I}_{j,x} = \alpha \tilde{I}_{j-1,x} + \sum_{i=1}^{p} \phi_i \Delta \tilde{I}_{j-i,x} + \varepsilon_j \tag{22}$$

where

$I_{j,x}$ is the time series of the end-of-day undelivered x parcels (x is the size of the parcels, i.e., large, medium, small);
$\tilde{I}_{j,x}$—the detrended time series;
$\Delta \tilde{I}_{j,x} = \tilde{I}_{j,x} - \tilde{I}_{j-,x}$—first difference of the detrended series;
α—the key coefficient, β—detrended series coefficients;
ϕ_i—the coefficients of the lags;
ε—the error;
p—the lag order of the autoregressive process.

The DF-GLS test's hypothesis is as follows:

- $H_0: \alpha = 0$—unit root exists (non-stationary time series);
- $H_a: \alpha < 0$—the time series is stationary.

For three APL configurations that are feasible for different on-time delivery probabilities, the evolution of parcel inventories is depicted in Figure 11.

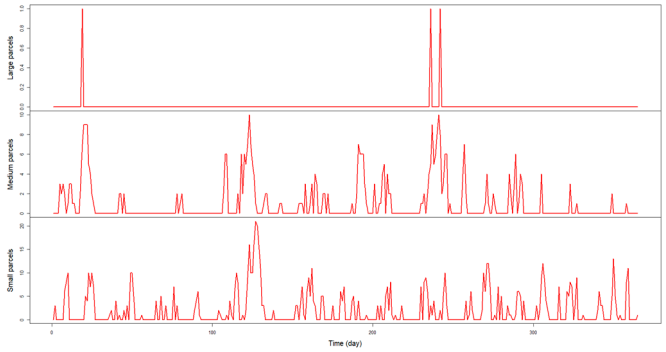
The DF-GLS test was conducted on all-time series configurations, including end-of-day inventory levels for large, medium, and small parcels (n = 365 daily observations). The results are presented in Table 4.

Table 4. DF-GLS test statistics.

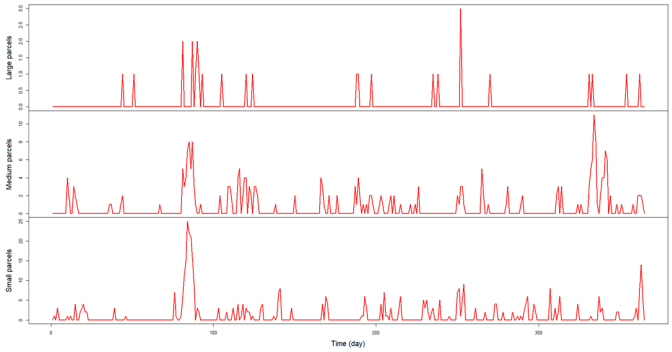
End-of-Day Inventory	Automated Parcel Lockers Configuration		
	$\langle L_l, L_m, L_s\rangle = \langle 6, 5, 36\rangle$	$\langle L_l, L_m, L_s\rangle = \langle 5, 6, 38\rangle$	$\langle L_l, L_m, L_s\rangle = \langle 5, 7, 36\rangle$
Large parcels	−8.57	−7.53	−7.98
Medium parcels	−5.90	−6.06	−5.57
Small parcels	−6.85	−6.69	−5.97

The DF-GLS is a one-sided (left) test, and the 5% critical value with n = 365 observations is −2.89 [43]. For all studied configurations and parcel size categories, the computed test statistics were more negative than the critical value (i.e., test statistic < −2.89). The results provide robust evidence that all inventory time series—regardless of parcel size category—are trend-stationary. This implies that fluctuations in postponed parcel inventory

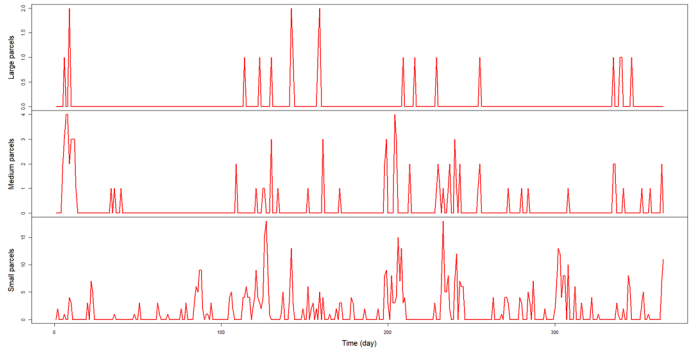
levels revert to a deterministic trend, and the system does not exhibit random-walk behavior. Ensuring customer satisfaction aligns with the effective management of end-of-day inventories for feasible APLs configurations, thereby addressing the perspectives of both customers and the company.



(**a**) APL configuration $\langle L_l, L_m, L_s \rangle = \langle 6, 5, 36 \rangle$



(**b**) APL configuration $\langle L_l, L_m, L_s \rangle = \langle 5, 6, 38 \rangle$



(**c**) APL configuration $\langle L_l, L_m, L_s \rangle = \langle 5, 7, 36 \rangle$

Figure 11. End-of-day undelivered parcel inventories (source: authors).

4. Discussion

The research highlights the relationship between operational performance metrics (including locker utilization rates and fluctuations in undelivered parcel inventory) and customer satisfaction, assessing how optimizing these metrics can enhance service fulfillment and user experience. The ability of larger lockers to flexibly store smaller parcels introduces an essential trade-off between flexibility and efficiency. The results demonstrate that an insufficient number of large and medium lockers can cause performance degradation, particularly for large and medium parcels, whose accommodation options are more limited compared to small parcels. Notably, when the number of large lockers is below four, the on-time delivery probability for large parcels drops below 0.5, indicating a clear service bottleneck. For 5–6 medium lockers the unsuccessful delivery rates for medium parcels are high, unless the number of large lockers increases. The on-time delivery rate for small parcels decreases as the number of large and medium lockers increases, due to the shrink in the number of small lockers (APLs space availability). System bottlenecks for small parcel delivery emerge when the configuration comprises 5–6 large lockers and 9–10 medium lockers.

Locker utilization rates serve as a critical efficiency metric for operational performance, demonstrating size-dependent spatial gradients across locker configurations. For large lockers, utilization follows a central-to-peripheral positive gradient, with minimum rates (0.62–0.65) observed for configurations of 4–5 lockers and peak rates (0.79–0.82) for 2 or 6 lockers (Figure 9a). This pattern arises because fewer large lockers restrain availability for large parcels, whereas higher numbers grant their use for medium/small parcels due

to availability. Furthermore, increasing large locker counts reduce the minimum required small lockers—a consequence of finite system capacity and the migration of smaller parcels to underutilized larger compartments. The medium-sized locker utilization rate exhibits a bidirectional (up–down/left–right) positive gradient (Figure 9b). Minimum utilization rates (0.53–0.58) occur with 9–10 medium lockers and few large lockers (2–3 units), a result of underutilized medium capacity and expanded small locker availability. Conversely, fewer medium lockers yield higher utilization rates (0.76–0.81). Configurations with more medium (9–10) and large lockers (5–6) show an increased medium locker utilization rate as small parcels are displaced to larger units under capacity constraints. The small locker utilization rate also shows a bidirectional positive gradient (bottom–up/left–right), as illustrated in Figure 9c. The lowest utilization rates (0.53–0.61) occur in configurations with 2–3 large lockers and 5–6 medium lockers, reflecting excess capacity in small compartments. As the number of large and medium lockers increases, the available capacity for small lockers decreases, leading to significantly higher utilization rates (0.78–0.80) in systems configured with 5–6 large and 9–10 medium lockers.

While this flexibility helps reduce undelivered inventory in some configurations, it may also create resource competition among parcel types. This was evident from the increased frequency of small and medium parcels being relocated to larger lockers when their designated compartments were insufficient. The balanced proportion of locker types and the frequency of such reallocations correlates with system performance and customers' on-time delivery expectancy. Only seven system configurations meet the $\geq$80% on-time delivery target (Figure 10a). For the configurations $\langle L_l,\ L_m, L_s\rangle = \langle 4,\ 10,\ 34\rangle$, the 95% confidence interval for large parcel on-time delivery is (0.778, 0.837), while for the configuration $\langle L_l,\ L_m, L_s\rangle = \langle 5,\ 9,\ 32\rangle$, the 95% confidence interval for small parcel on-time delivery is (0.797, 0.8132). Given these lower marginal performance bounds below the 0.8 threshold, both configurations demonstrate inconclusive feasibility and should be excluded from optimal solution sets. With a $\geq$85% successful delivery target, there are four feasible APL configurations (Figure 10b). For the configurations $\langle L_l,\ L_m, L_s\rangle = \langle 4,\ 7,\ 40\rangle$, the 95% CI for large parcel on-time delivery is (0.848, 0.895), while for the configuration $\langle L_l,\ L_m, L_s\rangle = \langle 5,\ 6,\ 38\rangle$, the 95% CI for medium parcel on-time delivery is (0.847, 0.879). These two last configurations demonstrate indeterminate feasibility within the specified performance parameters. The feasible set narrows substantially for on-time delivery thresholds above 90% (Figure 10c). Only two configurations meet the target $\langle L_l,\ L_m, L_s\rangle = \langle 5, 7, 36\rangle$ and $\langle L_l,\ L_m, L_s\rangle = \langle 5, 8, 34\rangle$. A comparison of Figure 9a or Figure 10a reveals that feasible configurations align with the lower utilization rate observed in large parcels. An optimal balance in the number of large lockers ensures adequate storage capacity for large parcels while also accommodating excess demand from medium and small parcels. Moreover, this configuration maintains sufficient capacity in medium and small lockers, thereby supporting overall system efficiency. The fast decline in feasible configurations at higher thresholds highlights the trade-off between service quality and resource allocation.

Furthermore, the study emphasizes the importance of inventory dynamics as a critical determinant for system stability. The Dickey–Fuller Generalized Least Squares test results confirm the stationarity of the end-of-day undelivered parcel inventories across all tested configurations and parcel sizes. This indicates that despite daily fluctuations, the system tends to revert to a long-term equilibrium, which is desirable in logistics settings. A stationary inventory dynamic ensures that the system remains resilient over time, avoiding excessive warehouse capacity.

Despite the robustness and versatility of the simulation model, several limitations should be acknowledged. The study assumes uniform distribution for daily parcel generation, which may not capture real-world temporal variations such as peak seasons or irregu-

lar delivery intervals. Real-world data could also fit different parcel demand distributions (i.e., normal, Erlang, Poisson). Additionally, customer behavior related to pick up times was modeled using fixed probabilities, although these behaviors may vary significantly across demographics or urban contexts. The model also excludes operational disruptions such as locker maintenance or failed delivery attempts due to locker access issues.

Looking ahead, future research could extend this work by incorporating dynamic delivery routing, adaptive locker allocation policies, and real-time decision-making capabilities. Integrating customer behavior models, e-commerce growth rate, including acceptance of alternative locker redirection and responsiveness to notifications, would enhance realism. Moreover, economic evaluations of locker configuration strategies, incorporating installation and maintenance costs, could complete the service-level findings and offer more comprehensive policy guidance. Finally, the role of APLs in smart-city ecosystems—particularly their synergy with public transit and autonomous delivery—permits further investigation to maximize urban logistics efficiency.

5. Conclusions

The simulation-based study presented in this paper provides valuable insights into the operational behavior of automated parcel lockers under stochastic demand conditions and constrained capacity, emphasizing the interplay between locker configurations, utilization efficiency, and service performance. The paper develops a discrete-event simulation model implemented in ARENA software to optimize the configuration of automated parcel lockers. The study examines a system with three parcel size categories and three corresponding locker types, with larger lockers capable of storing smaller parcels—a design feature that introduces trade-offs between flexibility and space efficiency. The model seeks to meet the probability of on-time parcel delivery by determining the optimal mix of locker sizes, accounting for variable dwell times (time-to-pick-up) and dynamic demand patterns. Key contributions of this research include the following:

- Optimal locker configuration for service efficiency: Configuration of locker types significantly influences the system's ability to maintain high customers service levels, as measured by on-time parcel delivery probabilities. The higher the customers' satisfaction target, the smaller the number of feasible configurations. A small number of large lockers (typically ≥ 4 units for testing dataset) is essential to accommodate large parcels and prevent service degradation. While additional large lockers enable flexible storage of smaller parcels, they simultaneously reduce available capacity for medium and small lockers, creating a critical system design compromise.
- Utilization patterns and spatial efficiency: While flexibility in locker allocation helps manage excess demand in some configurations, it may also create resource competition among parcel types. Large lockers show a central-to-peripheral utilization gradient, while medium and small lockers display bidirectional utilization gradients but in opposite trends. This nonlinear relationship underscores that optimal APLs configurations must balance absolute locker counts with their size-dependent functional interdependencies.
- System resilience and delayed parcels inventory stationarity: Dickey–Fuller GLS tests confirm stationarity in undelivered inventories, indicating inherent system stability despite daily fluctuations, a critical feature for long-term logistics planning.

Policymakers and logistics operators can leverage these findings to design systems that maximize delivery reliability while adapting to evolving e-commerce demands. Further research integrating real-time adaptive policies and economic evaluations will strengthen practical applicability in urban logistics networks.

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