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A SIMULATION-OPTIMIZATION APPROACH FOR LOCATING AUTOMATED PARCEL LOCKERS IN URBAN LOGISTICS OPERATIONS

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ABSTRACT

Experts propose using an automated parcel locker (APL) for improving urban logistics operations. However, deciding the location of these APLs is not a trivial task, especially when considering a multi-period horizon under uncertainty. Based on a case study developed in Dortmund, Germany, we propose a simulation-optimization approach that integrates a system dynamics simulation model with a multi-period capacitated facility location problem (CFLP). First, we built the causal-loop and stock-flow diagrams to show the APL system's main components and interdependencies. Then, we formulated a multi-period CFLP model to provide the optimal number of APLs to be installed in each period. Finally, Monte Carlo simulation was used to estimate the cost and reliability level for different scenarios with random demands. In our experiments, only one solution reaches a 100% reliability level, with a total cost of 2.7 million euros. Nevertheless, if the budget is lower, our approach offers other good alternatives.

1 INTRODUCTION

Researchers have used simulation-optimization (SO) techniques for solving complex transportation and logistics problems for many years (Figueira and Almada-Lobo 2014). Exploring the behavior of logistics systems, and estimating their response to various changes in their environment, is the primary purpose behind the use of simulation (Crainic et al. 2018). In logistics systems, SO enables to represent and estimate different scenarios for policy changes and environmental regulations, enabling better accommodation of logistics schemes. In this context, we focus on SO models in urban logistics (UL) systems. Urban logistics has been a subject of interest for researchers during the last decades. UL is defined by Gonzalez-Feliu et al. (2014) as "The multi-disciplinary field that aims to understand, study and analyze the different organizations, logistics schemes, stakeholders and planning actions related to the improvement of the different goods transport systems in an urban zone and link them in a synergic way to decrease the main nuisances related to it". Hence, UL includes different stakeholders who are seen in urban logistics, as well as a wide variety of aims, which imposes challenges to decision makers.

This paper focuses on the usage of automated parcel locker (APL) systems, such as pack-stations or locker boxes, as one of the most promising initiatives to improve the UL activities. The APL has electronic lockers with variable opening codes, so that it can be used by different consumers whenever it is convenient for them. APLs are located in apartment blocks, workplaces, railway stations, or near to consumers' homes, to which parcels are delivered. The costs of APL deliveries are lower than those of home deliveries, and the risk of missed deliveries is avoided. Some studies confirm that online shoppers will use APLs more frequently in the future (Moroz and Polkowski 2016). Despite there are limitations to the concept, many third-party logistics providers, such as DHL, InPost, Norway Post, PostDanmark, UPS, or Amazon continue to invest in APLs to gain a competitive advantage (Moroz and Polkowski 2016). As remarked by Verlinde et al. (2018), an APL has multiple benefits in comparison to home deliveries: economic benefits, less traffic in city centers, no double parking in front of customers' homes, no failed home deliveries, fewer kilometers and stops, off-hour deliveries, and cost reduction for e-retailers and delivery operators. Besides, the use of APL offers environmental benefits as well, i.e., less pollutant emissions (Faulin et al. 2018). Moreover, there are also social benefits, as improved quality of life and less noise. E-customers are free to choose the pick-up time of their parcels (24/7). Also, the APL can be a focal point for the local community. However, APLs have at the same time some disadvantages as difficulties with the APL interfaces, limited payment flexibility *in situ*, limited storage possibilities, and sensitivity to crime or vandalism (Vakulenko et al. 2018).

On the one hand, Jlassi et al. (2018) highlight the almost absence of system dynamics (SD) simulation applied in the UL field, and no application of this approach investigates the components of APL systems as well as their interdependencies. On the other hand, the location of the APL is one of the critical issues related to the users' expectations. These facilities should be located close to customers' homes, on their way to work, or in places with a high availability of parking spaces (Iwan et al. 2016). Furthermore, Guerrero and Díaz-Ramírez (2017) point out that the APL strategy has not been discussed in the scientific literature, but is observed in practice. For example, many studies did not look at the installation costs of the APLs, their suitable locations, as well as the required capacity for seasonal peaks in e-commerce.

This work addresses the case of Dortmund city, which is located in the Land of North Rhine-Westphalia, Germany. Its population, of about $600,000$ people, makes it the seventh largest city in Germany and the 34$^{\text{th}}$ largest in the European Union. We use a system dynamics simulation model (SDSM) to understand the components' behavior of APL systems regarding the specific customers and characteristics of Dortmund. A planning horizon of ten years is considered, and the problem is modeled as a multi-period capacitated facility location problem (CFLP). While considering the users' demand that needs to be satisfied, the goal is to find the minimum-cost number of APLs that need to be installed every year inside the time horizon, as well as their locations. Multiple scenarios considering different estimates for the demands in future periods are considered and solved. Then, the performance of the associated solutions in a stochastic environment is assessed by using Monte Carlo simulation.

2 A SYSTEM DYNAMICS SIMULATION MODEL

System dynamics was initially developed to aid the understanding of industrial processes. The SD methodology was developed by Forrester (1968). The methodological approach serves as a basis to illustrate the effects of decisions in complex dynamic systems. In particular, the time functions of the SD approach are emphasized. The specific features of SD are its non-linear feedback structures and functions. An SD model involves identifying major stocks and flows, the factors that impact flows, as well as the primary feedback loops. Causal diagrams are used to link stocks, flows, and information sources. Equations are developed for representing flow levels. SD permits linked systems to be specified with delay and feedback loops, thus allowing counter intuitive behavior to be understood (Sterman 2000).

The first step of the modeling process is to identify the issue and the relevant stakeholders. Initially, the problem owners provide essential information about the issue at hand, and are then involved in every iterative modeling step. It is essential that the problem owners comprehend the basic functioning of the model and continuously validate the output of the model. After identifying and selecting the dynamic problem, the conceptualization is to decide upon a provisional list of variables and a suitable time horizon for the model. The formulation is based on the available data resources and the identified problem. The modeler defines what kind of model is to be created – e.g., for some dynamic problems, a qualitative model might suffice. The model can start as a causal loop diagram (CLP). If a quantified model is the goal, then a stock and flow diagram (SFD) should be considered more suitable. In the case of a quantified model, after translating the variable list into an SFD, the modeler populates the variables with values to create a first iteration of the simulation model.

Initially, the values and functions added to the model can be estimates, as the modeler will revise them at every iterative step and continuously increase their precision. For the scenario and policy analysis, when the modeler is satisfied with the current quality of the model, he or she can start analyzing and evaluating policies and scenarios. The scenarios are analyzed by changing exogenous variables to simulate different developments in the environment of the system. After agreeing on the most important scenario settings and most effective policies, the modeler applies these conditions to the model and discusses the results with the stakeholders. They can then evaluate and define the most effective way to apply the policies in the system.

We use an SDSM to understand the APL systems, the components' behavior of the system and their interdependencies. We define the main variables that have an impact on the system dynamics, using the Vensim software tool to build the set of diagrams, including the CLD and SFD, according to SD standard procedures (Sterman 2000). We developed the CLD based on a previous work presented by Rabe et al. (2020). Figure 1 shows the APL system's CLD of the main components and their interdependencies.

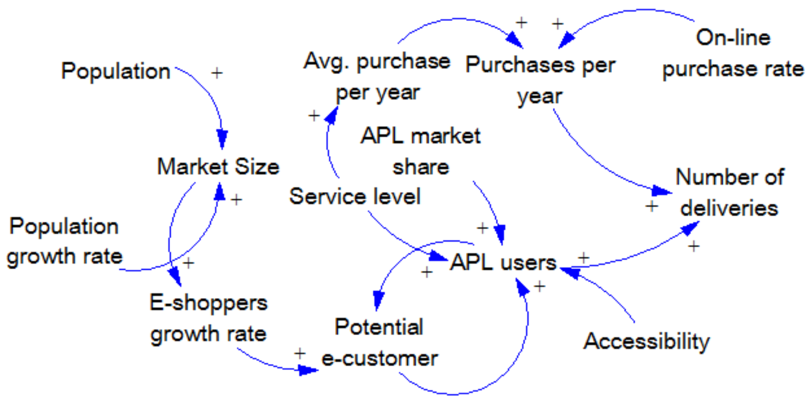


Figure 1: The APL system's CLD.

The CLD shows that the market size is positively influenced by the population and the population growth rate. The potential new e-customers are positively influenced by the e-shoppers rate and balanced by the APL users: when the number of APL users grows, the amount of potential new e-customers decreases. The APL users are also positively reinforced by the APL market share. In turn, they are constrained by service level and accessibility. The number of purchases per year is positively influenced by the average purchase per year and the on-line purchase rate. The number of deliveries (demand) is positively influenced by the purchases per year and by the number of APL users. Figure 2, based on Rabe et al. (2020), shows the SFD related on the respective CLD. Table 1 shows main variables and their initial values used in the SDSM for the Dortmund city as study case.

3 A MULTI-PERIOD FACILITY LOCATION PROBLEM MODEL

The facility location problem (FLP) is a well-known optimization challenge in which the typical goal is to find the minimum-cost number of facilities, as well as their locations, that must be open in order to satisfy the customers' demands, either if these are deterministic (Melo et al. 2009) or stochastic (De Armas et al. 2017; Pagès-Bernaus et al. 2019). Also, when routing decisions are incorporated as well, the FLP transforms into the so-called location routing problem (Quintero-Araujo et al. 2017; Quintero-Araujo et al. 2019). In general, FLPs are classified either as capacitated or uncapacitated. The former refers to the case in which facilities have a known limit on the demand they can serve. The latter is the case in which the service capacity of each facility exceeds the total customers' demand. Figure 3 illustrates the capacitated FLP (CFLP) for the APL network in the city of Dortmund.

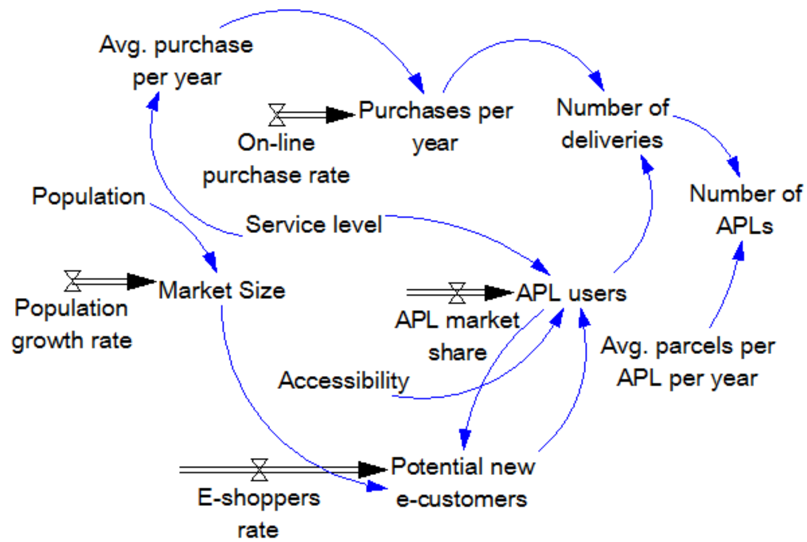


Figure 2: The APL system's SFD.

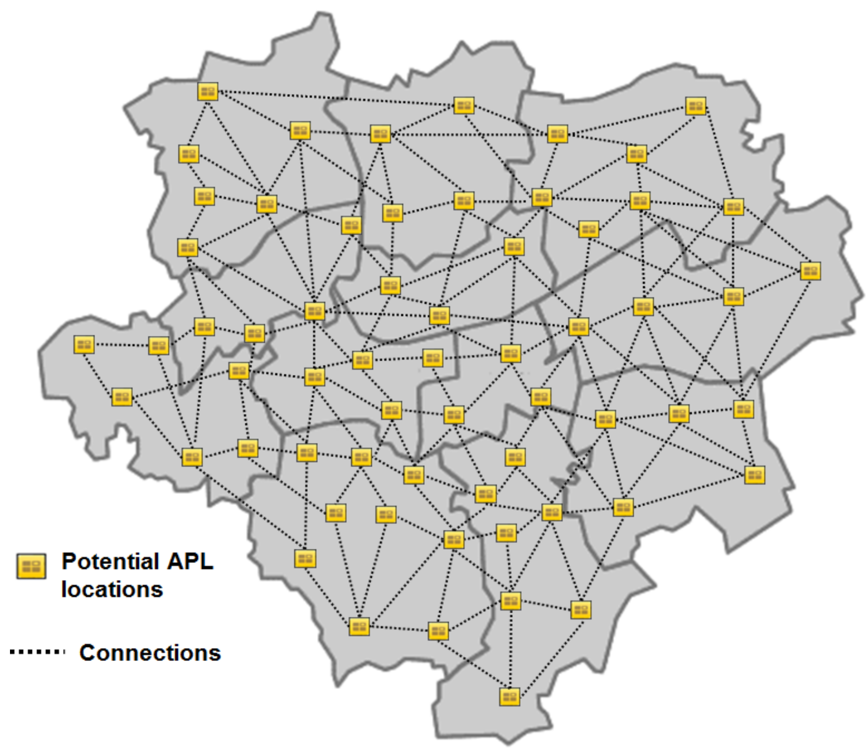


Figure 3: Illustrative CFLP for APLs in the city of Dortmund.

Table 1: List and characteristics of variables used on the SDSM of the APL systems.

Parameter	Definition	Initial Values
Population	Number of inhabitants in Dortmund city	602,566 inhabitants
Population growth rate	Factor	0.2 (%) per year
Market Size	Population*Population growth rate	Population
Service level	Factor	90 (%)
Accessibility	Factor	70 (%)
Potential new e-customers	Market Size*E-shoppers rate	331,411 inhabitants
E-shoppers rate	Factor	55 (%)
APL market share	Factor	15 (%)
Avg. purchase per year	Constant*Service level	36 units per year
On-line purchase rate	Factor	10 (%)
Purchases per year	Avg. purchase per e-customer* On-line purchase rate	Avg. purchase per year
Number of deliveries	APL users*Purchases per year	0 Units

In our case, a multi-period CFLP is considered. Decisions taken in a particular period affect future periods over a time horizon T. In particular, since demand is expected to grow during the next periods, we will assume that whenever an APL is opened inside a period $t \in T$, it has to remain open until the end of the time horizon, i.e., for all $t' \in T : t' > t$. Similarly, third-party logistics providers state that a minimum percentage $m \in (0,1)$ of the total installed capacity has to be utilized. Hence, let us denote by I the set of nodes that represent all districts in the city. Each district $i \in I$ might contain none, one, or several APLs, each of them with a known capacity $a_i > 0$. Likewise, each district $j \in I$ has an aggregated demand during period $t \in T$, $d_{jt} > 0$. Given two districts $i, j \in I$, the unitary cost of assigning an APL located in district i to a customer located in district j is given by $c_{ij} > 0$. Likewise, the cost of opening an APL in district $i \in I$ during period $t \in T$ is given by $f_{it} > 0$. In this context, the binary variable x_{ijt} takes the value 1 if customers in district $j \in I$ are assigned to an APL in district $i \in I$ during the period $t \in T$, being 0 otherwise. Similarly, the integer variable y_{it} represents the number of APLs that are open in district $i \in I$ and period $t \in T$. Then, our multi-period CFLP can be formulated as follows:

$$Minimize \quad \sum_{i\in I}\sum_{j\in I}\sum_{t\in T} c_{ij} d_{jt} x_{ijt} + \sum_{i\in I}\sum_{t\in T} f_{it}(y_{it} - y_{it-1}) \tag{1}$$

subject to:

$$\sum_{i\in I} x_{ijt} = 1 \quad \forall j \in I, \forall t \in T \tag{2}$$

$$y_{it} \geq y_{it-1} \quad \forall i \in I, \forall t \in T \tag{3}$$

$$\sum_{j\in I} d_{jt} x_{ijt} \leq a_i y_{it} \quad \forall i \in I, \forall t \in T \tag{4}$$

$$\sum_{j\in I} d_{jt} \geq m \sum_{i\in I} a_i y_{it} \quad \forall t \in T \tag{5}$$

$$x_{ijt} \in \{0,1\} \quad \forall i \in I, \forall j \in I, \forall t \in T \tag{6}$$

$$y_{it} \in \mathbb{Z}^+ \quad \forall i \in I, \forall t \in T \tag{7}$$

Expression (1) displays the objective function, which minimizes the total cost: the first term indicates the APLs' service cost, while the second one represents the fixed cost of opening new APLs during the time horizon. Constraints (2) ensure that, for each period $t \in T$, each district $j \in I$ is assigned to exactly one APL. Constraints (3) guarantee that once an APL is opened, it remains in that status until the end of the time horizon. Constraints (4) ensure that, for each APL in district $i \in I$ and period $t \in T$, the demand serviced by that APL does not exceed its capacity. Constraints (5) guarantee, for each period $t \in T$, a minimum utilization percentage of the APLs' total installed capacity. Finally, constraints (6) and (7) indicate the ranges of the decision variables.

4 AN INTEGRATED SO APPROACH

One of the main goals of SO methods is to efficiently address both optimization and uncertainty. The possibilities of combining SO are vast and the appropriate design depends highly on the problem characteristics. Figueira and Almada-Lobo (2014) describe in detail the main classification of different SO combinations. According to their classification, we consider an analytical model enhancement approach by using simulation to improve the model results, either by refining its parameters or by extending them, e.g., considering different scenarios. In this context, based on a simulation-optimization concept for APLs presented by Rabe and Chicaiza-Vaca (2019), the SDSM offers a suitable methodology to determine the behavior of the parameters in our multi-period CFLP model. Then, this model provides an optimal location for the APLs considering expectations on users' demands. Nevertheless, in real-life, the demand of each district $j \in I$ during period $t \in T$ is subject to uncertainty, so it is usually modeled as a random variable, D_{jt}, with $E[D_{jt}] = \mu_{jt}$. A well-tested SO approach to address this type of problems are simheuristic algorithms (Juan et al. 2015; Juan et al. 2018), although in this article we employ the Cplex exact solver instead of heuristic algorithms. Particularly, our approach consists of the following stages (Figure 4): *(i)* for each district $j \in I$ and period $t \in T$, use the SDSM to generate an estimate of the expected demand μ_{jt}; *(ii)* for different scenarios $s \in S$, with each scenario defined by a different level of demand d_{jts} (e.g., lower than expected, as expected, or higher than expected), solve the associated CFLP model; and *(iii)* use a Monte Carlo simulation to evaluate the solutions obtained in the previous step when they are employed in a stochastic environment.

For each scenario $s \in S$, testing its associated solution in a stochastic environment via simulation does not only allow us to obtain an estimate of its stochastic cost, but also an estimate of its reliability level. Studies about reliability in supply chains can be found in Adenso-Diaz et al. (2012) and Peng et al. (2011). For each scenario $s \in S$, we define the reliability of its associated solution plan, R_s, as the probability that the plan can successfully meet the stochastic demands of all districts in the city, i.e.:

$$R_s = \left(1 - \frac{b_s}{n}\right) \cdot 100\% \quad \forall s \in S \tag{8}$$

where b_s is the total number of simulation runs in which the plan fails to cover all district demands, and n is the total number of runs.

5 COMPUTATIONAL EXPERIMENTS

Based on a real-world case from the city of Dortmund, a set of experiments considering a ten years planning horizon has been tested. Table 1 shows the parameters provided by the SDSM. It yields multiple outputs, from which the yearly demand per district is the most relevant one to feed the multi-period CFLP model. Then, the integrated SO approach described in Section 4 is applied to obtain a set of solutions assessed in terms of stochastic cost and reliability level.

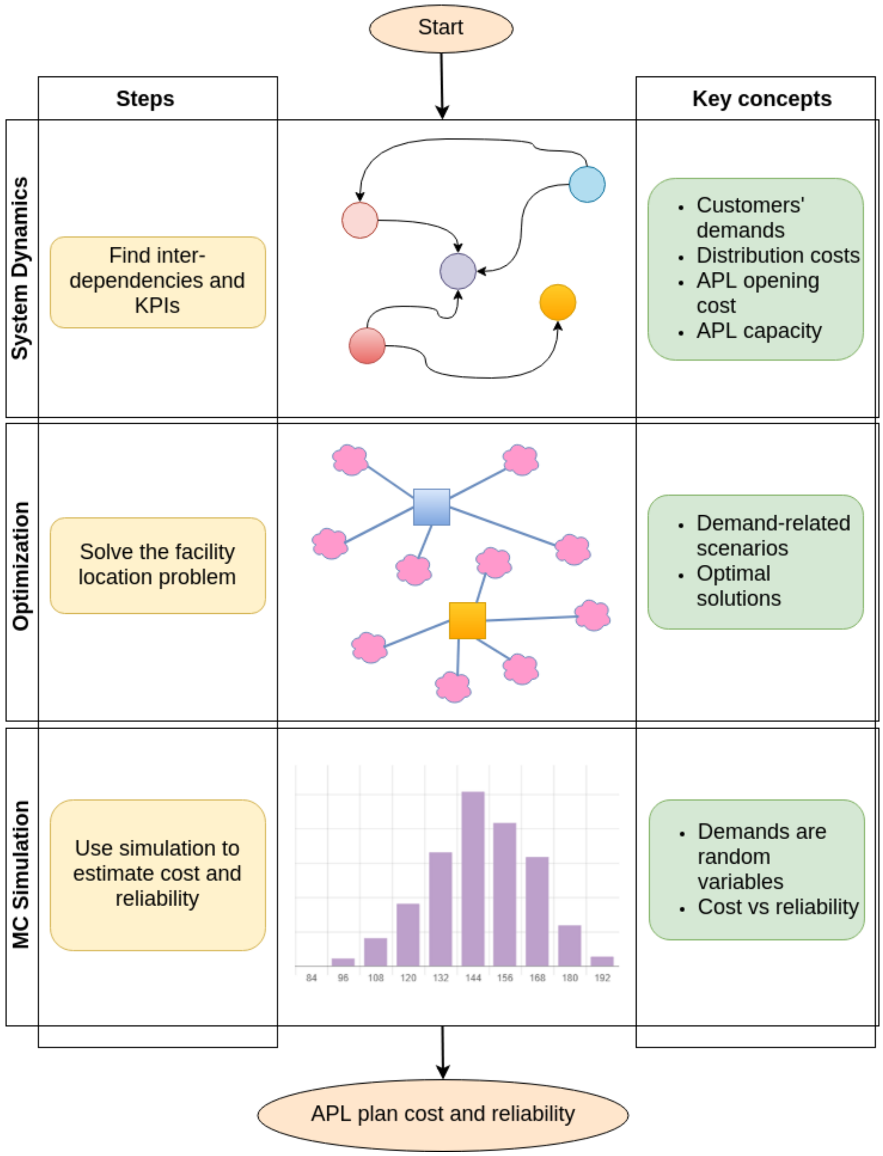


Figure 4: Schema of the integrated simulation-optimization approach.

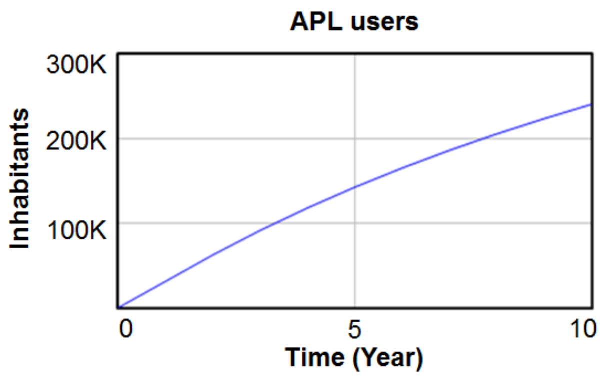
5.1 Results from the System Dynamics Simulation Model

Table 2 shows the SDSM results of market size (in thousands), potential new customers (in thousands), APL users (in thousands), average purchase per year per customer, and number of deliveries (in millions of units) during the planning horizon.

The market size increases, according to the population growth rate, from $603,800$ in year 1 to $614,700$ inhabitants in year 10. The potential new customers decrease year by year, since this variable is negatively correlated with the APL users, who are not "potential" users anymore. The purchases per year, number of deliveries, and number of APLs show an increasing trend over time. The number of deliveries increases from 1.08 to 14.81 million parcels per year. These results are used as an input for our multi-period CFLP model. Figure 5 shows the behavior of APL users and the average purchases per year per customer. Figure 6 displays the number of deliveries in the city, considering a ten-year planning horizon.

Table 2: Results generated by the SDSM.

Output parameter	Year									
	1	2	3	4	5	6	7	8	9	10
Market size (thousands)	603	605	606	607	608	609	611	612	613	614
Potential new customers (thousands)	331	306	282	259	239	221	205	191	178	167
APL users (thousands)	62	90	116	140	162	182	201	219	235	251
Avg. purchases per year	35	38	41	44	47	50	53	56	59	62
Number of deliveries (millions)	1.08	2.34	3.71	5.14	6.64	8.19	9.78	11.42	13.10	14.81



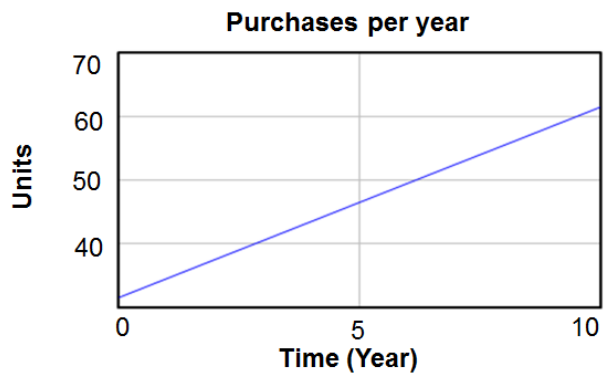


Figure 5: Market size (left), and potential new customers (right).

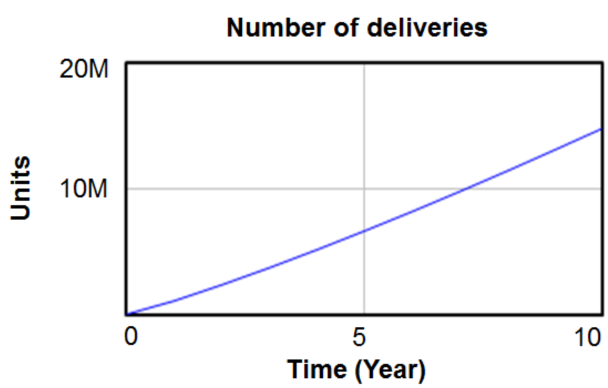


Figure 6: Number of deliveries.

5.2 Scenario Solving and Simulation of Solutions

For scenario generation purposes, we built a total number of $|S| = 20$ scenarios to be solved using the CFLP model and then analyzed them in a simulation. The assumptions for building the scenarios are presented below. The random demand of each district $j \in J$ during the period $t \in T$ in scenario $s \in S$, D_{jts}, is assumed to be uniformly distributed. However, its base mean, $\mu_{jt} = E[D_{jt}]$, is increased in each new scenario considered. Moreover, a factor $\delta = 0.05$ is also introduced to increase the size of the uniform interval as we move forward into future periods. Therefore, the scenario- and period-dependent demand D_{jts} is modeled according to Equation (9):

$$D_{jts} \sim U\left(\left[1+\frac{s-1}{|S|-1}\right](1-\delta\cdot t)\mu_{jt}, \left[1+\frac{s-1}{|S|-1}\right](1+\delta\cdot t)\mu_{jt}\right) \tag{9}$$

The variable cost c_{ij} is proportional to the distance between each pair of districts. It was estimated using a web mapping service. The fixed cost is $f_{it} = 5{,}500$ for the first year and every district, and increases according to an average inflation of 2% every year. The capacity of each APL in a district $i \in I$ is $a_i = 72{,}000$ units, and the minimum utilization percentage is $m = 40\%$. Then, our CFLP model is solved 20 times using Cplex, one per scenario. Five out of the resulting 20 solutions are depicted in Figure 7, which displays the number of open APLs per year. The lowest and the highest lines represent solutions to Scenarios 1 and 20, respectively. The rest of the solutions are located in between. As the base average demand, μ_{jt}, increases over time according to the SDSM results, the same is true for the number of APLs. However, this steady behavior does not go beyond year 6, when the total installed APLs are sufficient to meet the total demand until the end of the planning horizon. In other words, no additional APLs are required from years 7 to 10, and this is true regardless of the considered scenario. Notice, however, that the total number of installed APLs significantly differs from one scenario to another, e.g., while Scenario 20 requires up to 501 APLs, only 260 APLs are installed in Scenario 1.

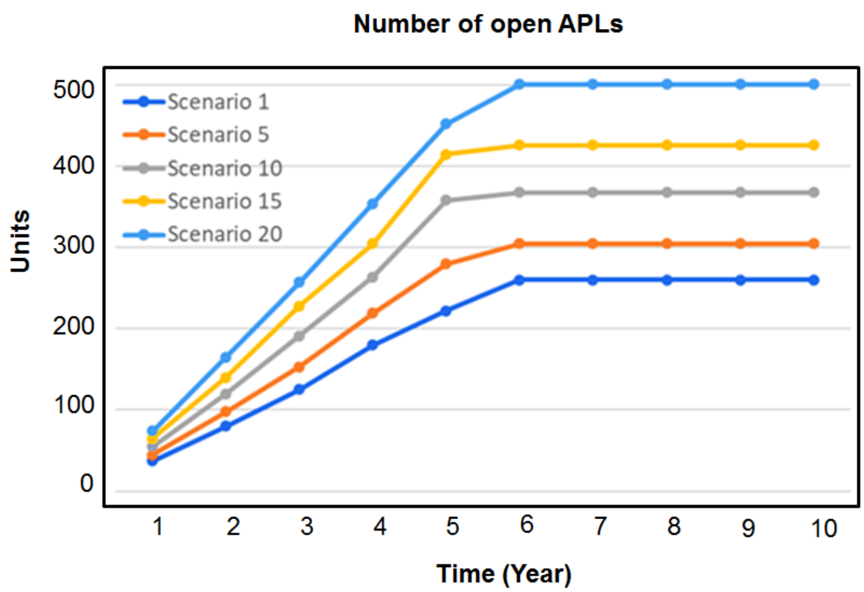


Figure 7: Number of total open APLs along the planning horizon for 5 scenarios.

Once the solutions have been obtained for each scenario, the next step is to run a simulation to evaluate them in a stochastic environment. Without loss of generality, the demand is assumed to be independent between customers; however, our methodology can be easily adapted to consider correlated demands. Two probability distributions are tested for the demand realization. Notice that for carrying out an appropriate comparison between both distributions results, previously generated scenarios are not further modified. Initially, the random demand D_{jt} is uniformly simulated as defined in Equation (10). We are now assuming that $D_{jts} = D_{jt}\ \forall s \in S$, which allows us to test each scenario-based solution under the same demand conditions. Then, the random demand is simulated following a log-normal distribution as defined in Equation (11), where $\sigma_{jt} = \frac{\sqrt{3}}{3}\delta \cdot t \cdot \mu_{jt}$ is the standard deviation. The coefficient of $\frac{\sqrt{3}}{3}$ is useful to preserve the same standard deviation as the case in Equation (10). A total of $n = 5{,}000$ runs are executed for each scenario-related solution.

$$D_{jt} \sim U\left(\left[1-\delta \cdot t\right]\mu_{jt}, \left[1+\delta \cdot t\right]\mu_{jt}\right) \tag{10}$$

$$D_{jt} \sim Lognormal\left(\mu_{jt}, \sigma_{jt}\right) \tag{11}$$

Figure 8 shows the main results of the simulation process for each solution. Orange points represent the results from the uniform-distribution demand, and blue points represent the results from the log-normal-distribution demand. In general, more costly solutions yield a higher reliability, since they tend to include a larger number of APLs installed. Regardless of the probability distribution, total costs are the same for all scenarios since the input conditions remained the same for both distributions. However, when the demand follows a log-normal distribution, the solution's reliability is smaller than in the case where the demand is uniformly distributed. Five solutions are not reliable at all, since at least one APL fails in all (or almost all) runs – i.e., its installed capacity is lower than the simulated demand. In our experiments, only one solution reaches a 100% reliability level, with a total cost of $2,782,319$ €. Nevertheless, if the budget is lower, our approach offers other good alternatives for decision-makers.

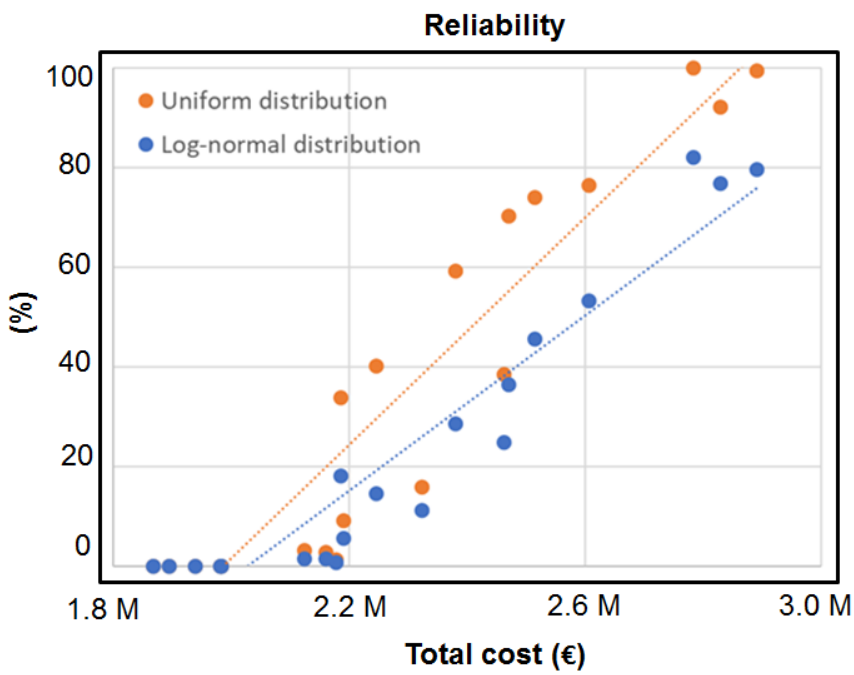


Figure 8: Optimal solutions evaluated in terms of stochastic cost and reliability.

6 CONCLUSIONS

With the aim of determining the optimal number and location of automated parcel locker (APL) systems in a multi-period time horizon, this work has proposed the use of an integrated simulation-optimization approach that combines system dynamics with exact optimization and Monte Carlo simulation. The analysis is based on a real-world case study, where servicing demands are considered to be random variables that evolve over time. Firstly, a system dynamics simulation model is designed to determine the ten-year performance of parameters such as market size or demand. Then, these results feed a multi-period facility location model, which delivers the optimal number and location of APLs. To deal with demand uncertainty, different scenarios are considered and solved using exact methods. Then, the solutions associated with each scenario are sent to a Monte Carlo simulation in order to estimate both their cost and reliability level.

All in all, the work illustrates the potential of combining different simulation and optimization techniques to properly address complex optimization problems in real-life urban logistics, where uncertainty has to be considered as well. The following research lines are still open for the future: *(i)* increasing the level of detail in the demand side, considering correlated demands and individual customers' demands instead of aggregated ones – which will noticeably increase the size of the problem; *(ii)* develop a metaheuristic-based approach for the optimization stage, since this will be a necessary step if larger-sized instances are to be analyzed; and *(iii)* extend the approach into a full simheuristic algorithm, in a way that the feedback provided by the Monte Carlo simulation can be re-used to guide the metaheuristic search.

ACKNOWLEDGMENTS

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