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A DYNAMIC FORECAST DEMAND SCENARIO ANALYSIS TO DESIGN AN AUTOMATED PARCEL LOCKERS NETWORK IN PAMPLONA (SPAIN) USING A SIMULATION-OPTIMIZATION MODEL

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ABSTRACT

The disruptions experienced by the last mile delivery processes during the SARS-CoV-2 pandemic have inevitably raised the dilemma of alternative last mile approaches in Urban Logistics (UL). Self-Collection Delivery Systems (SCDS) suppose an improvement for both courier companies and customers, providing flexibility of time-windows and reducing overall mileage, delivery time and, gas emissions. Drawing a distinction from previous works involving hybrid modeling for automated parcel lockers (APL) network design, this study integrates a System Dynamics Simulation Model (SDSM) to forecast e-commerce demand in Pamplona (Spain), and considers the scalability of the model for other cities. A bi-criteria Facility Location Problem (FLP) is proposed and solved with an ε-constraint method, where ε is defined as the level of coverage of the total demand, and four different cases of demand coverage are run. The simulation and demand forecast was carried out using Anylogic software, being CPLEX the optimization solver.

1 INTRODUCTION

The spread of SARS-CoV-2 in 2020 proliferated unknown challenges for society. As an effect of the regulations applied to overcome the pandemic, both local and global supply chains (SCs) experienced disruptions in their performance, while e-commerce demand skyrocketed. Thus, the pandemic has forced urban logistics to opt for alternative last-mile approaches and for that reason different delivery methods have been on the radar of researchers and delivery companies for years (Sawik et al. 2017b). This situation has allowed the implementation of some well-known procedures (Faulin et al. 2019) into the urban logistics field.

Self-collection delivery systems (SCDS) seem to be an attractive alternative to traditional home delivery in last mile, providing flexibility to both couriers and customers, and reducing out-of-vehicle delivery times and consequently vehicle dwell times (Ranjbari et al. 2023). Therefore, SCDS suppose and advantage for courier companies as overall mileage is reduced and road congestion is mitigated, leading to a positive impact in gas emission. This paper focuses on the common-carrier automated parcel lockers (APLs), which are the evolution of the earlier employed pickup points. Parcel lockers are automated multi-compartment storage systems that allow couriers to dispose parcels and permit temporary and secure storage of those online purchases until their pick-up by customers. During delivery, customers receive a unique code via electronic notification that allows them to open the locker that has been assigned to their parcel and pick-up their package at a convenient time. Customer convenience is one of the main benefits of parcel lockers, which are usually located in residential buildings, stores, transit stations, petrol stations, workplaces, financial areas or neighborhood hubs, serving people clustered in groups. Any location with high concentration of population and high e-shopping frequency is a potential site for installing automated lockers.

This paper builds upon previous contributions (Sawik et al. 2022a; Sawik et al. 2022b) which developed an APL network simulation-optimization framework to perform a comparison between the example cases of Pamplona (Spain), Zakopane, and Krakow (Poland). The aim of this study is to develop a model able to solve the APL system network for the proposed demand scenarios scalable to any European city. The novelty of this research that differs from the previous work can be stated in three contributions. First of all, a new approach for the optimization problem is stated, relying on the courier companies business perspective. Secondly, richer input data has been collected for the case study, reaching to a finer APL distribution network providing visual solution in maps. The scalability of the problem has also been considered in the formulation, to develop a model which can be applied to any city. Lastly, a new e-shopper demand forecast has been implemented by means of System Dynamics, Additionally, it is worth mentioning that the effect of locker vicinity in customer behavior is also implemented in the System Dynamics model, achieving a deeper integration of the simulation-optimization framework (Serrano-Hernandez et al. 2021).

Thus, next section presents a review of relevant literature about APL networks, and optimization and simulation approaches, Section 3 describes the proposed methodology, and Section 4 displays the computational experiments and Section 5 reveals the obtained results. Finally, Section 6 highlights the main findings an concludes the analysis.

2 LITERATURE REVIEW

This section presents an extended review of the literature that is related to the applied methodology. On the one hand, works related to APLs utilization, organization, popularity, and customer behavior are presented. On the other hand, studies based on Facility Location Problem (FLP) optimization, Agent-Based Modeling and System Dynamics simulation are reviewed, all of them applied to the field of urban and last mile logistics.

2.1 Studies on the Application of Automated Parcel Lockers Systems

The growth of e-commerce flows has led to an increase of courier vehicles such as vans in the cities, causing a negative environmental impact. Cano et al. (2022) presents a literature review to identify publications in recent years about the sustainability of logistics operations in e-commerce environments. In that context, Bonomi et al. (2022) study the role of customers (their eco-conscious behavior) as one of the main drivers for controlling the environmental impact of last mile logistics (Abdullahi et al. 2021). That way, they propose an optimization model to minimize the environmental impact in terms of distances travelled by both delivery couriers and customers, deciding the location and the number of APLs to be opened. The success of APLs is mainly due to the flexibility they offer to all the players of the last mile supply chain. This is demonstrated in a real experiment in downtown Seattle (Ranjbari et al. 2023), as their results show that by implementing parcel lockers in a residential building the time spent on parcel delivery and the dwell time show a statistically significant decrease.

2.2 Facility Location Problem Applied to Locker Locations

The advantages previously mentioned have involved the need for optimizing the APLs networks by solving facility location problems taking advantage of different methodologies of simulation-optimization techniques. The study developed by Che et al. (2022) proposed a multi-objective optimization mathematical model for investigating the planning of the location service areas of smart parcel locker facilities, based on three optimization objectives, namely maximum facility coverage, minimum facility overlap, and minimum total idle capacity. Similarly, Lin et al. (2022) propose a profit-maximizing facility location problem, estimating the revenue by means of the Threshold Luce Model (TLM) to predict customers' likelihood of using the locker service. Lockers become attractive when opened near a customer zone, since customers are more willing to use the locker service compared with far away located lockers. The robust optimization model proposed by Wang et al. (2022) deals with the risk of unsatisfied demands as they consider demand uncertainties and the allocation of large and small parcels for each location. Additionally, they consider acceptable walking distance as a constraint of the location selection optimization problem. Uncertainty is also considered by Kahr (2022), as an integer linear programming formulation is proposed to determine the locations and the design of the layouts of the parcel lockers.

2.3 Simulation in Urban Logistics

Simulation techniques have been widely used to model and analyze complex logistics systems in urban areas. Agent-based modelling (ABM) and System Dynamics (SD) are two commonly used simulation methods that can be applied to urban logistics. Despite its potential, there are relatively few ABM applications that address urban logistics issues (Maggi and Vallino 2016). As Mehdizadeh et al. (2022) suggest in their review, ABM can provide a framework for simulating complex decision systems considering an heterogeneous population. Moreover, unlike econometric methods, ABM considers the dynamic nature of evolving features, which characterise mobility and behavioral change of demand. Therefore, ABM is a flexible approach suited to capture this complexity. On the other hand, Thaller et al. (2017) presented a specific application of SD in urban logistics operations, and De La Torre et al. (2019) developed an SD model to study customer behavior from a last-mile context perspective. In this context, Rabe et al. (2021) proposed a simulation-optimization approach integrating a system dynamics simulation model with a multi-period capacitated facility location problem.

3 METHODOLOGY

3.1 The Simulation-Optimization Framework

As stated previously, this paper is an extension of Sawik et al. (2022a), in which a hybrid model was presented combining agent-based modeling approach with a FLP for APL network design. As a novelty, a System Dynamics Simulation Model has been designed to estimate future three-year horizon demand of online purchases, based on socio-economic factors in the city of Pamplona. Additionally, the optimization model proposed is a bi-criteria FLP, which aims to minimize the number of APLs and maximize the coverage of the demand. This bi-objective optimization model is addressed by means of ε-constraint approach. The hybrid model is defined over the set of nodes $i \in \mathscr{I}$ and $j \in \mathscr{J}$ representing the APL potential locations and potential customer demand points, respectively. Combining simulation and optimization approaches for APLs implies that the simulation environment supplies the input data for the facility location model, while the optimization model provides the initial simulation data. It is important to highlight that once the FLP is solved, the APL network obtained as a result has an impact in the estimation of the future demand of the system dynamics simulation model. This impact is the effect of APL proximity, which increases exponentially both the number of people willing to use APLs and the number of purchases per customer per week. This effect is formulated within the System Dynamics simulation model as described in Equation 1:

$$\varphi_{ijt} = 1 + e^{-dl_{ij}}, \forall i \in \mathscr{I}, \forall j \in \mathscr{J} : t > 0 \tag{1}$$

Where dl_{ij} is the distance from a customer node $j \in \mathscr{J}$ to an available (located) locker $i \in \mathscr{I}$ in any nonzero time t. Therefore, the actual presence of an APL nearby a potential customer, encourages an e-shopper to become an APL user and the closer a locker is installed the greater is its shopping frequency.

The dynamics of the simulation starts with initial data of the population, internet users, eShoppers, APL users, and parcel purchases that feed the first facility location problem. As a consequence, the initial APL network in the city is created. Parallelly, these variables begin to evolve according to the expected growths through the System Dynamics model on a weekly basis. Every month, the FLP is launched considering the simulated data at that point and feed-backing the simulation model by determining the optimal number and location of APLs. This new APL network affects the forthcoming demand, as the availability of APLs

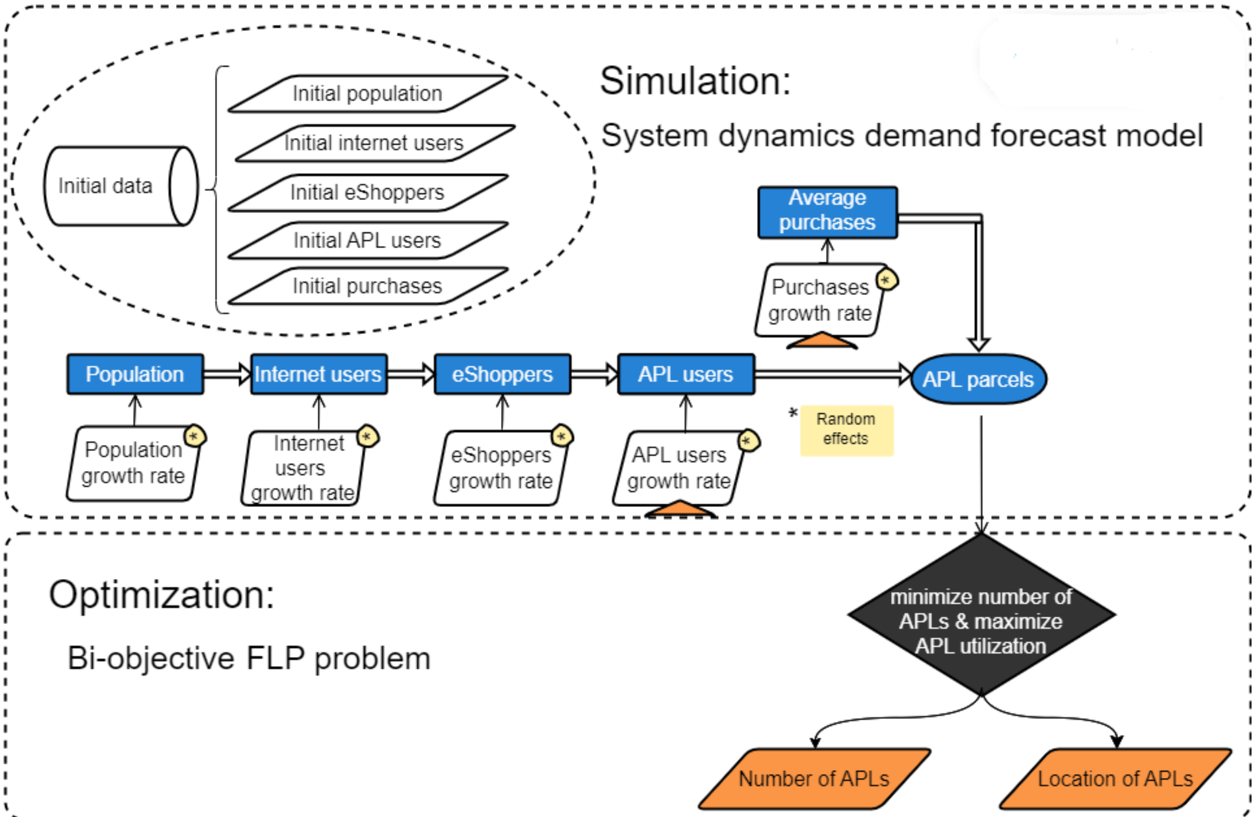

Figure 1: Simulation-Optimization framework flowchart.

nearby positively impacts the number of APL users and the online purchases, as it is described in Equations 1 and Figure 1. This allows to achieve a deeper integration of the simulation-optimization framework, due to the effect of the solution of the optimization model on the simulation model's solution.

3.2 The Facility Location Model

The FLP integrated within the simulation framework seeks finding the optimal APL location network and assigning the customers to the installed APLs such that two objectives are met: Firstly, minimum number of lockers is desired, which is a analogy of minimizing the cost. Secondly, the maximization of utilization of lockers is pursued, willing to cover the maximum demand of parcels of the system. This is solved using IBM®ILOG CPLEX 12.6.2 API for the Java Environment solver and it is defined over the same set of nodes $i \in \mathscr{I}$ and $j \in \mathscr{J}$ for APL potential locations and demand points, respectively.

Therefore, the FLP is defined by Equations (2) - (10) with variables and parameters described in Tables 1 and 2, respectively.

Table 1: Model variables.

Variable	Description
x_{ij}	1 if customer node $j \in \mathscr{J}$ is assigned to APL located at node $i \in \mathscr{I}$, 0 otherwise
y_i	Number of APLs located at node $i \in \mathscr{I}$

Table 2: Model parameters.

Parameter	Description
ε	Level of the coverage of total demand
$maxDist$	Maximum distance a customer is up to travel to pick up its parcel
$maxNL$	Maximum number of APLs that can be installed at the same location node $i \in \mathscr{I}$
dl_{ij}	Distance from customer node $j \in \mathscr{J}$ to an APL location $i \in \mathscr{I}$
c_{ij}	1 if distance dl_{ij} from customer node $j \in \mathscr{J}$ to an existing APL in location $i \in \mathscr{I}$ is smaller than $maxDist$ and 0 otherwise
d_j	Number of parcel demand of customer node $j \in \mathscr{J}$
$\hat{y}_{i,(t-1)}$	Number of previously existing APL installed at location node $i \in \mathscr{I}$
a_i	APL capacity at location $i \in \mathscr{I}$

$$Min \quad \sum_{i \in \mathscr{I}} y_i \tag{2}$$

subject to

$$\sum_{\substack{i \in \mathscr{I} \\ j \in \mathscr{J}}} d_j c_{i,j} x_{i,j} \geq \varepsilon \sum_{j \in \mathscr{J}} d_j \tag{3}$$

$$M \sum_{j \in \mathscr{J}} c_{i,j} x_{i,j} \geq y_i, \quad \forall i \in \mathscr{I} \tag{4}$$

$$c_{i,j} x_{i,j} \leq y_i, \quad \forall i \in \mathscr{I}, \forall j \in \mathscr{J} \tag{5}$$

$$\sum_{j \in \mathscr{J}} d_j c_{i,j} x_{i,j} \leq a_i y_i, \quad \forall i \in \mathscr{I} \tag{6}$$

$$y_i \geq \hat{y}_{i,(t-1)}, \quad \forall i \in \mathscr{I} \tag{7}$$

$$\sum_{i \in \mathscr{I}} c_{ij} x_{ij} \leq 1, \quad \forall j \in \mathscr{J} \tag{8}$$

$$x_{ij} \in \{0,1\}, \quad \forall i \in \mathscr{I}, \forall j \in \mathscr{J} \tag{9}$$

$$y_i \in [0, maxNL] \subset \mathbb{Z}^+, \quad \forall i \in \mathscr{I} \tag{10}$$

Minimum utilization for a given demand is accomplished by setting $\varepsilon \in (0,1)$ as the portion of total demand that is desired to be met. This is defined in constraint (3) and it implies that not all demand nodes will necessarily be assigned to a locker, but some of the demand will be unattended. Constraints (4) and (5) ensure that whenever a demand point is assigned to a potential location, a locker must be installed in that location. M stands for a sufficiently large number - highest estimation. Constraint (6) guarantees that the installed capacity is sufficient to meet the total demand assigned in a given location. Since fixed lockers are considered in this problem setting, the number of lockers installed in a location is kept from one period to another, as stated in constraint (7). Constraint (8) ensures that only a single locker is assigned to a customer, if assigned. Finally, expressions (9) and (10) define the variable ranges, where the maximum number of APLs that can be installed in a potential location is defined. Note that the binary parameter c_{ij} is used to force the FLP to only assign potential APL nodes to client nodes that are within a distance $maxDist$, since this is the maximum distance a customer is up to travel to pick up its parcel. Otherwise, the APL cannot be assigned to a customer.

3.3 Demand Forecast System Dynamics Model

Following the methodological approach of Forrester (1968), the system dynamics model elements are identified. This model is applied to each of the demand points $i \in \mathscr{I}$ of the city in order to calculate the parcel demand allocated to APLs. As a first step, the model is featured as a Causal Loop Diagram (CLD) where all the interdependences of the APL system are shown, from stocks and flows to the feedback structures (Figure 2) that are summarized as follows:

- Population. It is the stock of population of each demand node i on a district basis. This variable grows as a consequence of the population rate.
- Internet users. It is the stock that emulates the amount of people of the population that uses internet weekly, that is based on the share of internet uses and varies with the flow of internet users rate.
- Online shoppers. It is the portion of the internet users who order online, which evolves with the flow affected by the both internet users and eShoppers rate.
- APL users. It is the portion of eShoppers that choose APLs as delivery method. Likewise, it varies with the flow of APL users rate, affected by the number of eShoppers and its own growth rate.
- Online purchases per week. It is the stock that represents the average number of online purchases that an individual online shopper makes in the demand node i. It is varied by the flow online purchase rate, that depends on the purchase growth rate and the initial number of online purchases.
- Number of e-commerce parcels. Total number of parcels in the given demand node i.
- Number of parcels using APLs. This is the number of orders place by an APL user.

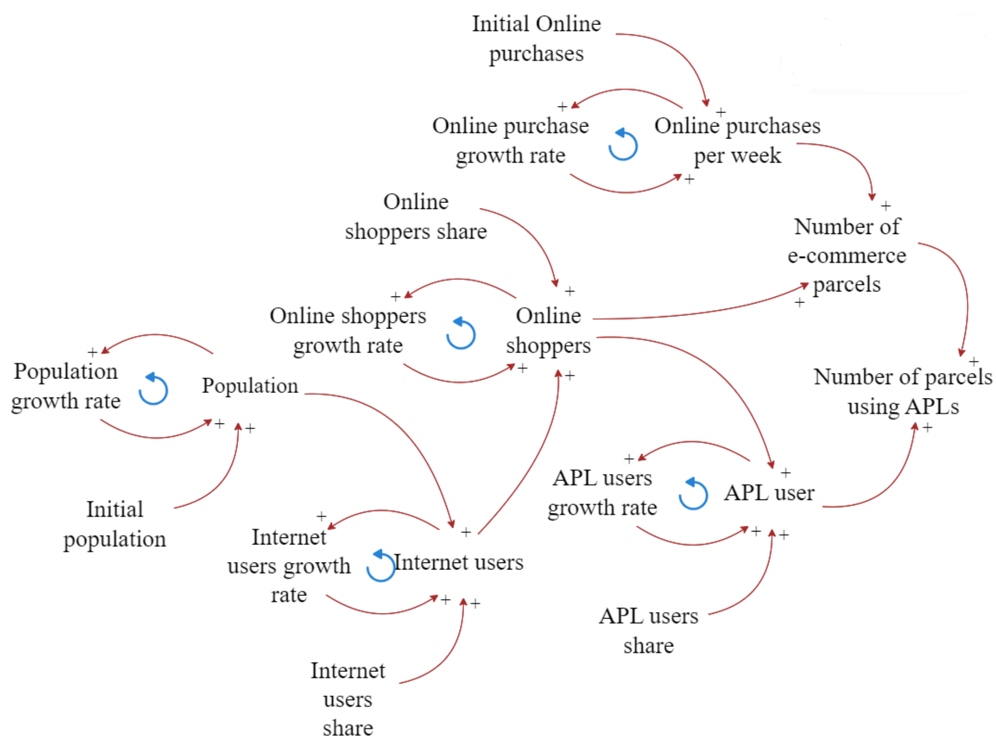

Figure 2: Causal Loop Diagram of the demand forecast System Dynamics model.

As shown in the CLD, the population is positively affected by the initial population and its growth rate. Similarly, internet users are positively influenced by the internet users share, its growth rate and internet users themselves. Internet users positively reinforce online shoppers, as online shoppers share and growth rate do. The number of e-commerce purchased parcels is correspondingly positively reinforced by purchases per week, the growth rate of online purchases and online shoppers. Finally, the number of parcels using APLs is positively reinforced by the number of parcels and APL users, which is previously positively affected by the number of e-shoppers, APL user growth rate and the APL users share.

The random effects shown at Figure 2 correspond to a uniform random variable η in the interval $[a,b]$ ($\eta \sim \mathscr{U}[a,b]$) that affect to the growth rates of all the flows of the system dynamics model. Moreover, the population of each demand node is calculated with a random variable for historical population growth of the city based on a time series analysis using historical data for the last 24 years (Foro-Ciudad. 2021) in the city of Pamplona. This shows that population growth rate follows a $Weibull(\lambda,\kappa)$ distribution with $\lambda = 1.24252$, and $\kappa = 0.01646$. Additionally, the effect of proximity φ_{ij} is applied on both APL users growth rate and the online purchases growth rate, since they are considered to be the most affected factors of customer behavior due to an APL nearby. Additionally, it is worth mentioning that the effect of locker vicinity in customer behavior is implemented in the system dynamics model, achieving a deeper integration of the simulation-optimization framework.

4 COMPUTATIONAL EXPERIMENTS

4.1 Parameter Setting

The model is tested in Pamplona (Spain), for a weekly 3 year time horizon, i.e., $|\mathscr{T}| = 151$. The total population considered for metropolitan area of Pamplona is of 221846 inhabitants. This population is distributed in 184 demand nodes (i.e. $|\mathscr{J}| = 174$), which correspond to urban bus stops that are homogeneously distributed across the 13 districts of the city. Accordingly, supermarkets, gas stations and shopping malls were chosen as potential nodes for siting APLs, selecting a total of $|\mathscr{I}| = 85$ possible APL locations inside the city and in the nearby towns. Driving distances between this two sets of nodes were computed by an API for BingMaps. All the data related to Pamplona necessary to conduct the simulation-optimization analysis was retrieved from related literature (Rabe et al. 2021) for simplicity reasons. Initial values of the parameters used in the simulation-optimization model are available in Table 3. Yearly growth rates are translated into weekly growths by week = $\sqrt[52]{1+year}-1$ and lockers are assumed to have similar size to typical Amazon lockers, which have 10 parcel locker units. Additionally, it is considered that at most 10 locker units can be installed together at a potential location node $i \in \mathscr{I}$ (i.e. $maxNL = 10$). Finally, we assume that the maximum distance a customer is up to travel to pick its parcel up from a APL is 4.5 km (i.e. $maxDist = 4.5$).

Table 3: Initial values (at $t = 0$) for simulation.

Parameter	Description	Initial value
$population_{j0}$	Current inhabitants per demand node $j \in \mathscr{J}$	
$InternetUsers_{j0}$	Current internet users per demand node $j \in \mathscr{J}$	$0.936 population_{j0}$
$eShoppers_{j0}$	Current e shoppers per demand node $j \in \mathscr{J}$	$0.675 InternetUsers_{j0}$
$APLusers_{j0}$	Current APL users per demand node $j \in \mathscr{J}$	$0.022 APLusers_{j0}$
$AvPurchases_{j0}$	Average purchases per week done per demand node $j \in \mathscr{J}$	1.00
α_{j0}	Yearly population growth rate in demand node $j \in \mathscr{J}$	$A \sim \mathscr{W}(1.24, 0.016)$
β_{j0}	Yearly internet users growth rate in demand node $j \in \mathscr{J}$	0.10
γ_{j0}	Yearly e shoppers growth rate in demand node $j \in \mathscr{J}$	0.10
ν_{j0}	Yearly parcel demand growth rate in demand node $j \in \mathscr{J}$	0.20
δ_{j0}	Yearly APL users growth rate in demand node $j \in \mathscr{J}$	0.15

5 RESULTS

The solution of the bi-criteria FLP is obtained with the ε-constraint method, where the factor ε is defined as the level of coverage of total demand (i.e. $\varepsilon \in [0,1]$). Based on a real-world case from the city of Pamplona, a set of experiments considering a three years planning horizon has been tested. The simulation-optimization model is run for different values of this factor ($\varepsilon = 0.25, 0.50, 0.75, 0.90$) , considering in each case that at least that percentage of the total demand must be covered with the obtained APL network.

5.1 Demand Analysis

A standard scenario of demand was selected to test the simulation-optimization model, where servicing demands are considered to be random variables that evolve over time. For all experiments , the expected total demand of the system shows an increasing rate, although the shape is maintained every year, having its peak before every Christmas (mid December) ($t = 45, 90, 135$). When it comes to the actual assigned demand, results start to differ from one experiment to another as the coverage of demand fits strictly the utilization constraint (3). For instance, as shown in Figure 4, in the case where $\varepsilon = 0.5$, the assigned and unassigned demand evolve together being 50 % of the total parcel demand. In all cases, the coverage reached in the network at the end of the simulation is greater than the one required in the utilization constraint, i.e. for $\varepsilon = 0.25$ a 27.5 % coverage is obtained, for $\varepsilon = 0.5$ a 52.6 %, $\varepsilon = 0.75$ a 83.3 % and finally for $\varepsilon = 0.9$ a 93.1 %. In the maximum coverage experiment, a total of 9,895 parcels are attended in the last week, being the highest demand attendance during the last Christmas period (mid December) ($t = 145$) considered in the simulation time.

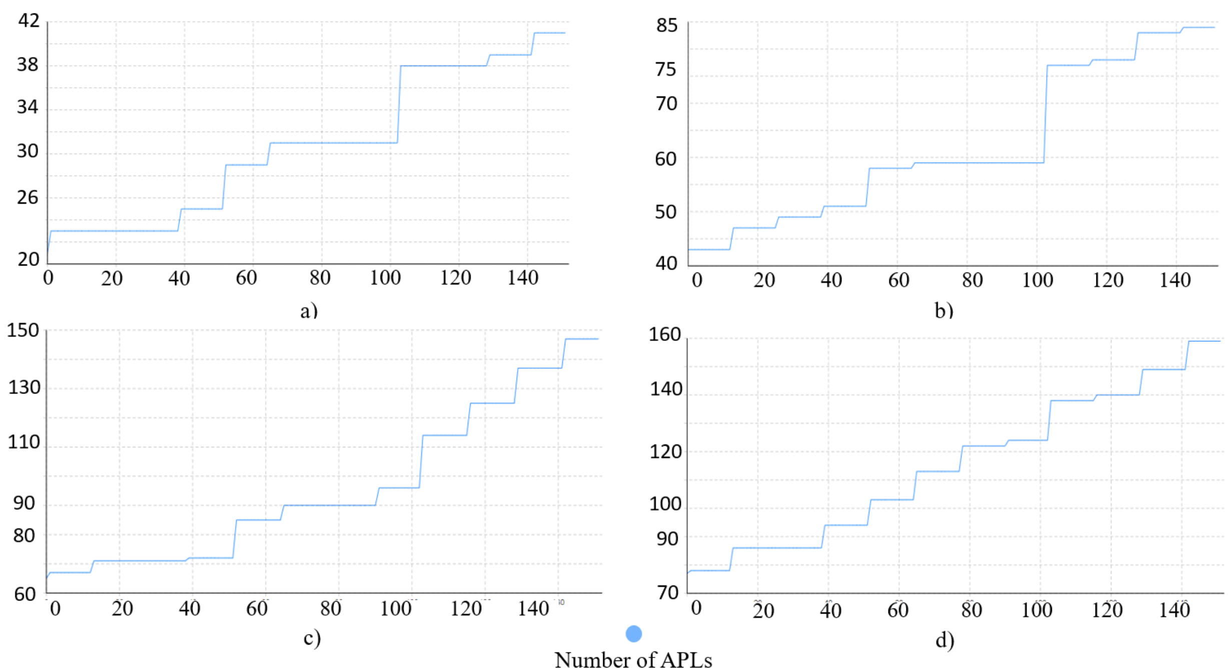

Figure 3: Number of installed APL evolution during the simulation in a three-year time horizon for Pamplona APL network for a) $\varepsilon = 0.25$, b) $\varepsilon = 0.50$, c) $\varepsilon = 0.75$, and d) $\varepsilon = 0.90$.

5.2 APL Network Analysis

The results show that the number of APLs that compose the network follow the same tendency of demand, increasing step-wise according to the number of parcels that must be attended in the system and the desired

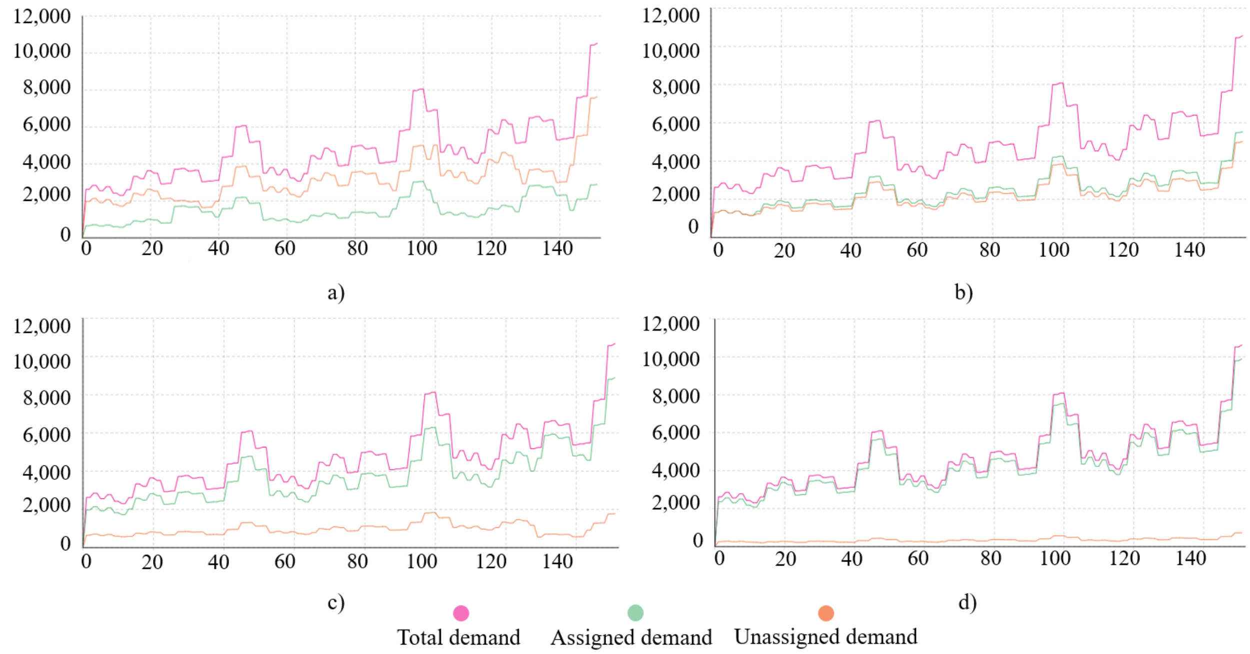

Figure 4: Parcel demand evolution during the simulation in a three-year time horizon for Pamplona APL network for a) $\varepsilon = 0.25$, b) $\varepsilon = 0.50$, c) $\varepsilon = 0.75$ and d) $\varepsilon = 0.90$.

coverage. This shape agrees with the fact that the APLs are considered to be fixed once installed, therefore the potential demand that can be attended is accumulated in the existing APLs. Given a different coverage constraint, the final number of APLs in the network changes as expected. As seen in Figure 3, for 25 % coverage experiment, a network of 41 APLs is built to cover 2,900 parcels, while in the 75 % coverage experiment a total of 147 APLs are installed to attend 8,898 parcels. Similarly, for the 50 % coverage experiment 84 APLs are needed for 5,540 parcels and lastly, in 90 % coverage experiment a total of 9,894 parcels are assigned to 159 APLs.

Figure 6 shows the APL network obtained from each experiment, where the potential customer nodes are depicted as white dots and the installed APLs show up in yellow once the FLP problem is solved and an APL is installed. Similarities can be identified in the obtained results, as in all cases the lockers are dispersed homogeneously throughout the city, covering all the districts. It is important to emphasize that in the smallest coverage experiment (25 %), lockers are installed neither in the outskirts nor the outermost districts of the city. On the contrary, as the the desired demand coverage increases, the higher is the number of APLs in the outskirts. This fits the constraint of only assigning lockers to customers that are at a maximum distance of 4.5 km, as stated in Table 2.

5.3 Bi-criteria Problem Analysis

The model was run increasing the value of ε by 0.05 in each run, obtaining as results the final number of APLs that will form the network and the satisfied demand at the end of the simulation. Thus, the set of non-dominated Pareto solutions are displayed in Figure 5. This corresponds to the Pareto front for the bi-objective FLP problem, where a trade-off between satisfied demand and the number of lockers in the network, and therefore the cost of building the network is obtained.

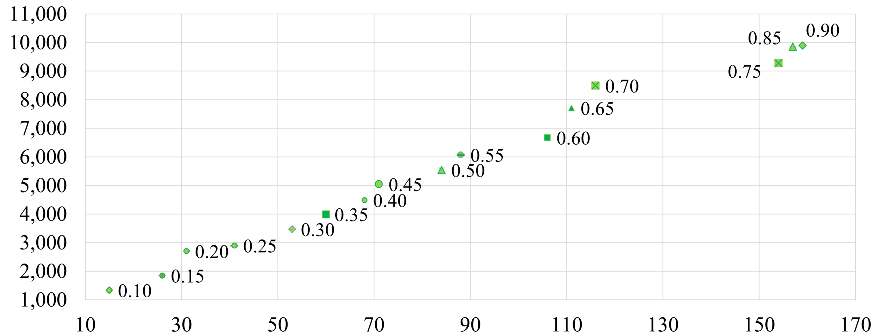

Figure 5: Pareto front for the bi-objective Facility Location Problem at $t = 151$ for a selection of ε values.

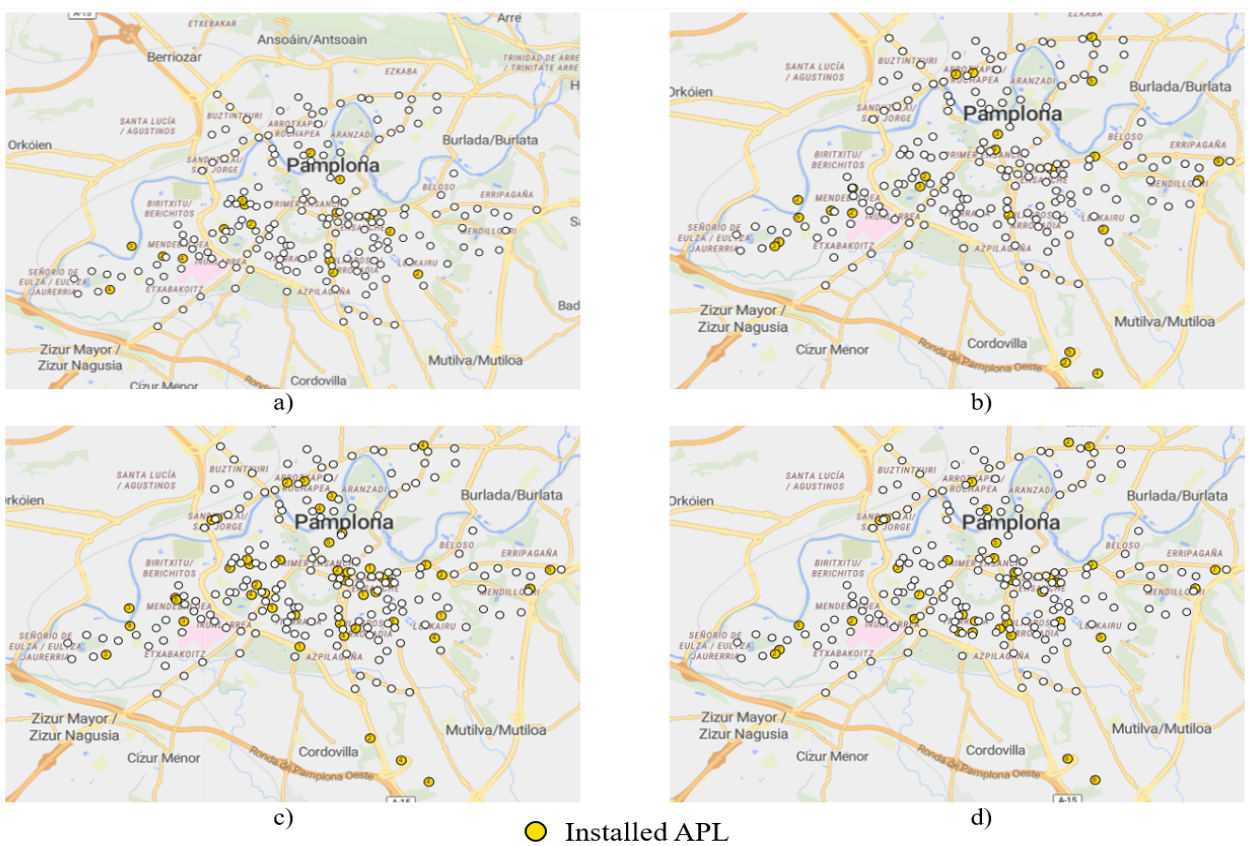

Figure 6: Satellite view of the APL network at the end period of simulation ($t = 151$) in Pamplona for a) $\varepsilon = 0.25$, b) $\varepsilon = 0.50$, c) $\varepsilon = 0.75$, and d) $\varepsilon = 0.90$.

6 CONCLUSIONS

With the aim of determining the optimal number, location and the assignment of automated parcel lockers in a network in a three-year time horizon, this paper has proposed the use of an integrated simulation-optimization approach that combines system dynamics with exact optimization. A list of conclusions can be drawn after the analysis:

1. *Increase of the level of detail in the demand data*: Thus, the consideration of individual customers' demands instead of aggregated in districts, notably improves the quality and details of the obtained results. An example of this situation is the capability of obtaining graphical results of the network, being able to locate the APLs on their exact coordinates in a Pamplona interactive map (Figure 6).
2. *Demand forecast by means of System Dynamics simulation*: The development of a model to forecast the demand allows to control this process in a more accurate way. This analysis gives more convenient results than other simulation approaches for estimating flows of people with individual behaviors.
3. *Outcome of the performed experiments*: After experimentation it is clearly observed, in a reasonable computational time, that the rise of e-shoppers and the purchase rate, increases the APL usage. As it is understood by intuition, the number of lockers and the parcel demand are directly proportional, such that the higher the demand that is desired to cover, the greater the number of APLs in the network. Besides, it is important to notice that alternative optimal solutions are obtained from the FLPs, so that the number of APLs is kept, while their location in the network varies.
4. *Considering multi-criteria approach*: The non-dominated solution set of bi-criteria mathematical programming model is gained by the parametrization of ε, and leads to the Pareto Frontier - a trade-off between number of lockers and parcel demand satisfied. We propose a decision support optimization model that will design an APL network for a desired demand satisfaction of the decision maker.
5. *Enhancement of simulation-optimization methodology*: The APL user proximity effect considered in the hybrid model has proven that the results obtained in the optimization model strictly influence the results of the simulation model.

Finally, the potential of merging simulation and optimization techniques to handle difficult real-world problems is being investigated along this contribution and this paper has shown that a hybrid model is a suitable procedure to properly address complex optimization problems in urban logistics. Moreover, it has been shown that the use of system dynamics is beneficial for real-life feature simulation, particularly when considering correlated demands of individual customers. The future work should overcome the main limitation of this research which is the parameter tuning, followed by advanced statistical methods for better estimating the socioeconomic parameters that describe the parcel demand system and APLs network.

ACKNOWLEDGMENTS

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REFERENCES

Abdullahi, H., L. Reyes-Rubiano, D. Ouelhadj, J. Faulin, and A. A. Juan. 2021. "Modelling and Multi-Criteria Analysis of the Sustainability Dimensions for the Green Vehicle Routing Problem". *European Journal of Operational Research* 292(1):143–154.

Bonomi, V., R. Mansini, and R. Zanotti. 2022. "Last Mile Delivery with Parcel Lockers: Evaluating the Environmental Impact of Eco-conscious Consumer Behavior". *IFAC-PapersOnLine* 55(5):72–77.

Cano, J. A., A. Londoño-Pineda, and C. Rodas. 2022. "Sustainable Logistics for E-Commerce: A Literature Review and Bibliometric Analysis". *Sustainability* 14(19):12247.

Che, Z.-H., T.-A. Chiang, and Y.-J. Luo. 2022. "Multiobjective Optimization for Planning the Service Areas of Smart Parcel Locker Facilities in Logistics Last Mile Delivery". *Mathematics* 10(3):422.

De La Torre, G., T. Gruchmann, V. Kamath, A. Melkonyan, and K. Krumme. 2019. "A System Dynamics-Based Simulation Model to Analyze Consumers' Behavior Based on Participatory Systems Mapping – A Last Mile Perspective". In *Innovative Logistics Services and Sustainable Lifestyles: Interdependencies, Transformation Strategies and Decision Making*, edited by A. Melkonyan and K. Klaus Krumme, 165–194. Cham: Springer International.

Faulin, J., S. Grasman, A. Juan, and P. Hirsch. 2019. *Sustainable Transportation and Smart Logistics: Decision-Making Models and Solutions*. Elsevier, Cambridge, MA.

Foro-Ciudad. 2021. "Evolución de la Población desde 1900 hasta 2020". https://www.foro-ciudad.com/navarra/pamplona-iruna/, in Spanish. Online; accessed 15th April 2023.

Forrester, J. W. 1968. "Industrial Dynamics – After the First Decade". *Management Science* 14(7):398–415.

Kahr, M. 2022. "Determining Locations and Layouts for Parcel Lockers to Support Supply Chain Viability at the Last Mile". *Omega* 113:102721.

Lin, Y., Y. Wang, L. H. Lee, and E. P. Chew. 2022. "Profit-Maximizing Parcel Locker Location Problem under Threshold Luce Model". *Transportation Research Part E: Logistics and Transportation Review* 157:102541.

Maggi, E., and E. Vallino. 2016. "Understanding Urban Mobility and the Impact of Public Policies: the Role of the Agent-Based Models". *Research in Transportation Economics* 55:50–59.

Mehdizadeh, M., T. Nordfjaern, and C. A. Klöckner. 2022. "A Systematic Review of the Agent-Based Modelling/Simulation Paradigm in Mobility Transition". *Technological Forecasting and Social Change* 184:122011.

Rabe, M., J. Gonzalez-Feliu, J. Chicaiza-Vaca, and R. D. Tordecilla. 2021. "Simulation-Optimization Approach for Multi-Period Facility Location Problems with Forecasted and Random Demands in a Last-Mile Logistics Application". *Algorithms* 14(2):41.

Ranjbari, A., C. Diehl, G. Dalla Chiara, and A. Goodchild. 2023. "Do Parcel Lockers Reduce Delivery Times? Evidence from the Field". *Transportation Research Part E: Logistics and Transportation Review* 172:103070.

Sawik, B., J. Faulin, and E. Pérez-Bernabeu. 2017b. "A Multicriteria Analysis for the Green VRP: A Case Discussion for the Distribution Problem of a Spanish Retailer". *Transportation Research Procedia* 22:305–313.

Sawik, B., J. Faulin, A. Serrano-Hernandez, and A. Ballano. 2022a. "A Simulation-Optimization Model for Automated Parcel Lockers Network Design in Urban Scenarios in Pamplona (Spain), Zakopane, and Krakow (Poland)". In *Proceedings of the 2021 Winter Simulation Conference*, edited by B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C. Corlu, L. Lee, E. Chew, T. Roeder, and P. Lendermann, 1648–1659. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Sawik, B., A. Serrano-Hernandez, A. Muro, and J. Faulin. 2022b. "Multi-Criteria Simulation-Optimization Analysis of Usage of Automated Parcel Lockers: A Practical Approach". *Mathematics* 10(23):4423.

Serrano-Hernandez, A., S. Martinez-Abad, A. Ballano, J. Faulin, M. Rabe, and J. Chicaiza-Vaca. 2021. "A Hybrid Modeling Approach for Automated Parcel Lockers as a Last-Mile Delivery Scheme: A Case Study in Pamplona (Spain)". In *Proceedings of the 2021 Winter Simulation Conference*, edited by S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo, and M. Loper, 1–12. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Thaller, C., F. Niemann, B. Dahmen, U. Clausen, and B. Leerkamp. 2017. "Describing and Explaining Urban Freight Transport by System Dynamics". *Transportation Research Procedia* 25:1075–1094.

Wang, Y., Y. Zhang, M. Bi, J. Lai, and Y. Chen. 2022. "A Robust Optimization Method for Location Selection of Parcel Lockers under Uncertain Demands". *Mathematics* 10(22):4289.

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