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A HYBRID MODELING APPROACH FOR AUTOMATED PARCEL LOCKERS AS A LAST-MILE DELIVERY SCHEME: A CASE STUDY IN PAMPLONA (SPAIN)

Adrian Serrano-Hernandez
Sergio Martinez-Abad
Aitor Ballano
Javier Faulin

Institute of Smart Cities
Public University of Navarra
Campus Arrosadia, s/n
Pamplona, 31006, SPAIN

Markus Rabe
Jorge Chicaiza-Vaca

Department of IT in Production and Logistics
Technical University Dortmund
Leonhard-Euler-Str. 5
Dortmund, 44227, GERMANY

ABSTRACT

Recently, last-mile distribution in cities has been constrained by fast-delivery options, hard time windows, and no-show-up customers. The promotion of automated parcel locker (APL) systems is seen as a way to mitigate the aforementioned problems. Thus, this paper analyzes APL users in the city of Pamplona (Spain), and proposes the use of hybrid modeling for APL network design. Moreover, agent-based modeling is used to estimate future demand based on a number of socio-economic parameters, i.e., population, e-commerce growth rates, among others. Likewise, the APL location optimization model is dynamically executed within the simulation framework to minimize the operational and service costs. Our hybrid methodology forecasts an increase of eShoppers by 10%, while the number of APLs increases up to 500% in a 3-year time horizon. In light of those results, the use of simulation and optimization tools leverages the promotion of APLs as a last-mile distribution scheme.

1 INTRODUCTION

Urban Logistics (UL) is becoming increasingly important due to the global rise of e-commerce with home deliveries of small but frequent orders from consumers. Alternative delivery methods have been on the radar of researchers and delivery companies for years (Sawik et al. 2017). Technological breakthroughs on electrical vehicles are helping to reduce energy consumption and the accumulation of pollutants in cities, but still contribute to traffic accidents and congestion, which is expected to increase by 50 % until 2050 (European Commission 2011). The introduction of self-collection delivery systems (SCDS) is an innovation for last mile delivery (LMD) operations in urban areas and brings new benefits. SCDS have been developed in response to the current UL systems to streamline LMD. The main benefits of SCDS are fewer failed home deliveries, improved order fulfilment, consolidated freight, reduced overall mileage and greenhouse gas emissions, and mitigated road congestion (Yuen et al. 2018). APLs, also referred to as smart lockers, self-pickup lockers, or parcel lockers, are the evolution of receiving boxes, delivery boxes, and pickup points, which have been earlier developments in SCDS (Allen et al. 2007).

Hence, this work proposes the use of a hybrid formulation approach that combines an Agent-Based Modeling (ABM) with an adapted Facility Location Problem (FLP) for APL systems as a last-mile delivery scheme. The analysis is based on the city of Pamplona (Spain) as a real case study. Like other modeling approaches, the ABM technique has advantages, but also important limitations. The ABM was chosen as the modeling method, because the main component for using APLs is people. These people can be managed as agents who make their online purchases using a APL as a delivery scheme. Nevertheless, the problem can also be designed using other simulation techniques, subject to their respective assumptions. In

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our case, we designed an ABM to determine the three-year performance (divided into weeks) to estimate the future demand based on a number of socio-economic parameters. Then, these results are incorporated into an FLP that provides the optimal number and location of APLs. To deal with demand uncertainty, different scenarios have been considered and solved using exact methods.

This paper builds upon previous contributions to the Winter Simulation Conference and to *Algorithms* (Rabe et al. 2020b, Rabe et al. 2021), where integrated models of APLs have been studied at the example of the city of Dortmund (Germany). With respect to the optimization, the simulation framework integrates a FLP optimization model for defining the APL network, i.e., selecting the number and location of APLs over time. The presented hybrid approach has shown that simulation and optimization mutually benefit from each other. From the application side, the novelty of this paper lies in the application for a different city, namely Pamplona (Spain), which has about one third of Dortmund's population. From the methodological point of view, the method is enriched by introducing the use of mobile APLs, i.e., a number of APLs can be relocated according to the demand. Furthermore, the effect of having APLs nearby available on the growth rate of APL users is investigated by intertwining the simulation and optimization models in such a way that the optimization outputs will affect the simulation inputs and vice-versa.

The paper is organized as follows. After this introduction, Section 2 presents the relevant literature about mobile APLs and simulation-optimization models. Section 3 describes the proposed methodology, where the simulation and the optimization models are introduced. Section 4 presents the main findings of our research. Finally, Section 5 concludes the paper and draws future research directions.

2 RELATED WORK

In this section, we present an analysis of the literature related to the two main innovations addressed by the proposed methodology. On the one hand, some applications of APLs as LMD scheme are discussed. On the other hand, the ABM applied to UL initiatives are also presented. In addition, recent works on APLs location design are presented.

2.1 Applications and Benefits of APL Systems

Iwan et al. (2016) examined the acceptance of APLs by Polish citizens, looking at the strengths related to ease of use and location. The authors found that location is the main factor in customer acceptance. Similarly, Moroz and Polkowski (2016) analyzed the connection between APLs and the environment for the Y generation. The main finding is that convenience for receiving is more important than environmental considerations. However, some customers would pay higher prices for cleaner delivery methods. Collins (2015) finds that shorter distances to APLs can lead to a modal shift from cars to cleaner transportation. The reduced number of trips could lead to environmental benefits and a reduction in driven vehicle kilometers. Keeling et al. (2020) explore the potential of APL in various transportation facilities in Portland (OR, USA). Proactive development of a public and private partnership with logistics companies is suggested, as different benefits are observed in the available facilities. Thus, using APLs, emissions are reduced by 97 %, traffic congestion is avoided, and time window constraints are reduced.

2.2 Agent-Based Modeling for Urban Logistics Initiatives

On an abstract level, ABM is a representation of agents and their interactions with each other. The agents can mirror organisms, people, companies, institutions, or any other entities that want to pursue a particular goal (Abar et al. 2017). There is no clear definition of the term "agent". Researchers have quite different points of view on the term ABM, constantly debating whether the definition should be made by the application or the agent environment. However, definitions tend to agree on more points than they disagree (Macal and North 2010). ABM can be an effective tool capable of describing the behavior of an agent or a group of homogeneous agents and their relationships. ABM allows for assigning different characteristics, decision-making processes, and goals to each agent. The literature review of specific applications of ABM has shown that only a few of them focus on UL issues (Maggi and Vallino 2016). For example, Tamagawa et al. (2010) analysed the interaction between shippers, forwarders, administrators, and residents by using multi-agent models with reinforcement learning for the evaluation of logistics measures in the city. They pointed out that win-win situations for stakeholders are possible when restrictions on truck flow and common delivery systems are implemented. Similarly, Suksri and Raicu (2012) developed a framework for modelling the dynamic behavior of different participants in urban freight distribution to enable the evaluation of different strategic measures.

2.3 Automated Parcel Lockers Location Design

Two main streams for APL configurations were first introduced by Dell'Amico and Novellani (2017): monolithic bank and modular bank. These design concepts were further developed by Faugère and Montreuil (2017) extending the concept into four design schemes: fixed configuration, modular tower, modular locker, and Physical Internet handling container. In a recent study, Faugère and Montreuil (2020) propose a design method for APL systems in an omnichannel supply chain environment. The authors compare two conceptual designs: a fixed configuration and modular tower-based trains. Their approach incorporates a multi-stakeholder perspective that deals with uncertainty through a set of probabilistic scenarios to maximize expected profit. From a macro-location perspective, Rabe et al. (2020a), Rabe et al. (2020b), and Rabe et al. (2021) study the use of fixed APLs in the city of Dortmund combining simulation and optimization models to represent different scenarios and enabling better support to APL macro localization optimization as a tool for UL. In these papers, a system dynamic simulation model is used to find interdependencies and KPIs for the problem. A multiperiod capacitated FLP is solved as an optimization model, and Monte Carlo simulation (MCS) uses simulation experiments as a tool to estimate cost and reliability of different plausible solutions. From the micro-location point of view, Deutsch and Golany (2018) study the optimal location and size of fixed APL, proposing a first quantitative approach to solve an APL location problem. In this model, deterministic customer decisions are assumed and the objective of the algorithm is to maximize the operator's profit. Moreover, Schwerdfeger and Boysen (2020) analyze the dynamic location model of mobile APLs. As an assumption for model development, the APL's location can change at any moment, optimizing locations. The objective is to minimise the number of mobile APLs while having sufficient service available to customers.

3 METHODOLOGY

Hybrid modeling approaches reflect the complexity of real systems and combine different modeling approaches to solve complex system problems (Martinez-Moyano and Macal 2016). By combining different modeling approaches, a hybrid model could provide a holistic view of the system and a very powerful approach to understand the complexity of systems like UL. In our case, we combine an agent-based modeling approach with an adapted FLP for APL systems. The analysis is based on the city of Pamplona (Spain) as a real world case study. Firstly, an agent-based model (ABM) is designed to determine the three-year performance (divided into weeks) to estimate the future demand based on a number of socio-economic parameters. Then, these results are integrated into a facility location model, which provides the optimal number and location of APLs. An overview of the simulation-optimization framework is shown in Figure 1, which will be discussed in the following subsections.

3.1 The Simulation Model

The simulation model was implemented in Anylogic 8.7.3 (AnyLogic 2021) using an agent-based modeling approach over city district nodes $i \in \mathscr{I} = \{1,2,3,...,I\}$, customer nodes $j \in \mathscr{J} = \{1,2,3,...,J\}$, and time $t \in \mathscr{T} = \{0,1,2,...,T\}$.

The simulation starts with given initial values at $t = 0$ related to the population, eShoppers, APL users, and parcel demands. The simulation is built using the districts as the basic agents. Therefore, the previous

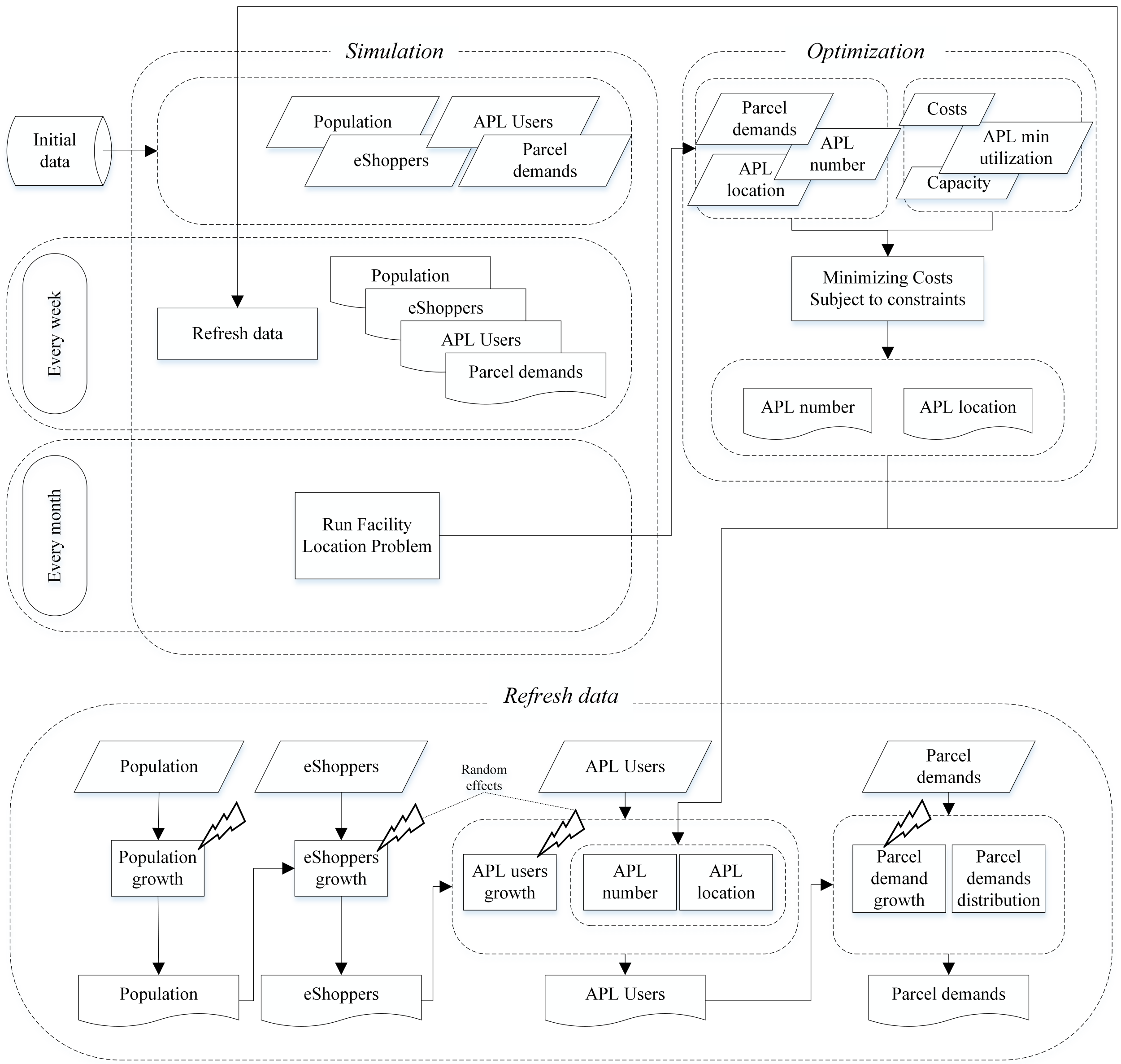

Figure 1: The Simulation–Optimization framework.

magnitudes are referred to each district $i \in \mathscr{I}$. Afterwards, these data are updated on a weekly basis for population, eShoppers, APL users, and parcel demands following the procedure described at the bottom of the Figure 1:

$$population_{it} = population_{i,t-1}\alpha_{it}\varepsilon, \forall i \in \mathscr{I}, \forall t \in \mathscr{T} : t > 0$$

$$eShoppers_{it} = eShoppers_{i,t-1} + \beta_{it}(population_{i,t-1} - eShoppers_{i,t-1})\varepsilon, \forall i \in \mathscr{I}, \forall t \in \mathscr{T} : t > 0$$

$$APLusers_{it} = APLusers_{i,t-1}\gamma_{it}\varphi_{it}\varepsilon, \forall i \in \mathscr{I}, \forall t \in \mathscr{T} : t > 0$$

$$parcelDemand_{it} = APLusers_{it}\,ppu_{it}\,\delta_{it}\varepsilon, \forall i \in \mathscr{I}, \forall t \in \mathscr{T} : t > 0$$

where α_{it} is a random variable for historical population growth in the city, whereas β_{it}, γ_{it}, and δ_{it} are the growth factors for eShoppers, APL users, and purchases per user, respectively from $t-1$ to t such that $\beta_{it} = \beta_{i,t-1}\varepsilon$, $\gamma_{it} = \gamma_{i,t-1}\varepsilon$, and $\delta_{it} = \delta_{i,t-1}\varepsilon$ $\forall i \in \mathscr{I}, \forall t \in \mathscr{T} : t > 0$. The β_{it} variables need to be adjusted at

$t = 0$ by dividing the real eShoppers yearly growth rate over the eShoppers share initial value. Moreover, ε is a uniform random variable in the interval [a,b] ($\varepsilon \sim \mathscr{U}[a,b]$) that represents the random effects shown at the bottom of Figure 1. Additionally, φ_{it} stands for the effect of APL availability (the number and location of APLs in district i at time t). This effect is formulated in our simulation model as follows: $\varphi_{it} = 1 + \omega \frac{y_i}{\sum_{i \in \mathscr{I}} y_i}, \forall i \in \mathscr{I}, \forall t \in \mathscr{T} : t > 0$ being ω the sensitivity of increasing the number of APL users and y_i the number of APLs available in district $i \in \mathscr{I}$. Furthermore, the purchases per APL user (ppu_{it}) are obtained by combining the average purchases per year and APL user (ppy) with the demand distribution (dd_t) on a yearly basis:

$$ppu_{it} = ppy\ dd_t, \forall i \in \mathscr{I}$$

Finally, every month, the FLP solver procedure 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 process is further detailed in Section 3.2.

3.2 The Facility Location Model

An FLP is integrated within the simulation framework and solved using IBM®ILOG CPLEX 12.6.2 API for the Java Environment solver. This optimization model is defined over the same set of nodes $i \in \mathscr{I}$ and $j \in \mathscr{J}$ representing the districts and customers, respectively. This FLP seeks the optimal location of APLs and assignment of customers to districts hosting APLs in such a way total costs are minimized subject to a number of constraints. In this respect, Table 1 shows the model variables whereas Table 2 shows the model parameters.

Table 1: Model variables.

Variable	Description
x_{ij}	1 if customer $j \in \mathscr{J}$ is assigned to APL located at district $i \in \mathscr{I}$
y_i	Number of APLs located at district $i \in \mathscr{I}$
yIn_i	Number of new APLs set up at district $i \in \mathscr{I}$
$yOut_i$	Number of APLs retired from district $i \in \mathscr{I}$
$h1_i$	Auxiliary variable
$h2_i$	Auxiliary variable

Table 2: Model parameters.

Parameter	Description
c_{ij}	Cost of assigning customer $j \in \mathscr{J}$ to an APL located at $i \in \mathscr{I}$
d_j	Demand of customer $j \in \mathscr{J}$
sc_i	Cost of setting up an APL at district $i \in \mathscr{I}$
dc_i	Cost of decommissioning an APL at district $i \in \mathscr{I}$
uc_i	Cost of keeping working an APL at district $i \in \mathscr{I}$
m	Minimum percentage of an APL capacity utilization
a_i	APL capacity at district $i \in \mathscr{I}$
$y_{i,t-1}$	Number of previously existing APL at district $i \in \mathscr{I}$

Afterwards, the FLP is defined as follows:

$$TotalCosts = \sum_{\substack{i \in \mathscr{I} \\ j \in \mathscr{J}}} c_{ij} d_j x_{ij} + \sum_{i \in \mathscr{I}} sc_i (yIn_i) + \sum_{i \in \mathscr{I}} dc_i (yOut_i) + \sum_{i \in \mathscr{I}} uc_i (y_i) \tag{1}$$

such that,

$$yIn_i = y_i - y_{i,t-1} + h1_i, \forall i \in \mathscr{I} \tag{2}$$

$$yOut_i = y_{i,t-1} - y_i + h2_i, \forall i \in \mathscr{I} \tag{3}$$

$$\sum_{i \in \mathscr{I}} x_{ij} = 1, \forall j \in \mathscr{J} \tag{4}$$

$$Mx_{ij} \geq y_i, \forall i \in \mathscr{I}, \forall j \in \mathscr{J} : i = j \tag{5}$$

$$\sum_{j \in \mathscr{J}} d_j \geq m \sum_{i \in \mathscr{I}} a_i y_i \tag{6}$$

$$x_{ij} \in \{0,1\}, \forall i \in \mathscr{I}, \forall j \in \mathscr{J} \tag{7}$$

$$y_i, yIn_i, yOut_i, h1_i, h2_i \in \mathbb{Z}^+, \forall i \in \mathscr{I} \tag{8}$$

The objective function (1) defines the total costs that comprise the items described in the following lines, beginning with the service costs of assigning costumers to districts where an APL is available. These service costs depend on the distance and demand. The second term represents the costs of setting up the APL and the third one the costs of decommissioning an existing APL. Fourthly, the cost of maintaining an APL from one time period decision to the following is included. Constraints (2) and (3) define the number of new APL to set up and the number of APL to retire, respectively. The auxiliary variables $h1$ and $h2$ are used for each $i \in \mathscr{I}$ in order to fulfill the equations. Constraints (5) force each customer $j \in \mathscr{J}$ to be assigned to a district $i \in \mathscr{I}$ where an APL is available. Similarly, constraints (5) force each customer $j \in \mathscr{J}$ to be assigned to its own district if there is an APL located. M stands for a sufficiently large number. Besides, equation (6) ensures a minimum APL utilization for a given demand, whereas expressions (7) and (8) define the variable ranges. Finally, this FLP is solved at given time periods t according to the planned horizon.

3.3 Limitations

Nevertheless, our results are based on a number of assumptions and limitations. Firstly, data quality can be improved to obtain a better estimate of the parameters in our models. This in particular applies to those related to the growth of eShoppers and APL users, as these are highly volatile values and depend on many uncontrollable factors. Secondly, our model updates the data on a weekly basis from annual magnitudes. This implies that the increases are homogeneously distributed over the weeks, which is not always the case. Similarly, the FLP is started each month with the data available at that time. This implies that APL companies can change their APL-related decisions every month, and this time can be longer or shorter.

4 COMPUTATIONAL EXPERIMENTS

4.1 Parameter Setting

The model is tested in the city of Pamplona, in Northern Spain, for a time horizon of 3 years divided in weeks, i.e., $|\mathscr{T}| = 157$. The Pamplona metropolitan area accounts for 203,944 inhabitants (Instituto de Estadística de Navarra 2020) spreading over 13 districts and customers (*i.e.* $|\mathscr{I}| = |\mathscr{J}| = 13$). In this sense, Table 3 (left) shows the districts and their current population.

A time series analysis using historical data for the last 24 years (Foro-Ciudad 2021) in the city of Pamplona shows that population growth rate α_{it} follows a $Weibull(\lambda, \kappa)$ distribution with $\lambda = 1.24252$, and $\kappa = 0.01646$. As from the national survey conducted in IAB Spain (2021), 93.2 % of the Spanish population has internet access and 67.5 % of those people buy online, giving an e-shopper share of 63 %. The average purchase in Spain is 3.5 parcels per month or 42 parcels per year. Some international second sources offer information used for weekly demand distribution assessment: the value of internet retail sales monthly (Coppola 2021) is adjusted taking the daily trends in sales volume per month (Ward 2021) and integrated into the simulation model. These monthly data are shown in Table 3 (right). These monthly values are distributed on a weekly basis during the time horizon. Based on data available in related literature (Rabe et al. 2021), the yearly e-shopper growth rate is set to 10 % and the APL user growth rate is assumed to be the same for simplicity reasons. The APL user share is initially set to 2.2 % of the total population and recomputed in every period in accordance with the system environment. A summary of the initial values for the simulation is available in Table 4. Finally, yearly growth rates are translated into weekly growths by $week = \sqrt[52]{1+year} - 1$.

Table 3: Pamplona district population (left) and monthly demand distribution (right).

District	Population
Azpilagaña	7,374
Buztintxuri	8,771
Casco viejo	11,187
Chantrea	19,450
Ensanche	25,994
Ermitagaña	16,798
Echavacoiz	5,255
Iturrama	22,976
Mendillorri	10,966
Milagrosa	17,552
Rochapea	25,739
San Jorge	11,994
San Juan	19,888
Total	**203,944**

Month	dd_t
January	0.0686
February	0.0653
March	0.0705
April	0.0740
May	0.0791
June	0.0805
July	0.0800
August	0.0763
September	0.0784
October	0.0869
November	0.1171
December	0.1232

Table 4: Initial values (at $t = 0$) for the simulation.

Parameter	Definition	Initial value
$population_{i0}$	Current inhabitants per district	See Table 3 (left)
$eShoppers_{i0}$	Current eShoppers	$0.63 population_{i0}$
$APLusers_{i0}$	Current APL users	$0.022 eShoppers_{i0}$
ppy	Average e-purchases per year	42
α_{i0}	Yearly population growth rate	$A \sim \mathscr{W}(\lambda = 1.24, \kappa = 0.02)$
$\beta i0$	Yearly eShoppers growth rate (adjusted)	0.158
$\gamma i0$	Yearly APL users growth rate	0.1
$\delta i0$	Yearly parcel demand growth rate	0.2
dd_t	Demand distribution	See Table 3 (right)
ω	Sensitivity of increasing APL users	0.01
ε	Random effects	$\varepsilon \sim \mathscr{U}(0.8, 1.2)$

With respect to the parameters in the FLP, the set-up costs of an APL are fixed to $sc_i = 3,300$ €, decommissioning costs per APL are $dc_i = 150$ €, and the maintenance costs are $uc_i = 300$ €. The costs of assigning a customer to an APL in a different district (c_{ij}) are computed considering the distance among any pair of node from its centroid. Likewise, customer parcel demands (d_j) are given from the simulation model. No public data are available regarding e-commerce in Pamplona and initial data are gathered primary data from direct observation and using different national and international secondary resources. According to these primary data (observations), the mean size of APLs already active in Pamplona is 72 cubicles, which can be used for the delivery of a new parcel from Monday to Friday, adding up to a total capacity of a_i = 360 parcels per week. In addition, minimum capacity utilization can be fixed to m = 30 % after analysis of the gathered real data.

4.2 Scenario Definitions

To test the proposed methodology we defined a set of scenarios based on key parameter levels. On the one hand side, the initial APL user growth rate γ_{i0} will clearly affect the overall performance of the system and is difficult to be estimated from existing literature. On the other hand, the sensitivity ω is of utmost interest as feedback to the simulation model, originating from the output of the optimization model. These scenarios are shown in the Table 5.

Table 5: Considered scenarios for the simulation–optimization model.

		ω		
		0.00	0.01	0.03
	0.05	$S1$	$S2$	$S3$
γ	0.10	$S4$	$S5$	$S6$
	0.25	$S7$	$S8$	$S9$

4.3 Results

The results are based on 100 runs for any scenario and are given in the key magnitudes described in the methodology.

Population and eShoppers do not depend on the scenarios, because they are not affected by the parameters included there. Figure 2 shows 100 runs for projected population (left) and eShoppers (right). Mean values over the 100 runs are also available in Table 6 at the beginning of the simulation ($t = 0$), year 1 ($t = 53$), year 2 ($t = 105$) and the end of year 2 ($t = 156$). Our simulation projects an increase of population of around $9,000$ ($sd = 164$) inhabitants (~ 4 %) and $18,000$ ($sd = 3,638$) eShoppers (~ 13 %).

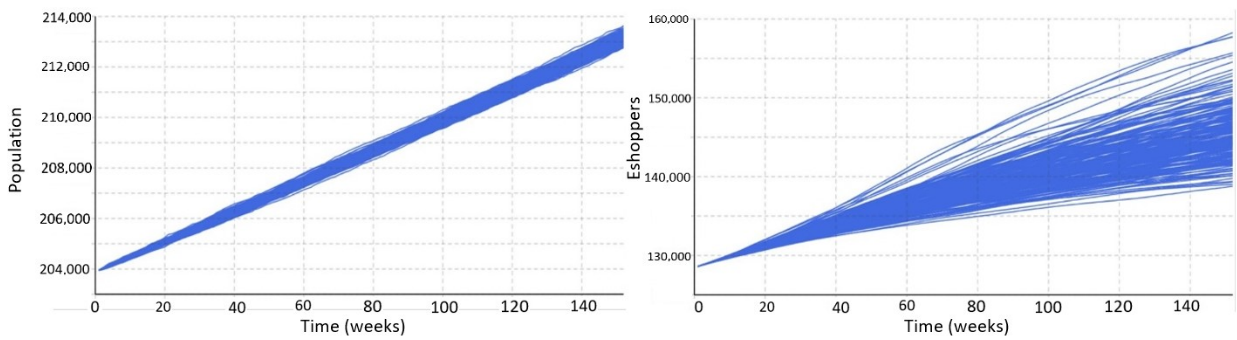

Figure 2: Simulations for population (left) and eShoppers (right) evolution based on 100 runs each.

Table 6: Population and eShoppers values for given moments based on 100 runs.

	Population		eShoppers	
	mean	sd	mean	sd
$t = 0$	203,944.00	0.00	128,623.96	4.56
$t = 53$	207,045.95	93.52	135,465.70	1,042.50
$t = 105$	210,211.47	139.98	141,155.86	2,468.93
$t = T$	213,118.80	163.76	145,462.41	3,637.91

Focusing on the scenarios described in Section 4.2, Figure 3 shows the expected evolution on APL users (left) and parcel demands (right) in scenarios S4 (blue) and S5 (red). Scenario S4 accounts for a 10 % average APL users growth ($\gamma = 0.10$) and $\omega = 0.00$, that is, there is no effect from APL availability on increasing the APL users growth rate, whereas $S5$ considers ω to be set at 0.01. Similarly, we can see the expected evolution in the same scenarios for the number of APLs in the city for any time (Figure 4). This number of APL pattern in Figure 4 approximately matches the demand pattern shown in Figure 3 (right). In all cases, we can see the effect of the optimization feedback on the number of APL users ($+600, \sim 16\%$), parcel demands ($+1,305, \sim 16\%$), and number of APLs ($+4.55, \sim 17\%$).

The actual numbers including all the scenarios considered are shown in Table 7. There, we can see how scenarios $\omega \neq 0$ clearly boost the number of APL users up to 118% that increases the parcel demand, the number of APLs in the system, and their total costs. For example, $S9$ (that stands for a rapid growth in APL users ($\gamma = 0.25$) and a huge effect of having an APL nearby ($\omega = 0.03$)) is more than twice the

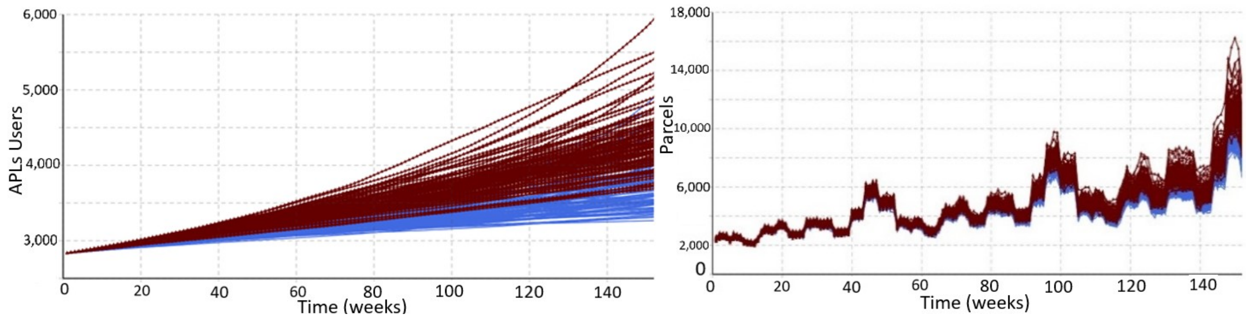

Figure 3: Simulations for APL users (left) and parcel demands (right) in $S4$ (blue) and $S5$ (red) evolutions based on 100 runs each.

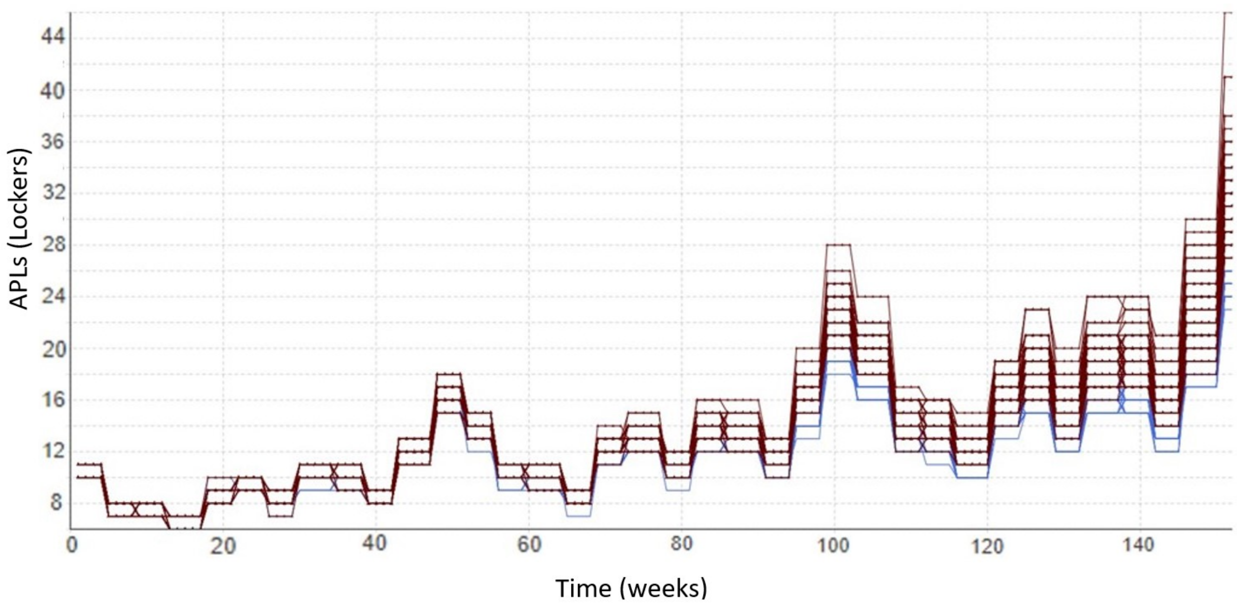

Figure 4: Simulations for the number of APLs in $S4$ (blue) and $S5$ (red) evolutions based on 100 runs each.

values obtained in $S8$ and $S7$ in which ω is reduced to 0.01 and 0, respectively. Therefore, an $\omega = 0.03$ seems to be not realistic.

More interesting are the comparisons between scenarios with $\omega = 0$ and $\omega = 0.01$ (without, and with, APL effects, respectively). In this sense, in a slow APL growth ($S1$ and $S4$) the ω effect is 16 % increase of APL users, 17 % increase in parcel demands and number of APLs (from average 24 to 27, and 9 % increase in costs at the end of the simulation. In the case of moderate APL growth ($S4$ and $S5$), the increase is similar, but in rapid APL growth ($S7$ and $S8$) it falls to around 11 %: the greater the APL growth rate, the lower the APL (ω) effect.

5 CONCLUSIONS

This work proposes the use of a hybrid model by combining simulation and optimization to deal with automated parcel locker (APL) systems in the city of Pamplona (Spain). In this context, several scenarios were tested for a range of growth levels of APL users and the sensitivity of eShoppers to become APL users once there is an APL nearby.

A list of conclusions can be drawn after the analysis of the results.

Table 7: APL users, parcel demand, number of APL, and total costs means and standard deviations for the considered scenarios based on 100 runs at $t = T$.

	APL users		Parcel demand		Number of APLs		Total costs	
	mean	sd	mean	sd	mean	sd	mean	sd
$S1$	3,272.09	172.49	7,186.89	429.46	23.85	1.43	657,993.26	16,526.37
$S2$	3,810.17	235.36	8,411.82	638.78	27.81	2.02	719,537.78	25,343.42
$S3$	7,660.02	2,422.42	16,974.89	5,373.24	54.79	16.80	1,032,920.00	196,625.69
$S4$	3,747.24	329.08	8,194.55	810.25	27.16	2.505	708,084.39	27,324.62
$S5$	4,347.51	386.85	9,499.57	888.88	31.71	3.049	775,766.00	32,739.59
$S6$	8,356.39	2,574.75	18,399.59	5,637.25	58.51	16.38	1,111,699.28	194,046.28
$S7$	5,703.36	1,475.215	12,533.51	3,429.23	40.61	9.924	892,937.53	95,438.61
$S8$	6,357.13	1,791.49	13,921.99	3,932.89	45.14	11.81	950,118.11	107,879.39
$S9$	12,393.40	5,455.88	27,288.83	11,995.51	87.03	35.97	1,420,313.75	308,629.55

- **Costs and suggested number of lockers:** Firstly, our results anticipate an increase in the magnitudes of population, eShoppers, APL users, parcel demands, and number of APLs for the coming years in the city of Pamplona, considering different scenarios for it. In particular, population would raise up to the 212,500–213,500 interval, whereas eShoppers would do up to the 138,000–158,000 range. These figures will represent an average increase of about 4 % and 13 %, respectively, in relation to their current values. Similarly, APL users and parcel demands will continue increasing according to our experiments. Likewise, depending on the considered scenario of APL growth and sensitivity, APL users are expected to increase up to about 13,000, i.e., around 10 % of eShoppers, the current value being of 2.2 %. In the case of the city of Dortmund application, the number of APLs increases after 36 months from 99 at lowest demand to 165 at maximum demand, at a total costs of approximately €$750,000$ for a medium demand configuration. In the city of Pamplona application, we expect the number of APLs to increase from 23 to 87 over the same planning horizon at high demand, at an approximate cost range from €$650,000$ to €$1,400,000$. The results in these two applications in terms of number of APLs and costs have a non-obvious economy of scale relative to the number of eShoppers. The relationship between the number of eShoppers and the number of APLs is directly affected by the APL users share and average e-purchases per year, not just by the population that typically buys online.
- **Mobile APLs:** Secondly, our model explores the use of mobile APLs. As can be seen in Figure 4, as a result of the demand distribution, the fluctuations show different peaks and troughs where mobile APLs can be adjusted more efficiently and cost-effectively than if fixed APLs were used instead. Note that the decisions about the number and location of APLs are obtained from an optimization model (Equations (1)–(8)).
- **APL user sensitivity:** Thirdly, the sensitivity to increase the number of APL users is revealed as a catalyst for increasing both values: APL users and demands. Definitely, these effects have to be taken into account in order to promote APLs among customers.
- **Enhancement of simulation-optimization methodology:** Finally, this paper encourages the use of the hybrid methodology of simulation and optimization to deal with complex real world problems. In effect, complex systems require a combination of methodologies that are able to conveniently cope with a problem.

After completing this work, several research opportunities remain open. This is the case of a deeper analysis about the APL availability impact on increasing the APL users. Thus, a planned future research will collect data about these aspects. Additionally, this approach is particularly important in the case of mobile APLs. As discussed in this research, they can be adapted to anticipated peaks in demand. Nevertheless, they will lead to other problems that can also be mastered from an operations research perspective, e.g., optimization of the APL size, time windows design for products pickup, and so on.

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AUTHOR BIOGRAPHIES

ADRIAN SERRANO-HERNANDEZ is an Assistant Professor in Statistics and Operations Research at the Public University of Navarra (Pamplona, Spain). He holds a PhD in Business and Economics and a MSc in Financial and Economic Analysis. His research interests are within transportation, logistics, and supply chain management. His email address is adrian.serrano@unavarra.es.

SERGIO MARTINEZ-ABAD is a junior researcher at the Public University of Navarre (Spain) and a double MSc in Industrial Engineering and Business Administration student. He holds a BSc in Industrial Technologies Engineering. His email address is martinez.105254@e.unavarra.es.

AITOR BALLANO is a MSc student in Industrial Engineering at the Public University of Navarre (Spain). He holds a BSc in Industrial Technologies Engineering. Currently, he is working as a research assistant in the project TRA2016-76914-C3-3-P "Robustness, Efficiency, and Recoverability of Public Transportation Systems" at the Rey Juan Carlos University (Madrid, Spain). His email address is aitor.ballano@urjc.es.

JAVIER FAULIN is a Full Professor of Statistics and Operations Research at the Public University of Navarre (Spain). He holds a PhD in Economics and Business and a MSc in Applied Mathematics. His research interests include transportation and logistics, vehicle routing problems, and simulation modelling and analysis, along with the use of metaheuristics and simheuristics in real problems. His work is also related to the evaluation of the environmental impact of freight transportation. His email address is javier.faulin@unavarra.es.

MARKUS RABE is Full Professor for IT in Production and Logistics (ITPL) at the Technical University Dortmund. Until 2010 he had been with Fraunhofer IPK in Berlin as head of the corporate logistics and processes department, head of the central IT department, and a member of the institute direction circle. His research focus is on information systems for supply chains, production planning, and simulation. Markus Rabe is vice chair of the "Simulation in Production and Logistics" group of the simulation society ASIM, member of the editorial board of the Journal of Simulation, member of several conference program committees, has chaired the ASIM SPL conference in 1998, 2000, 2004, 2008, and 2015, Local Chair of the WSC'2012 in Berlin and Proceedings Chair of the WSC'18 and WSC'19. More than 200 publications and editions report from his work. His e-mail address is markus.rabe@tu-dortmund.de.

JORGE CHICAIZA-VACA is a PhD student at the Technical University Dortmund in the IT in Production and Logistics (ITPL) department. He holds a BSc in Industrial Engineering and a MSc in Operations Management. His work is related to Behavioral Operations Research combining simulation and optimization approaches to solve logistics problems. His email address is jorge.chicaiza@tu-dortmund.de.