The impact of optimal parcel locker locations on costs and the environment

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Abstract

Purpose – Last-mile delivery is associated with a negative environmental impact and high costs. The purpose of this paper is to develop an approach to designing stationary parcel locker (SPL) networks while minimizing both CO2 equivalent (CO2e) emissions and costs during delivery and pick-up.

Design/methodology/approach – This study uses a multinomial logit model to evaluate recipients' willingness to use SPLs based on their availability at home and travel distance. To determine optimal SPL locations, this study formulates a mixed-integer linear programming model.

Findings – The empirical study of different regional clusters reveals that optimal SPL locations can generate cost savings of up to 11.0%. SPLs have a positive impact on total CO2e emission savings in urban areas (i.e. up to 2.5%), but give rise to additional emissions (i.e. 4.6%) in less populated areas due to longer travel distances during the pick-up process.

Originality/value – This paper optimizes SPL locations and the ecological effect of SPLs by minimizing emissions and costs simultaneously. Furthermore, it extends existing discrete choice models by also including recipients' availability at home, increasing the accuracy of recipients' preferences. So far, the effect of SPLs has been studied for metropolitan areas only. A global logistics service provider shared a real dataset which allows us to study seven different regional clusters ranging from rural areas to large cities. Thus, this study contributes to the field of sustainable urban logistics.

Keywords Last-mile delivery, Parcel locker location, Sustainable delivery, Mixed-integer linear programming, Scenario analysis

Paper type Research paper

1. Introduction

E-commerce sales have grown rapidly in the past decade (Eurostat, 2021). Online sales of goods accounted for USD 3.53tn in 2019, and are expected to reach USD 6.39tn in 2024 (Statista, 2020). The volume of parcel shipments to consumers is increasing correspondingly. For example, parcel volumes grew globally by 9.1% in 2018 (IPC, 2019). This trend has been intensified by the COVID-19 pandemic and the resulting shift in consumers' online ordering behavior (Coppola, 2021; UPS, 2021). For instance, the share of e-commerce sales in Europe will reach 15% after the pandemic (UPS, 2021).

However, this trend poses challenges for many stakeholder groups, including logistics service providers (LSPs), recipients, retailers, municipalities, and environmentalists (Vakulenko et al., 2018). Within the whole business-to-customer (B2C) supply chain...
process, the last mile can account for 41–50\% of shipment costs (Jacobs et al., 2019; Joerss et al., 2016) and is associated with inefficient processes, congestion, pollution, and other negative effects on the environment, safety, and health (Boysen et al., 2018; Gevaers et al., 2014; Savelsbergh and Van Woensel, 2016). The whole road freight traffic, for instance, is responsible for 4.8\% of greenhouse gas emissions (Ritchie and Roser, 2020). The majority of delivery vehicles are still powered by internal combustion engines that exacerbate these adverse effects (Winston, 2018; Statista, 2018), however, LSPs announced to include significantly more battery electric vehicles (BEV) into their fleets (DHL, 2021b; Tomlinson, 2020) which can lead to high emission savings (Giordano et al., 2018).

In addition to these negative effects, LSPs face four key problems associated with last-mile delivery (LMD): lack of economies of scale, slow identification of handover points, long walking distances, and the not-at-home problem (Allen et al., 2018; Gevaers et al., 2011). To tackle these challenges, LSPs have been investigating new delivery technologies (for an overview, see Allen et al., 2018; He, 2020; Lagorio et al., 2016; Mangiaracina et al., 2019; Savelsbergh and Van Woensel, 2016). One of the most promising technologies LSPs applied in the past two decades is the concept of stationary parcel lockers (SPL) (Deutsch and Golany, 2018; Morganti et al., 2014b; Vakulenko et al., 2018; Wang et al., 2019; Lim et al., 2018). SPLs are automated, unattended locker solutions that are accessible at all times and located in highly frequented places such as train stations, apartment blocks, supermarkets, and gas stations (Deutsch and Golany, 2018; Schwerdfeger and Boysen, 2020). Consumers operate SPLs using built-in terminals or apps to open a specific compartment to receive or drop-off parcels. More than 400,000 SPLs are deployed in China (Wang et al., 2020). In Germany, DHL announced a new SPL expansion target for 2023 which shows that DHL will triple their SPL network within a five-year period (DHL, 2021a). In addition, Posten Norge has created an SPL network from scratch at the beginning of 2020, which amounted to 3,000 SPLs by the end of 2021 (SwipBox, 2021). The SPL supplier “SwipBox” constantly improved the SPL technology so that recipients can access SPLs with their own app while LSPs benefit from the fast installation of SPLs in less than five minutes (SwipBox, 2021), enabling a fast extension of SPL networks. SPLs are expected to remain an integral part as LMD (Peppel et al., 2022). Examples of SPLs used by both traditional LSPs and e-retailers that have entered the last-mile market (Ducret, 2014) are shown in Figure 1. This technology has been installed globally, and its application and growth have been investigated in Europe, including France, Germany, the Netherlands, and Poland (Iwan et al., 2016; Morganti et al., 2014b), the US and Canada (Deutsch and Golany, 2018), South America (De Oliveira et al., 2017), and Asia (Jiang et al., 2019; Lin et al., 2020; Yuen et al., 2019). SPLs are distinct from the similar concept of individual

\[\text{Figure 1.}\]

SPLs from the LSP DHL (left) and e-commerce retailer Amazon (right)

Note(s): Pictures used with permission of Deutsche Post DHL Group and Amazon Deutschland Services GmbH, respectively
reception boxes at recipients’ homes (Kämäräinen et al., 2001; Punakivi et al., 2001) and retailers offering in-store parcel pick-up and drop-off services (Allen et al., 2018; Morganti et al., 2014b).

From the perspective of LSPs, major benefits of SPLs include higher first-time delivery rates, reductions in delivery miles, pooling of shipments, and optimized delivery routes, while operational expenses decrease by approximately 16% (Morganti et al., 2014a, b; Van Duin et al., 2020). From the consumer perspective, 24/7 accessibility, safety, and more sustainable shipments are benefits of SPLs; however, customers classify location as the key factor for using them (De Oliveira et al., 2017; Iwan et al., 2016; Kedia et al., 2017).

Some studies focused on finding optimal SPL locations. For instance, Deutsch and Golany (2018) determine suitable SPL locations in a parcel locker network to optimize profit. Their study replicates real life only to a limited extent: they omit the fact that LSPs also need to deliver parcels to homes, assume unlimited SPL capacity, and use deterministic customer preferences based on recipients’ travel distance to SPLs. Furthermore, Lin et al. (2020) account for the probabilistic dimension for individual customer choice by applying a discrete customer choice model covering recipients’ distance to SPLs. Their model estimates suitable SPL locations to optimize the service level; however, they only evaluate an SPL network without considering a holistic LMD network of home and SPL delivery. While these two studies highlight the optimal SPL location, other researchers evaluated also the environmental savings potential of SPLs. Giuffrida et al. (2016) investigate an urban and suburban region based on 20 expert interviews. However, no detailed information about their model, customer behavior, and studied regions is available. Prandtstetter et al.’s (2021) study also explore emission savings generated by existing SPLs. They rely on a survey among 25 SPL users, who used SPLs over a year, to retrieve information about pick-up distances. Nevertheless, they do not illustrate their simulation model in mathematical terms. Further, we question the validity of their results and the transferability to real life since they only generate a random dataset for potential recipients within a radius of interest without providing more details. Both studies do not consider networks with optimal SPL locations.

Thus, this paper combines both research streams and addresses some shortcomings of past studies. It aims to represent real-life LMD as close as possible and explores a holistic LMD network, including home and SPL delivery. Further, it investigates how to locate SPLs to minimize overall LMD costs by taking into account CO$_2$ equivalent (CO$_2$e) emissions by both LSPs and recipients. We formulate an SPL location problem by a mixed-integer linear programming (MILP) model that determines the optimal number and location of SPLs and evaluates the total ecological and economic impact associated with LMD on homes and SPLs. We use the multinomial logit (MNL) model as a discrete choice model that includes next to the recipients’ travel distance to SPLs also their availability at home, improving the accuracy of existing MNL model results. The SPL location model is applied to a large dataset provided by an undisclosed global LSP, covering approximately 750,000 parcel shipments in 15 cities across 7 regional clusters ranging from less than 2,000 to more than 500,000 inhabitants. To illustrate recipients’ pick-up behavior when using SPLs, we build on a survey of about 850 SPL users to determine the share of extra pick-up tours generating CO$_2$e emissions. Further, we perform sensitivity analyses to identify key levers for a successful SPL network. Growth and consolidation cases are also investigated, highlighting the environmental savings potential of pooled shipments. This paper addresses the following research questions:

Q1. What is the impact of optimized SPL locations on CO$_2$e emissions and delivery costs?

Q2. What regional differences in city sizes may affect the savings potential of SPLs?
Q3. How will future growth in parcel volumes and potential consolidation of shipments influence the attractiveness of SPLs?

In the remainder of this paper, Section 2 provides an overview of related literature and explains our research contribution, and Section 3 introduces the MNL and MILP model formulation. In Section 4, the results of the model are presented and discussed. Managerial and research implications are elucidated in Section 5. The final section, Section 6, draws conclusions and makes suggestions for further research.

2. Literature review

Research on strategies and practical concepts to improve the last-mile distribution process and tackle its challenges has increasingly focused on sustainability and new technological solutions (Ducret, 2014; Savelsbergh and Van Woensel, 2016; Speranza, 2018). SPLs are proven to mitigate problems associated with LMD by pooling parcels in a single reception point (Janjevic and Ndiaye, 2014; Morganti et al., 2014a, b; Van Duin et al., 2020). This section presents research streams relevant to SPLs, including criteria for customers’ use of SPLs, their locations, sustainability, and order consolidation.

2.1 Customer acceptance

Although home delivery is still customers’ preferred option, SPLs have been introduced in more than 20 countries in the past two decades (Deutsch and Golany, 2018). Hence, many studies have examined key criteria for customers’ use of SPLs. These focus on various regions, including Australia (Lachapelle et al., 2018), Brazil (De Oliveira et al., 2017), China (Yuen et al., 2019), France (Morganti et al., 2014b), the Netherlands (Weltevreden, 2008), New Zealand (Kedia et al., 2017), Poland (Iwan et al., 2016; Lemke et al., 2016), Singapore (Yuen et al., 2018), and Sweden (Vakulenko et al., 2018).

A key question for LSPs when designing SPL networks is how to account for customer acceptance of SPLs. The location of and travel distance to SPLs have been found to be the most crucial factors influencing customers’ willingness to use the service, whereas accessibility, tracking, ease of use, reliability, and safety are less important criteria (Iwan et al., 2016; Kedia et al., 2017; De Oliveira et al., 2017). For instance, Lemke et al. (2016) find that 15% of parcel recipients would increase their SPL usage if the locations were more convenient. Iwan et al. (2016) and Lemke et al. (2016) reveal that recipients prefer locations close to their home or on their way to or from work. To the best of the authors’ knowledge, recipients’ availability at home has not yet been studied to model the acceptance of SPLs. However, we assume that it is a crucial criterion to select SPL delivery. Therefore, establishing SPLs in the right locations addressing recipients’ needs will be an important success factor in LSPs’ strategies to expand their SPL networks.

2.2 Stationary parcel locker location

Deutsch and Golany’s (2018) study is the first to investigate an SPL location problem by focusing on optimizing total profit, using a 0–1 integer linear programming model. They only explore an SPL network without taking the perspective of an LSP who operates an LMD network, offering both SPL and home delivery to its clients. They assume no capacity limitations, diluting the transferability to reality. In addition, they assume deterministic customer choices, however, in real-life recipients’ preferences are unknown to the LSP. Thus, discrete choice models covering probabilistic customer choice are considered more accurate (McFadden, 1981; Rusmevichientong et al., 2010). They optimize the SPL locations for a small network with 100 nodes. Veenstra et al. (2018) address a similar problem in healthcare logistics. They combine a facility location problem with routing to supply all patients with
their medication while minimizing total delivery costs. Due to the different focus of their study, they assume that patients located in the catchment area of SPLs are served and the remaining demand must be satisfied with home delivery. In this manner, they ignore recipients’ probabilistic choices.

In contrast, Lin et al. (2020) optimize an SPL network by maximizing the service level. They account for discrete customer choices and apply an MNL model to predict customer demand for the SPL service. Lin et al. (2020) reformulate their initial multi-ratio linear-fractional 0–1 program to a MILP, by adding multiple variables and constraints, which impedes the application to large-scale problems. This study reveals that optimal SPL locations are highly dependent on customer choice. Kedia et al. (2020) use an existing infrastructure of supermarkets, gas stations, and other sites as potential SPL locations and determine optimal locations based on customer density. However, they ignore costs and environmental aspects. Lin et al.’s (2022) study determines suitable SPL locations maximizing profit. They apply a threshold Luce model representing discrete customer choice based on a binomial and multinomial logit model, i.e. SPL users choose the closest facility or can select an SPL from a set of SPLs. However, they only focus on revenue and facility costs while they ignore shipping costs. Their artificial dataset covers up to 400 customers and 150 SPL candidate locations, i.e. their study results can be transferred to real-life to a limited extent and might apply to small cities only. A recent study in this field takes a dynamic approach and optimizes the changing locations of mobile parcel lockers (Schwerdfeger and Boysen, 2020). The locations of these flexible lockers can be changed according to recipients’ whereabouts, which may vary in different time periods.

Nonetheless, these studies do not consider a holistic LMD network of both home and SPL deliveries and, thus, do not represent an LSP’s perspective accurately. Furthermore, most studies simply rely on recipients’ travel distance to SPLs without accounting for other criteria affecting recipients’ decision-making process, which dilutes the accuracy of recipients’ probability to select SPL delivery used in their models. Moreover, they omitted external effects such as CO2e emissions generated during the delivery process and SPL usage. Since LSPs and e-commerce retailers realigned their corporate strategies to minimize CO2 emissions (DHL, 2021b; Zalando, 2019), considering the environmental impact when designing SPL networks is of utmost importance. For instance, in-house operations as well as the shipping and return process of e-commerce retailer Zalando are carbon neutral (Zalando, 2019).

2.3 Sustainability

Some studies have investigated the effect of SPLs on the environment, claiming that SPLs have a positive impact on reducing greenhouse gas emissions (Giuffrida et al., 2016; Lemke et al., 2016; Schnieder et al., 2021). Giuffrida et al. (2016) report that in the base case where customer pick-ups occur without additional emissions SPLs can save two-thirds of emissions compared with regular home deliveries. Since in the base case, they only include customer trips to the depot instead of SPL pick-up trips, the emissions savings potential of SPLs are significantly high and are likely to be overestimated. In a sensitivity analysis, they show that pick-ups by car remain environmentally friendly if the distance traveled does not exceed 0.94 km (Giuffrida et al., 2016). Nevertheless, they build their study on an activity-based estimation model based on 20 expert interviews and do not share further information about their used model design, applied customer choice model, and assumed recipient behavior.

Prandtstetter et al. (2021) investigate SPLs in two areas (rural and suburban) in an experimental set-up. In their simulations, they measure the overall CO2 emissions from deliveries and pick-ups and find a positive effect in most instances, with up to 40% CO2 savings using SPLs. They estimate customer pick-up distances based on a survey among 25
SPL users with 900 parcel shipments within a year, omitting discrete customer choices and detailed information about their mathematical model formulation. Their artificial dataset includes SPL users within a radius of interest without sharing more granular assumptions.

In another recent study, Schnieder et al. (2021) evaluate the impact of SPLs on reducing several pollutants. They study the effect in New York City and use bike-sharing stations as potential SPL locations. In addition, they provide an overview of studies about emissions and parcel lockers which illustrates that none of these studies considered emissions when designing an optimal SPL network and a limited extent included customer pick-ups. To conclude, past studies evaluating the environmental impact of SPLs do not consider probabilistic customer choice models, cover only large cities or suburban areas instead of investigating diverse regions, do not consider BEVs apart from Schnieder et al. (2021), and do not use optimal SPL locations, to the best of the authors’ knowledge. In addition, they generate random datasets without using real parcel shipment data. Hence, we address these research gaps by improving the transferability to real life and describing impacts for LSPs more accurately.

2.4 Order consolidation

LSPs sometimes deliver several parcels to the same recipient throughout the week. Apart from positive effects on economies of scale (Dror and Hartman, 2007) and the environment (Ülkü, 2012), Zhang et al. (2019) introduce a consolidation approach in an LMD context. They suggest pooling certain shipments at the final distribution center in order to save trips to recipients. Their model evaluates the trade-off between singular and consolidated shipments and shows cost efficiencies of approximately 5%; however, no information about emission savings is available. In practice, both LSPs and e-commerce retailers offer customers opportunities to select one day of the week on which to receive all their parcels (Amazon, 2021; DHL, 2021c).

3. Model formulation

We undertook a two-step process to determine the optimal locations of SPLs. First, we designed an MNL model to take account of customers’ preferences for SPL delivery. We then developed a MILP model that included both economic and ecological costs to select suitable SPL locations while minimizing total costs. Table A1 of Appendix provides the notation.

3.1 Multinomial logit model

In order to determine discrete customer preferences for either home or SPL delivery, we devised an MNL model as described by McFadden (1974). Previous studies have applied MNL models to optimize SPL locations (Lin et al., 2020, 2022), and others have used MNLs in focusing on facility location problems (Aros-Vera et al., 2013; Zhang and Atkins, 2019). For instance, Zhang and Atkins (2019) determine the optimal locations of medical facilities based on customers’ choices of travel times to and waiting times at these facilities. As outlined in the literature review, previous studies have solely included travel distance to SPLs as a criterion to determine discrete recipient preferences. Lin et al. (2020, 2022) highlight that other factors are important to increase the accuracy of the derived customer choices. Thus, we included recipients’ availability at home besides their travel distance to SPLs to provide more precise probabilities of customer choices.

The MNL model posits that consumers will maximize their utility $U_{ln}$, which refers to the utility of recipient $n$ choosing option $l$, i.e. parcel locker delivery. Utility $U_{ln}$ is a combination of the deterministic component $V_{ln}$ and a stochastic component $e_{ln}$.
A similar expression can be derived for home delivery \( h \). We make four basic assumptions in the MNL model. First, we only consider two delivery options – SPL delivery \( l \) and home delivery \( h \). Second, we include the distance to SPLs within individual recipients’ utility function. Several studies have demonstrated that the distance to an SPL is the most crucial criterion influencing individuals’ selection of this delivery concept (Iwan et al., 2016; Lemke et al., 2016). We also include availability at home as a second component of the utility function. We assume that recipients will prefer SPL delivery if they spend less time at home, for example, when they are at work, and thus have less opportunity to accept their parcels. Third, we assume that recipients’ preferences for SPL or home delivery remain constant over time. Fourth, multiple recipients located in the same building are treated as a single recipient because our data were limited to this granularity level and no further specifications were available.

Based on these assumptions, \( V_{ln} \) depends on the distance \( X_{1ln} \) of recipient \( n \) from the nearest SPL \( l \), as well as on the availability at home \( X_{2ln} \) of recipient \( n \). \( \beta_0, \beta_1, \) and \( \beta_2 \) are constants.

\[
V_{ln} = \beta_0 + \beta_1 X_{1ln} + \beta_2 X_{2ln} .
\] (2)

Thus, recipients will choose between SPL delivery \( l \) and home delivery \( h \) as options in their choice set \( C \), based on their individual utility for these options. For instance, if the associated utility \( U_{ln} \) for SPL delivery is greater than the alternative utility of home delivery \( U_{hn} \), then the probability \( P_n(l) \) is given as follows (Temme, 2007; Train, 2009):

\[
P_n(l) = P(U_{ln} > U_{hn}), \ l, h \in C .
\] (3)

Hence, the probability of recipient \( n \) preferring SPL delivery \( l \) over home delivery \( h \) is given by the following equation:

\[
P_{ln} = \frac{e^{V_{ln}}}{e^{V_{ln}} + e^{V_{hn}}} .
\] (4)

Consequently, the probability of recipient \( n \) selecting home delivery \( h \) is as follows:

\[
P_{hn} = 1 - P_{ln} .
\] (5)

We divide each city into a grid with multiple squares of equal size and aggregate all individual probabilities into an average probability for all recipients per grid cell. Let \( \phi_d = \sum_{n=1}^{n_l} e^{V_{ln}} \) and \( \phi_h = \sum_{n=1}^{n_h} e^{V_{hn}} \). The proportion of recipients in grid \( i \) using an SPL is as follows:

\[
\omega_i = \frac{\phi_d}{\phi_d + \phi_h} .
\] (6)

Similarly, the proportion of recipients in grid \( i \) preferring home delivery is as follows:

\[
\lambda_i = 1 - \omega_i = \frac{\phi_h}{\phi_d + \phi_h} .
\] (7)

3.2 Mixed-integer linear programming model

We formulate the SPL location problem as a MILP model that minimizes economic and environmental costs per grid cell and determines whether an SPL should be in use in a particular grid cell \( i \). The objective function consists of three components (8).
The first component covers all costs associated with the SPL’s construction, including fixed set-up costs \( f_i \), operating expenses \( o_i \), and CO\(_2\)e emission costs \( e_p \) during operation. Home delivery is covered by the volume of parcels designated for home delivery \( H_i \), with associated shipping costs \( s_{ih} \) and environmental impact \( e_{ih} \). The expected value is calculated over \( \omega_i \). Note that \( \omega_i \) is captured by the expressions \( H_i \) in equation (8) and \( L_i \) in equation (10e) and (10f). The last component includes the volume of parcels for SPL delivery \( L_i \), with associated shipping costs \( s_{il} \) and CO\(_2\)e emission costs \( e_{il} \). These shipping costs and environmental effects consist of surcharge factors and cost factors for the shipping and environmental costs of the two delivery options (equations 9a–9d).

\[
\begin{align*}
    s_{ih}(H_i) &= s_h \frac{1}{H_i^a} + s_h, \\
    e_{ih}(H_i) &= e_h \frac{1}{H_i^b} + e_h, \\
    s_{il}(L_i) &= s_l \frac{1}{L_i^a} + s_l, \\
    e_{il}(L_i) &= e_l \frac{1}{L_i^b} + e_l.
\end{align*}
\]

The surcharge factor decreases with rising parcel volumes: few parcels incur a high surcharge factor, while many parcels result in a low surcharge factor. For instance, the volume of home deliveries decreases and becomes more costly if the average demand for SPL delivery within a grid cell rises owing to lower customer density for that delivery option (Winkenbach et al., 2016). Based on the experience of our industry partner, higher surcharge factors apply to home delivery than for SPL delivery in the case of a few parcels per grid cell and disappear for higher parcel volumes. The effect is lower for SPL deliveries due to a higher drop rate of parcels at SPLs than at home addresses. Figure 2 illustrates the sensitivity of the surcharge factor of \( s_{ih}(H_i) \) and \( s_{il}(L_i) \) based on parcel shipments to grid cells for an artificial example when \( s_l \) and \( s_h \) are set to 1 Euro. Based on this sensitivity analysis, we calibrated the surcharge factors in collaboration with our undisclosed industry partner: the surcharge factors include an exponent of 2 (\( a_h \)) in the denominator for SPL deliveries and 1.4 (\( a_l \)) for home deliveries.

In addition, the objective function includes emissions generated per parcel during the pick-up process \( e_i \) and a region-specific factor \( k_i \) that determines the percentage of users who take an extra trip to the SPL and do not choose emissions-free means of transportation. The SPL location problem is formulated as a MILP model (10).
min \ z \quad \quad (10a)

\text{s.t. :}
\begin{align*}
x_i & \in \{0, 1\} \ \forall i \in I, \quad (10b) \\
0 & < \omega_i < 1, \quad (10c) \\
L_i & \leq M_i \quad (10d) \\
H_i & = (1 - x_i \omega_i) V_i, \quad (10e) \\
L_i & = \omega V_i \quad (10f)
\end{align*}

Total costs are minimized in equation (10a). Equation (10b) defines a binary variable \( x_i \) that equals 1 if a locker should be installed within a grid cell and 0 otherwise. In Equation (10c), the average probability of SPL demand per grid cell based on the MNL ranges between 0 and 1. Equation (10d) determines that the parcel volume for SPL delivery cannot exceed the number of empty compartments \( M_i \). Parcels exceeding the SPL capacity are classified for home delivery before the final distribution. Equations (10e) and (10f) determine the parcel volume for either home or SPL delivery, and equation (10e) also ensures that all parcels will be shipped to recipients’ homes if no SPL is built within the designated grid cell.

We solve the MILP based on nine assumptions. First, LSPs will finance the construction, operation and maintenance of SPLs to reduce costs in their entire LMD network. Second, we assume that customers select a facility within the grid cell in which their homes are located. This assumption is based on Lemke et al.’s (2016) and Iwan et al.’s (2016) finding that recipients prefer locations close to home. Third, we assume that all parcels must be delivered. This implies that some customers who prefer SPL delivery will receive their parcels via home delivery if an SPL is not beneficial from an economic and ecological view in a particular grid cell. Fourth, we only include emissions generated during LMD in the model, since previous
emissions during the shipment process are constant for both delivery options. Fifth, our model focuses on LMD and does not cover first-mile parcel drop-offs at SPLs by customers. Sixth, all SPLs are identical, which means that an SPL’s maximum number of compartments and the size of those compartments are constant. We assume a locker of 40 medium-sized compartments. Since we ignore first-mile delivery, 40 medium-sized compartments account for only two-thirds of the regular locker capacity of 60 medium-sized compartments. The drop-off factor is on average 13 parcels per SPL stop. Thus, SPLs can significantly reduce the walking time of LSP’s, which can reach up to 62% of a parcel carrier’s time (Allen et al., 2018). Seventh, 30% of each SPL’s compartments are occupied. Eighth, as in Giuffrida et al.’s (2016) study, we assume that SPL users collect their parcels on average within three days. Ninth, we assume 0.3% (KBA, 2020) BEVs used by the general population and 25% BEVs in the LSP’s fleet, based on information provided by our industry partner.

4. Empirical study: parcel locker network design of a global logistics player

In this section, we apply the MNL and MILP to the case study dataset, provide an overview of the results of the base case, and present our sensitivity analyses. Since the LMD market is expected to undergo changes in the next couple of years (Savelsbergh and Van Woensel, 2016; Speranza, 2018), we identify two key topics: increased parcel shipments and adverse effects on the environment from further growth. Thus, we evaluate two additional scenarios: the growth case and the consolidation case.

4.1 Case study dataset

An international LSP provided us with a dataset of 742,457 parcel deliveries (150 MB in size) for a European country within a three-week period in February 2019. This time of year is considered to be regular and free from the large volume deviance of the Christmas and summer vacation seasons. The data covered 15 cities within 7 regional clusters based on population per area (Table 1).

Furthermore, we outline the city characteristics in Table 2. It reveals information about the population density as well as demand point density and shipment density per square kilometer based on our dataset. Although the cities are sorted by city size, it shows that population densities vary across cities and regional clusters. The initial base case evaluation was performed for all cities A–O. The data consisted of home, SPL, and post office deliveries. All post office deliveries were classified as SPL deliveries, as we assumed that recipients would be indifferent between the post office and SPL pick-ups because they might have chosen a post office owing to its closer proximity to their home or a lack of SPLs. We divided each city into a grid and tested grid widths of 0.25, 0.5, 1, 2, 4, and 8 km for each city.

We built the MNL using R with the package “nnet” to compute individual probabilities of choosing SPL delivery. Subsequently, we carried out computations in Python such as determining the potential distance between homes and the next available SPL in the case of

<table>
<thead>
<tr>
<th>Population</th>
<th>City selection</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;500,000</td>
<td>A, B, C</td>
</tr>
<tr>
<td>100,001–500,000</td>
<td>D, E</td>
</tr>
<tr>
<td>50,001–100,000</td>
<td>F, G</td>
</tr>
<tr>
<td>20,001–50,000</td>
<td>H, I</td>
</tr>
<tr>
<td>10,001–20,000</td>
<td>J, K</td>
</tr>
<tr>
<td>5,000–10,000</td>
<td>L, M</td>
</tr>
<tr>
<td>&lt;5,000</td>
<td>N, O</td>
</tr>
</tbody>
</table>

Table 1. Selected cities per regional cluster
home delivery. Finally, we solved the MILP in Python (equation 10). Further, we conducted sensitivity analyses for certain parameters. The computations were executed on an 8 GB memory Windows computer with a 2.6 GHz Intel Core i5 processor.

4.2 Base case
In this section, we present the results of the base case scenario and the sensitivity analyses. Table 3 provides an overview of the model estimations for all 15 cities and answers Q1–Q2. We selected the grid with the best result per city based on cost and CO2e savings.

<table>
<thead>
<tr>
<th>City</th>
<th>Population density*</th>
<th>25% quartile</th>
<th>Mean</th>
<th>75% quartile</th>
<th>25% quartile</th>
<th>Mean</th>
<th>75% quartile</th>
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<tbody>
<tr>
<td>A</td>
<td>2,438</td>
<td>3</td>
<td>20</td>
<td>105</td>
<td>8</td>
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<td>10</td>
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<td>9</td>
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<td>11</td>
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Note(s): *per square kilometer

Table 2. City characteristics

<table>
<thead>
<tr>
<th>Population</th>
<th>City</th>
<th>Grid width</th>
<th>Existing SPLs</th>
<th>Estimated SPLs</th>
<th>Relative estimated savings</th>
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<tr>
<td>&gt; 500,001</td>
<td>A</td>
<td>0.5 km</td>
<td>252</td>
<td>220</td>
<td>6.7% - 2.2% - 6.2% 0.2970 s</td>
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<tr>
<td></td>
<td>B</td>
<td>0.5 km</td>
<td>172</td>
<td>198</td>
<td>7.0% - 2.4% - 6.5% 0.2880 s</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>0.5 km</td>
<td>123</td>
<td>119</td>
<td>7.6% - 2.5% - 7.8% 0.1760 s</td>
</tr>
<tr>
<td>100,001–</td>
<td>D</td>
<td>0.5 km</td>
<td>24</td>
<td>22</td>
<td>4.4% - 1.0% - 3.9% 0.1360 s</td>
</tr>
<tr>
<td>500,000</td>
<td>E</td>
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<td>36</td>
<td>51</td>
<td>11.0% - 2.2% - 9.9% 0.1330 s</td>
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<tr>
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<td>F</td>
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<td>4</td>
<td>1.6% - 1.4% - 2.9% 0.1490 s</td>
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<td>G</td>
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<td>2</td>
<td>3</td>
<td>3.2% - 0.7% - 2.6% 0.1300 s</td>
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<tr>
<td>20,001–</td>
<td>H</td>
<td>1.0 km</td>
<td>3</td>
<td>5</td>
<td>5.2% - 2.2% - 5.7% 0.1070 s</td>
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<tr>
<td>50,000</td>
<td>I</td>
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<td>2</td>
<td>2</td>
<td>1.2% - 1.4% - 2.8% 0.0980 s</td>
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<tr>
<td>10,001–</td>
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<td>1</td>
<td>1.2% - 4.6% - 3.5% 0.0766 s</td>
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<tr>
<td>20,000</td>
<td>K</td>
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<td>3</td>
<td>1</td>
<td>1.8% - 4.6% - 3.7% 0.0720 s</td>
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<tr>
<td>5,001–10,000</td>
<td>L</td>
<td>2.0 km</td>
<td>1</td>
<td>0</td>
<td>~</td>
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<tr>
<td>&lt; 5,000</td>
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<td>1</td>
<td>0</td>
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<td></td>
<td>N</td>
<td>2.0 km</td>
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<td>0</td>
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Table 3. Results base case
In accordance with a report by the European Central Bank, we assumed a price of EUR 25 per ton CO$_2$e in 2019 (ECB, 2020).

The analysis reveals that smaller grid widths should be applied in cities with a high population density and vice versa. The estimated number of SPLs is close to the actual number of SPLs that existed in each city in 2019. The estimated relative savings potential between 100% home delivery and a mixed scenario of home delivery and SPL delivery is displayed in the last three columns of Table 3. Relative cost savings (including shipping and environmental costs) range between 1.2% and 11.0%.

We measured CO$_2$e from two perspectives: CO$_2$e considers the emissions generated during both deliveries and customers’ pick-ups of parcels, while CO$_2$e LSP includes only the former from the LSP’s perspective. Relative CO$_2$e savings are higher in highly populated areas, but more CO$_2$e is emitted in less populated areas when implementing SPLs. The results range between 2.5% and −4.6%. In contrast, all relative CO$_2$e LSP savings are positive and yield emission reductions of 2.6–9.9%. A comparison of the two measures indicates a high influence of customer pick-ups on CO$_2$e emissions when using SPLs. In this model, SPL users in more rural areas have longer distances to travel to SPLs and tend to choose emission-generating means of transportation more often than SPL users in urban areas. The computational times illustrate the practicality of our SPL location problem.

We focus on cities B and E for further analyses (e.g. sensitivity analyses and for the growth and consolidation cases) since they covered the largest regional clusters. These cities have the highest population density in their respective city cluster and they entail a comparatively high average shipment density. Moreover, our model estimates multiple SPLs for cities B and E, which helps to investigate differences across the cases more clearly. Thus, more granular changes can be explored than in less populated areas with limited numbers of SPLs, i.e. cities with less than 100,000 inhabitants.

Figure 3 shows maps of cities B and E. The edge length of each pixel corresponds with the grid width in Table 3 and is 0.5 km for both maps. The estimated SPL locations overlap with the existing SPL network in 36% (City B) and 43% (City E) of cases. For both base case estimations, optimized SPL locations tend to be in more highly populated areas, while the model does not suggest covering the outskirts. However, some existing SPLs are located within this region. We assume that in large metropolitan areas (like City B), many commuters use public transportation such as subway or suburban trains to access city centers. This effect is stronger for City B than for City E because larger cities tend to have correspondingly
larger metropolitan areas. Since our model uses only static data, it cannot account for the movements of parcel recipients.

In addition, we investigated the effects of the number of SPLs. The savings potential per SPL is initially high for both cities (Figure 4), but with an increasing number of SPLs, the additional savings effect per SPL flattens.

4.3 Sensitivity analyses

We conducted several sensitivity analyses and all parameters were kept constant unless indicated. Emission prices are expected to rise to EUR 55 per ton of CO₂e by 2025 (ECB, 2020). When the emission price is varied accordingly, the results show that relative cost savings decrease slightly, from 11.0% to 10.4% and from 7.0% to 6.7% for cities B and E, respectively (Figure 5). Since a proportional change in emission prices only changes absolute values, an increase in emission prices has only marginal effects on emission savings in our model.

We also changed the objective from minimizing total costs to minimizing CO₂e. As expected, this scenario has a negative effect on cost savings, with a slight decrease of 0.9% for both cities, while CO₂e savings rise by 0.7%–0.9% (Figure 6). The number of SPLs increases for City B but decreases for City E. As a result, CO₂e LSP savings decrease in City E, since the LSP is less able to leverage the positive emission effects of SPL delivery (Figure 6).

If we solely minimize costs and neglect emissions, the results deviate only slightly from the base case. Figure 7 reveals that two SPLs in City B would not be built in this case compared with the base case. Cost savings change only marginally, while emission savings decrease slightly for City B. All values remain constant for City E. Hence, our base case model is mainly influenced by economic factors that outweigh environmental effects. Policymakers might interpret this as a warning signal and increase CO₂e prices to strengthen the environmental factor in LSPs’ decision-making.

![Figure 4. Savings per SPL: base case](image)

![Figure 5. Increase in emissions price: base case](image)
Figures 8 and 9 show the effects of reducing SPLs’ set-up and operating costs. A reduction in set-up costs is a one-off event, so the savings potential is marginal. However, SPLs become cost attractive in some locations due to lower set-up costs. In contrast, reducing operating costs has a greater effect on potential savings since the effect is recurring.

Changing SPL recipients’ attitudes to SPL usage has the highest impact on potential savings. LSPs’ cost savings increase by between 23.5% and 37.2% and CO₂e LSP increases by between 5.5% and 24.8% when 20% more customers use SPLs (Figure 10). However, the effect on CO₂e savings varies between the two cities. In City E, 37% of recipients generate extra emissions during pick-ups, whereas the \( k_i \) factor is lower in City B, at 28%. Hence, pick-up behavior strongly influences potential CO₂e savings.

**Figure 6.** Minimization of CO₂e: base case. The number of SPLs increases by 11.6% for City B and decreases by 7.8% for City E.

**Figure 7.** Minimization of costs: base case. The number of SPLs decreases slightly by 2 SPLs for City B and remains constant for City E.

**Figure 8.** Change in set-up costs. In both cities, the number of SPLs increases by 3.0% when set-up costs are reduced by 10%, and 4.5% when reduced by 20%.
From a physical internet perspective, Faugère and Montreuil (2017) investigate the use of modular containers and evaluate different design scenarios for SPLs. In addition, Faugère and Montreuil (2020) perform design optimizations regarding the size of SPLs’ compartments. In our sensitivity analysis, we investigated the effect of changing the number of compartments of SPLs, which produced minor improvements in both economic and ecological dimensions for 20% fewer compartments per SPL and vice versa (Figure 11). When SPLs have fewer compartments, the total number of SPLs increases while cost savings and CO₂e LSP savings decrease. Less populated regions and regions with smaller demand for SPLs become more attractive. However, overall CO₂ emissions change only marginally. When installing SPLs, LSPs need to adjust their size according to local requirements and future growth prospects.

The proportion of BEVs has a large impact on the ecological component of SPLs (Figure 12). The number of SPLs, cost savings and CO₂e LSP savings remain constant when this proportion is increased for both LSP and population fleets. However, we see significant changes in CO₂e emissions for different proportions of BEVs (Figure 12).

Figure 9. Change in operating costs: base case. The number of SPLs increases by 7.6% for City B and by 5.9% for City E when operating costs are reduced by 10% and by 21.2% and 13.7%, respectively, with a 20% reduction in operating costs.

Figure 10. Change in preferences: base case. If the probability of using SPLs increases by 10% or 20%, the number of SPLs remains constant for City E, while it increases for City B by 8.6% and 17.2%, respectively.

Figure 11. Change in the number of compartments per SPL: base case. A 20% reduction in the number of compartments leads to 24.7% and 15.6% more SPLs for City B and E, while an increase in the number of compartments leads to 13.6% and 5.9% less SPLs, respectively.
savings in both scenarios. Since all factors were kept constant, these analyses confirmed our previous finding that overall emission savings depend highly on customer pick-ups.

4.4 Growth case
A major trend that will lead to the growth in LMD is the rapidly expanding e-commerce market (Statista, 2020). Consequently, LMD will grow accordingly. In the growth case, we estimated parcel volumes and preferences for using SPLs based on random values with normal distribution in five years’ time. All grid cells with only one shipment within the studied period in February 2019 were dropped since no random values could be generated: 7.7% or 8.1% of grid cells were omitted, affecting 0.04% or 0.06% of total shipments for City B and City E, respectively.

Parcel shipments are forecast to increase by 5% annually (Statista, 2019), while experts from our industry partner expected the proportion of BEVs in the LSP fleet to double from 25% to 50%. We assumed that the proportion of BEVs in the general public would increase from 0.3% to approximately 2.0%, based on a continuous annual growth rate and estimations of the BEV fleet size (Bundesregierung, 2021).

We generated random values for parcel shipments and SPL preferences by sampling from a normal distribution, where the mean values corresponded with the growth levels indicated below while the standard deviation was kept constant. The model estimated 204 SPLs for City B and 46 SPLs for City E as a new baseline. We defined a medium-growth scenario of +27.6% based on 5% per annum and added scenarios for low growth (+20.7%) and high growth (+34.5%), as well as extreme growth (+50%) due to the boost in e-commerce during the COVID-19 pandemic.

Figure 13 illustrates SPL locations for all growth scenarios. The SPL locations for medium growth include pixels from the baseline, low-growth, and medium-growth scenarios. For...
instance, for City B, more SPLs are located in the outskirts with lower population densities as the growth level rises compared with the base case.

In the two scenarios, the number of SPLs increases by 24.0% and 21.7% with medium growth and by 44.6% and 39.1% with extreme growth for City B and City E, respectively. In answer to the first part of Q3, cost savings may reach 15.1%, while CO₂e LSP savings amount to 10.1% in the growth case (Figure 14). CO₂e savings change slightly across the growth scenarios, but overall CO₂e savings are significantly lower than in the base case due to the different paces of BEV diffusion in the LSP and in the general public.

LSPs might also be interested in the fact how their existing SPL network is able to cope with demand growth. Thus, we kept the number of SPLs, which were estimated as the baseline, constant. The results reveal that even with the same number of SPLs, additional savings can be generated, although they are lower compared with an extension of the SPL network. Cost savings reach 9.1% and 12.8% in the medium-growth case with the same number of baseline SPLs (Figure 15), while they reach 9.4% and 15.1% for Cities B and E, respectively, in the regular growth case with a rising number of SPLs. Due to the lower number of SPLs and parcel collections, higher CO₂e savings can be realized than in the regular growth case due to less recipient pick-ups.

Furthermore, SPL usage might have increased significantly owing to the change in consumer behavior. Recipients tend to order more products online than before the global pandemic COVID-19 (UPS, 2021). Thus, LSPs might also increase SPLs capacity. We evaluated the effect for both an increase and decrease of SPL compartments for medium growth. Figure 16
illustrates that cost savings decrease for both cities from 9.4% to 13.2% to –9.0% and 11.7% for cities B and E, respectively, if LSPs increase SPLs’ capacity by 20%. However, total CO₂e emission savings improve for both cities. This scenario illustrates that LSPs need to select suitable locations for an SPL capacity increase instead of extending SPL capacity in general.

4.5 Consolidation case
The other major trend analyzed here is sustainability. Zhang et al. (2019) show that pooling shipments may reduce costs, whereas we apply this approach to the sustainability context. We evaluate the effect of consolidating shipments into a single weekly delivery per recipient on emissions generated during the last mile of delivery. For instance, DHL and Amazon already enable customers to select one weekly delivery day based on their preferences (Amazon, 2021; DHL, 2021c).

In the consolidation case, we evaluated a baseline scenario, a consolidation scenario, and a consolidation scenario with growth. In the first step, we generated random parcel shipments per location for one week, sampling from a normal distribution where the mean values corresponded with the daily shipments per location and keeping the standard deviation constant. We then assigned random delivery days. Since we assumed that recipients’ willingness to use SPLs would not depend on shipment day, we built on the mean MNL values per grid and sampled from a normal distribution while keeping the standard deviation constant. The same grid cells were dropped as in the growth case. In the second step, we assigned a preferred weekly delivery day to each location and consolidated the deliveries accordingly. In the third step, we estimated consolidated shipments in five years’ time based on medium growth (i.e. +27.6%) and with 2% and 50% shares of BEVs for public and LSP fleets, respectively. In general, we assumed that all recipients would participate in shipment consolidation and ignored LSPs’ warehousing costs.

Figure 17 reveals that more SPLs are estimated in the consolidation scenario than in the baseline: the number of SPLs increases by 2.4% and 4.2% for Cities B and E, respectively. In addition, Figure 18 demonstrates that up to 6.4% of total costs and up to 5.4% of total CO₂e emissions can be saved through consolidation, which confirms and extends the results of Zhang et al. (2019). In answer to the second part of Q3, relative savings improve for both cities on all dimensions in the consolidation case since more SPLs are estimated.

Varying the number of SPL compartments confirms previous evaluations in the base and growth case: if SPL capacity is increased, total cost savings decrease for both cities (Figure 19). CO₂e emission savings vary only marginally. Moreover, if LSPs decrease the number of SPL compartments, substantially more SPLs would be deployed and vice versa. Customers would appreciate a more dense SPL network.

In the consolidation scenario with growth (Figure 20), the effects on savings are similar to the growth case. The number of SPLs increases by 21.9% and 18.0%, cost savings range between 11.6% and 12.6%, and CO₂e LSP savings improve by 10.7% and 19.0% in comparison to the consolidation case without growth for Cities B and E, respectively. In this case, the model
Figure 17. Locker locations: consolidation case

Figure 18. Relative savings: consolidation case. The number of SPLs increases by 2.4% and 4.2% for Cities B and E, respectively.

Figure 19. Change in number of compartments per SPL: consolidation case. A 20% increase in the number of compartments yields 10.2% and 20.0% less SPLs for City B and City E, while a reduction of SPL capacity leads to 17.2% and 14.0% more SPLs, respectively.

Figure 20. Relative savings: consolidation case with growth. The number of SPLs increases by 21.9% and 18.0% for Cities B and E, respectively.
yields similar but smaller effects for City B. For both cities, CO\textsubscript{2}e savings decrease, confirming our previous findings that parcel pick-up behavior significantly influences CO\textsubscript{2}e emissions.

5. Managerial and research implications

In this section, we highlight managerial recommendations for relevant stakeholder groups, including LSPs, governments and municipalities, recipients, and e-commerce players and also outline research implications.

We derive seven managerial implications for LSPs. First, LSPs should increase the density of the SPL network, prioritize neighborhoods with a higher population density, and focus on highly used routes. When LSPs build SPLs closer to recipients, they reduce the travel distance and positively influence recipients’ willingness to use SPLs. Previous studies outlined that travel distance to an SPL is a key decision criterion for using an SPL service (Iwan et al., 2016; Lemke et al., 2016). Thus, extending the SPL network would create incentives for recipients to use SPLs more frequently, thereby increasing the probability of SPL usage and potential cost savings for LSPs. Our study finds considerable savings potential, when consumers are more likely to select SPL delivery.

Second, LSPs should focus their SPL network expansion on highly populated areas from an environmental perspective. As our study revealed, CO\textsubscript{2}e emissions savings through SPLs are positive if the threshold of 100,000 inhabitants is met. Since customer pick-ups have a strong lever, more advanced infrastructure such as a public transportation network and designated bicycle lanes in medium- to large-sized cities enables recipients to use more environmentally-friendly pick-up modes.

Third, LSPs should rather build smaller SPLs. Varying the number of compartments in the base, growth, and consolidation cases has demonstrated that the higher utilization of SPLs generates additional cost savings. Nonetheless, LSPs need to consider the SPLs’ utilization of the complete operating life and growth in parcel shipments for the entire time span to avoid unsatisfied demand for SPL delivery and corresponding missed cost savings.

Fourth, since SPLs tend to generate additional CO\textsubscript{2}e emissions due to longer travel distances and different consumer behavior in less populated areas with a population lower than 100,000, LSPs should test new technological concepts such as mobile parcel lockers. For instance, mobile parcel lockers can reduce the distance and be located in closer proximity to recipients. The application of this technology may have a positive environmental impact by saving CO\textsubscript{2}e emissions during pick-up. Thus, the use of SPLs can become attractive in less populated areas such as small- to medium-sized cities.

Fifth, LSPs should positively influence recipients’ pick-up behavior because our study finds a strong effect of parcel collections on CO\textsubscript{2}e emission savings. For instance, LSPs should educate recipients and promote more environmentally-friendly pick-ups by highlighting the positive effects of physical activities, such as cycling and walking, on recipients’ health. Since the parcel pick-up process strongly influences CO\textsubscript{2}e savings, LSPs should integrate SPLs into recipients’ daily routes to enable them to combine parcel pick-ups with regular activities and reduce the travel distance to SPLs. In addition, LSPs should extend their partner networks, for example, with local public transportation companies to reach a large proportion of recipients who use public transportation.

Sixth, LSPs should offer the possibility of pooling shipments into a single preferred delivery day. Our analyses reveal that CO\textsubscript{2}e emissions savings of up to 5.4% can be gained by implementing this measure and confirm that consolidating parcel shipments may reduce total costs. In the consolidation case with growth, SPLs become more attractive, so 21.9% more SPLs are suggested in our model. Consequently, LSPs should leverage the additional cost savings potential by emphasizing the positive environmental effect of consolidating deliveries.
Seventh, our sensitivity analysis reveals that operating costs are a strong lever. Thus, LSPs should continue to optimize this cost category to improve their attractiveness of SPLs. LSPs might negotiate new terms with their partner networks to reduce monthly fees for SPL locations. In addition, operational expenses such as energy consumption and maintenance work might be optimized by improving SPL design or process flow. Lower operational costs would enable new SPLs to be established as a result of better cost competitiveness compared with home delivery.

Furthermore, not only LSPs but also municipalities should promote the use of SPLs in large cities by offering LSPs additional space for new SPLs, especially at public transportation hubs such as subway stations. Our undisclosed industry partner reported that high administrative barriers exist for public space and that the approval process is very time-consuming and slow. Hence, LSPs partner with private entities due to lower barriers so that most SPLs are built on private ground such as supermarkets. Integrating SPLs into recipients’ daily lives, for example, on their way home from work, is likely to increase SPL usage (Iwan et al., 2016; Lemke et al., 2016) and cities might become less congested with delivery vehicles. In addition, municipalities can initiate or support local (e-cargo) bike-sharing initiatives (Hess and Schubert, 2019) to offer recipients more sustainable options to pick-up even large or heavy parcels conveniently.

Moreover, our study reveals that the slow diffusion of BEVs in public fleets also corresponds with relatively high CO₂e emissions in the future. Strong governmental incentives might accelerate the diffusion of BEVs. As a positive side effect, CO₂e emissions arising from the parcel pick-up process might be reduced. In addition, municipalities play a major role in developing and deploying sustainable policies (Freudendal-Pedersen, 2020). Thus, they could implement more rigorous environmental restrictions to accelerate the adoption of eco-friendly vehicles and BEVs. This measure will reduce CO₂e emissions from a more global perspective since passenger and commercial vehicles generate 11.9% of global greenhouse gas emissions (Ritchie and Roser, 2020). Further, low- or zero-emission zones can support the transformation towards e-mobility (Peters et al., 2021).

SPL users might switch to public transportation or emission-free vehicles such as bicycles and avoid single trips to SPLs by combining parcel pick-ups with other trips, i.e. trip chaining, especially in more rural regions. They might also consolidate shipments into a single delivery day per week, as suggested by the positive findings of our consolidation case.

Apart from LSPs and municipalities, e-commerce retailers might nudge consumers to select SPLs more often and pool shipments into specific delivery days. A recent study by Rai et al. (2021) reveals that social media as well as providing information about the delivery’s footprint before checkout influences consumers positively to choose sustainable delivery options. These measures would complement e-commerce retailers’ own initiatives to lower their carbon footprints (Zalando, 2019). The process for choosing these options should be convenient and easy to use. Since e-commerce is expected to grow (Statista, 2020), e-commerce retailers should collaborate more closely with LSPs to develop additional strategies to minimize the negative impact of parcel shipments.

In the following, we highlight some research implications. First, our SPL location problem relies on the assumption that recipients will only use an SPL if located in their home grid cell. Since recipients travel to multiple locations throughout the day, e.g. to work, grocery shopping, or recreational activities, they might also favor other SPL locations. Thus, integrating the effect of recipient movement could describe operations more realistically, although the data collection process might be difficult due to data privacy regulations.

Second, we improve the accuracy of the MNL models’ results by integrating recipients’ availability at home next to the travel distance to SPLs. The results could be improved even
further if more characteristics about recipients are used to determine the probability of choosing an LMD service. This data could be easily integrated into our MNL model. It is important that all further information corresponds with the exact locations of demand points.

Third, we focus only on SPLs in the LMD context. However, SPLs are also used for first-mile shipments, e.g., new parcels or returns. The number of SPL compartments and the rate of occupied compartments used in our study is based solely on LMD. Hence, the SPLs' capacity as well as the occupation rate needs to be adjusted when considering first-mile shipments next to LMD items.

6. Conclusion

LMD is characterized by high costs and negative external effects such as CO₂e emissions. This paper examines the effect of optimal SPL locations from both ecological and economic perspectives. We used an MNL model that included customer preferences for SPL usage based on the availability at home and travel distance. We also formulated a MILP model to determine optimal SPL locations and included regular shipping costs as well as CO₂e emissions generated during parcel delivery and pick-up. This paper shows that optimizing SPL locations may generate cost savings of up to 11.0% for LSPs and save up to 2.5% of CO₂e emissions associated with shipments and customer pick-ups.

We evaluated 15 cities across 7 regional clusters, generating new insights into regional savings effects through SPL usage from both economic and ecological perspectives. We find that the potential for both cost and CO₂e savings is higher in highly populated cities than in more rural areas and that SPLs entail higher levels of CO₂e emissions for cities with fewer than 100,000 inhabitants owing to longer travel distances to SPLs and different consumer behavior during the pick-up process. In a growth case, we find that the SPL network will grow by up to 44.6% within the next five years, while cost savings may reach as much as 15.1%. CO₂e emission savings will be lower than in the base case owing to the slow pace of BEV diffusion to the general public. Consolidating shipments into a weekly delivery day based on recipients' preferences may save up to 6.4% of overall costs and up to 5.4% of CO₂e emissions. In addition, the number of SPLs rises by up to 4.2%. In the consolidation case with growing parcel volumes in the next five years, the positive effects of consolidated delivery are amplified.

There are several opportunities for further research. Since our model focuses only on LMD, new approaches, including customer returns (i.e., drop-off of parcels at SPLs), should be developed. We expect the number of SPL locations as well as cost savings to increase owing to lower expenses for drop-offs at SPLs rather than post offices. Future research should include dynamic data on recipients' whereabouts throughout the day. This would enable the identification of additional relevant SPL locations that tend to be less populated, such as industrial parks and office districts. Furthermore, researchers should also test multiple objective models to illustrate non-dominant trade-offs between CO₂e emissions and costs. Meanwhile, we assumed in our study that LSPs will construct the SPL network. However, further studies should also investigate the case of a publicly built SPL network that can be used by LSPs at a charge. For instance, municipalities might mandate LSPs to collaborate (Peppel et al., 2022). In addition, our model assumes that all SPLs are uniform, whereas it would be beneficial to adapt the number and size of compartments to local requirements and growth prospects. Moreover, our study evaluates optimal SPL locations for different regional clusters within a European country. Other regions will have different regional set-ups, city designs, recipient habits, and population densities. Thus, it would be desirable to evaluate the potential for both ecological and economic savings by SPLs in other regions of the world.
References


UPS (2021), UPS Smart E-Commerce Report 2021.


Appendix

Sets

- $C$: Set of delivery options: SPL delivery $l$ and home delivery $h$
- $I$: Set of customer grid cells: $i = 1, \ldots$, maximum number of grid cells
- $N$: Set of recipients: $n = 1, \ldots$, maximum number of recipients

Parameters

- $a_h$: Calibration factor for surcharge factor of shipping costs to homes $h$
- $a_l$: Calibration factor for surcharge factor of shipping cost to SPL $l$
- $e_c$: Emission costs generated during the parcel collection by recipients [Euro]
- $e_h$: Emission cost factor for home delivery $h$ [Euro]
- $e_{ih}(H_i)$: Emission costs $e_h$ per parcel for home delivery $h$ in grid cell $i$ with an additional surcharge factor [Euro]
- $e_{il}(L_i)$: Emission costs $e_l$ per parcel for SPL delivery $l$ in grid cell $i$ with an additional surcharge factor [Euro]
- $e_{un}$: Stochastic component as a random error term for recipient $n$ favoring home delivery $h$ [Euro]
- $e_{pl}$: Emission cost factor for SPL delivery $l$ [Euro]
- $e_{ln}$: Stochastic component as a random error term for recipient $n$ favoring SPL delivery $l$ [Euro]
- $e_p$: Emission cost of SPL during its operation [Euro]
- $E_\omega$: Expected value [Euro]
- $f_i$: Fixed setup cost of SPL in grid cell $i$ [Euro]
- $H_i$: Volume of parcel shipments to homes in grid cell $i$ []
- $k_i$: Proportion of recipients generating additional CO$_2$e during pick-up at SPLs in grid cell $i$ [%]
- $L_i$: Volume of parcel shipments to SPL in grid cell $i$ []
- $M_i$: Maximum number of free compartments of SPL in grid cell $i$ []
- $o_i$: Operating costs of SPL per day in grid cell $i$ [Euro]
- $P_{h_n}$: Probability of choosing home delivery $h$ for recipient $n$ [%]
- $P_{l_n}$: Probability of choosing SPL delivery $l$ for recipient $n$ [%]
- $P_{l}(l)$: Probability of choosing SPL delivery $l$ based on individual utilities of available options of recipient $n$ [%]
- $s_h$: Cost factor for home delivery $h$ [Euro]
- $s_{ih}(H_i)$: Shipping costs $s_h$ per parcel for home delivery $h$ in grid cell $i$ with an additional surcharge factor [Euro]
- $s_{il}(L_i)$: Shipping costs $s_l$ per parcel to SPL $l$ in grid cell $i$ with an additional surcharge factor [Euro]
- $x_l$: Cost factor for SPL delivery $l$ [Euro]
- $U_{ln}$: Utility of an individual recipient $n$ choosing option SPL delivery $l$ []
- $U_{h_n}$: Utility of an individual recipient $n$ choosing option home delivery $h$ []
- $V_i$: Total volume of shipments to grid cell $i$ []
- $V_{hn}$: Deterministic component of utility for home delivery $h$ of recipient $n$ []
- $V_{ln}$: Deterministic component of utility for SPL delivery $l$ of recipient $n$ []
- $X_1^n$: Distance of recipient $n$ to the next SPL [km]
- $X_2^n$: Availability at home of recipient $n$ [%]
- $z$: Total cost [Euro]
- $\beta_j$: Constants of the deterministic component of the MNL model, $j = 0, 1, 2$ []
- $\lambda_i$: Proportion of recipients in grid cell $i$ using home delivery $h$ [%]
- $\phi_{hn}$: Aggregation of recipients $N$ in grid cell $i$ choosing home delivery $h$ []
- $\phi_{ln}$: Aggregation of recipients $N$ in grid cell $i$ choosing SPL delivery $l$ []
- $\omega_i$: Proportion of recipients in grid cell $i$ using SPL delivery $l$ [%]

Table A1. Notation

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_i$</td>
<td>$1$ if an SPL is recommended for grid cell $i$ and $0$ otherwise</td>
</tr>
</tbody>
</table>

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