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# Investigating multi-parcel crowdsourcing logistics for B2C e-commerce last-mile deliveries

B2C e-commerce last-mile delivery (LMD) is a critical process, considering both efficiency and effectiveness: it implies high costs, and online customers have stringent service level expectations. One promising LMD solution based on crowdsourcing logistics (CL) is the "multi-parcel" paradigm (each rider accomplishes different deliveries in the same tour). This work analyses the impact of multi-parcel CL on delivery costs compared to traditional by-van LMD. First, it develops an analytical model that –generating customers' demand and assigning deliveries to riders– computes both CL and traditional LMD costs. Second, the model is applied to a case in Milan, Italy. Third, sensitivity analyses are run on key variables/parameters. Multi-parcel CL entails significant benefits compared to traditional LMD (about 11% saving). On the academic side, this work contributes to the literature, proposing a model that investigates the performances of multi-parcel CL. On the managerial side, it may support practitioners in implementing this innovative delivery solution.

**Keywords**: last-mile delivery; crowdsourcing logistics; B2C e-commerce; multi-parcel

## 1. Introduction

In recent years the diffusion of Business-to-consumers (B2C) e-commerce has been increasing in many industries in both mature and emerging markets (Vakulenko et al., 2019). In 2019, online sales were worth about € 3,000 billions worldwide, showing a +20% increase if compared to the previous year (B2C eCommerce observatory). Selling products online introduces remarkable logistics challenges with respect to traditional commerce; one that has captured the interest of both academics and practitioners is last-mile delivery (LMD) (Mangiaracina et al., 2019), i.e., the final leg of the order fulfilment, aimed at delivering the products to the final consumer (Lim et al., 2018).

LMD is very critical in terms of both efficiency and effectiveness. On the one side, it is costly. Orders are typically composed by few lines and few pieces, they are unpredictable, and the destinations may be very dispersed (Macioszek, 2017). Moreover, B2C delivery attempts may fail if customers are not at home to collect the parcels, and re-scheduling missed deliveries entails very high costs. As a result, LMD costs can amount to half of the total logistic costs (Vanelslander et al., 2013). On the other side, e-customers have expectations in terms of delivery effectiveness that are increasingly stringent, looking for both punctuality and delivery speed (Savelsbergh and Van Woensel, 2016). Still, they are typically not willing to pay for such service performances (Borsenberger et al., 2016).

These being the premises, companies selling products online have been striving to find solutions to efficiently and effectively cope with the challenges of B2C last-mile deliveries. Among them, crowdsourcing logistics – i.e., the application of crowdsourcing to logistics processes, which calls on individuals "to perform basic logistics services on an ad-hoc basis" (Carbone et al., 2017) – has been recently gaining the attention of both scholars and managers.

Nonetheless, scientific works addressing this solution are still scarce (Carbone et al., 2017). This "paucity of academic contributions" colludes with the fact CL has been recently spreading in the business world, with many successful initiatives in different industries (e.g., *Deliveroo* for food in Europe, *Amazon Flex* for parcels in the USA). This is especially true if considering the so-called "multi-parcel" CL, in which each rider accomplishes different deliveries in the same delivery tour (Macrina et al., 2020); despite some initiatives are already in place, there are no academic contributions on this specific topic. Research opportunities are open, and both academics and practitioners would benefit from comparing this innovative solution to traditional last-mile deliveries.

Based on these premises, this work aims to investigate the economic performances of the implementation of multi-parcel CL to LMD, analysing its impact on delivery costs if compared to traditional by-van deliveries.

The remainder of this paper is organised as follows: section 2 presents the results of the literature review, section 3 defines the research objective and the methodology, section 4 illustrates the model development and its application, and section 5 summarises the conclusions stemming from the work.

## 2. Literature review

A recent and comprehensive definition of crowdsourcing logistics is provided by Rai et al. (2017), according to whom crowdsourcing logistics represents "*an information connectivity enabled marketplace concept that matches supply and demand for logistics services with an undefined and external crowd that has free capacity with regards to time and/or space, participates on a voluntary basis and is compensated accordingly*". These authors identify six main elements defining crowdsourcing logistics. They are: (i) the crowd, i.e., the mass of "common" (not specialised) people to whom activities are outsourced; (ii) the technical infrastructure, needed to reach people from the crowd and coordinate their work; (iii) the free capacity – in terms of space or time – of people from the crowd, which is the resource they aim to "sell"; (iv) the externality of the crowd from the company: people working according to a CL paradigm neither are employees nor undergo a traditional formal hiring process; (v) the compensation, which represents the economic incentive offered to the crowd, based on the amount of space/time they sell; (vi) the voluntary engagement of workers, who are free to choose whether and when they want to perform a logistics task.

While this definition allows excluding initiatives that do not fall within the CL field, it is still wide and general, and it may include a great variety of configurations. One of the earlier attempts to categorise CL initiatives is the framework by Carbone et al. (2017), which identifies four main CL types (based on the logistics activity outsourced to the crowd). First, the crowd storage; i.e., the provision of space, usually in garages or courtyards, where may be temporarily stored (warehousing function). Second, the crowd local delivery, i.e., the outsourcing of short-distance deliveries of parcels or food to riders, who are typically required to ensure high-speed services (LMD). Third, the crowd freight shipping, i.e., the delivery of odd-sized parcels covering both domestic and continental deliveries. Fourth, the crowd freight forwarding, i.e., the delivery of products, but mainly for intercontinental distances (in this case, riders usually move by planes or boats).

Among those models, the most diffused one – both in literature and industry – is the crowd local delivery. The technological infrastructure is an online platform, which riders can access through a mobile application to give their availability for the delivery tasks. Riders typically use their own mean of transport, which may be a van, a car, a scooter, or a bike; nonetheless, there are also cases in which they move just walking or relying on public transport. Outsourcing last-mile deliveries has been emerging as a very suitable option for the B2C e-commerce field, as it allows to perform low-cost and fast deliveries as well to gain high flexibility (Castillo et al., 2018; Frehe et al., 2017). Even within the crowd local delivery paradigm, scientific literature highlights the presence of different types of initiatives that – despite all referring to LMD – are characterised by specific peculiarities. Accordingly, the benefits they entail compared to by-van deliveries are different (Seghezzi et al., 2020). The four main models are detailed in Table 1.

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Please take in Table 1

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- For-free deliveries, in which people who already have to move collect and deliver parcels for friends or acquaintances, typically with a very little detour from their original route (Devari et al., 2017; Suh et al., 2012). The main advantages are social (social cohesion) and environmental (low emissions, since riders deliver the parcels without a significant additional distance to be travelled compared to their original path).
- Occasional – usually remunerated – deliveries performed on behalf of other members of a community (e.g., college mates) (Paloheimo et al., 2016; Kim, 2015). The main advantage is social, since providing the delivery service allows to strengthen relationships among community-mates.
- Hybrid solution, in which an e-commerce player integrates its own van fleet (traditional model) with a group of occasional riders performing crowdsourced deliveries, in order to exploit extra-resources (Dahle et al., 2017; Macrina et al. 2020). This model mainly entails economic benefits (flexibility), since companies may rely on the crowd to deal with demand peaks, which would otherwise require the "activation" of ad-hoc vans.
- Deliveries performed by an ad-hoc created fleet of riders, whose operations are centrally coordinated and optimised (Chen et al., 2018; Kafle et al., 2017). In this case, there are advantages in terms of both efficiency (due to the higher flexibility of the crowd compared to van drivers performing full-day tours) and effectiveness (since online platforms allow to offer value-added services, such as geo-localisation and real-time order collection).

Although the application of crowdsourcing logistics to B2C last-mile deliveries (i.e., the crowd local delivery) has already gained the interest of the academic community, there are still different aspects that could be further investigated. More in detail, the gaps in this field may be mainly attributed to two areas. First, the majority of the contributions perform high-level or qualitative analyses. Most of these works (e.g., conceptual frameworks or literature reviews) aim to provide a general overview of the potential CL business models and classify them. Second, considering instead the works addressing one specific solution, they mainly focus on the third CL model, i.e., the "hybrid fleet" one. In this configuration, which combines both owned vans and occasional drivers, the crowd delivers just few parcels, generally accomplishing the delivery task on the home-job path. Conversely, despite the chance to aggregate several parcels in the same delivery tour is as an effective and efficient opportunity, detailed analyses about the implementation of the fourth crowd local model (i.e., the "multi-parcel" option) seem to be missing.

## 3. Objectives and methodology

The main objective of this work is to address the two main gaps emerging from the literature analysis: (i) the scarcity of in-depth realistic economic analysis for crowdsourcing logistics and (ii) the low interest for multi-parcel crowdsourced LMD. More in detail, the following research question is addressed:

> RQ What are the economic performances of multi-parcel crowdsourcing logistics for last-mile delivery if compared to traditional LMD?

To answer the defined question, three main steps are performed. First, an analytical model is developed that, after the generation of customers' demand and the assignment of deliveries to the available riders, computes the delivery costs of multi-parcel crowdsourcing logistics. In addition, the costs associated with traditional van-deliveries are also estimated to compare the performances of the two LMD options. Second, the model is applied to a realistic case in Milan, Italy, to get numerical insights about the economic performances of both the solutions. These two-steps– i.e., the development of a model and the subsequent discussion of results "based on an exemplary case" (Pinto et al., 2019) – is widely adopted in recent literature addressing CL for LMD (Qi et al., 2018). Finally, sensitivity analyses are run on a set of key variables and parameters, to test the robustness of the model and to evaluate the impact of potential variations in the inputs (e.g., higher demand or different wage offered to the riders) on the performances of multi-parcel CL.

Similarly to other recent papers investigating logistics for B2C e-commerce, three different methodologies are used to support the model development and application:

- literature review, to both ground the research objective in the state of the art and identify insights for the model development and application (Mehmann et al., 2015);
- semi-structured interviews with practitioners (e-commerce retailers and logistics service providers) to define the significant variables to be considered and the associated values to

feed the model (Harrell and Bradley, 2009), as well as to discuss and validate the results (Harland et al., 2019);

- analysis of secondary sources (e.g., e-commerce websites, journals of logistics practitioners, reports) to triangulate information from the literature and the interviews (Jick, 1979).

Some clarifications should be made about the interviews with practitioners.

On the one hand, they had a threefold role during the work. Based on methodological papers that show how to combine different methodologies in the field of logistics (e.g. Mangan et al., 2004), interviews were performed in three subsequent moments, with three different goals.

(i) First, to develop the model: qualitative one-to-one interviews were conducted to gain insights about multi-parcel CL (Mangan et al., 2004). These interviews were semi-structured, as they allow the rising of ideas and the identification of parameters and variables not previously recognised by the authors (Harrell and Bradley, 2009).

(ii) Second, to apply the model: structured interviews were performed to gather quantitative data to feed the model. These data collection interviews were supported by checklists reporting all the main variables and parameters for which numerical values were needed (Nutting et al., 2002). Details about these interviews follow in section 5.1.

(iii) Third, to validate the model: once the results (for both the base case and the sensitivity analyses) were found, a group interview – in which all the practitioners discussed together guided by a moderator – allowed to both validate the outcomes and interpret them (Harland et al., 2019). The group interview is more effective than single interviews as the participants' simultaneous interviewing allows to combine and stimulate their mutual contribution (Urciuoli and Hintsa, 2017).

On the other hand, some details about the interviewees and the number of interviews must be highlighted. Four practitioners have been identified among volunteers from both previous research efforts and references from senior logistics professionals, as suggested by Huscroft et al. (2012). More in detail: two practitioners are from logistics express couriers (one general manager and one “e-commerce strategy” manager) and two from online retailers (i.e., the logistics manager from a merchant managing the last-mile delivery internally, and the e-commerce manager from a company that instead outsources the final part of the distribution). All the four practitioners were interviewed both individually, once in the first and second phases (thus reaching a total of 8 one-to-one interviews), and in-group, in the validation phase. All the interviews were chaired by one author, while the other documented the sessions by taking written notes, as suggested by Urciuoli and Hintsa (2017).

## 4. Model development

### *4.1 The process*

The delivery process considered in this work is in line with that adopted by *Amazon Flex*: this CL project is designated by many recent academic works as representative for the multi-parcel paradigm (e.g., Ibrahim, 2018; Li et al., 2019; Macrina et al., 2020). This section is devoted to providing an overview of the characteristics, the operating way, and the logic behind this initiative, since illustrating them may help the reader in better framing the subsequent model development and application. The reasons behind the choice of *Amazon Flex* as a reference case are different, and they pertain to both the academic and the managerial domains. On the academic side, different papers present Amazon as one of the companies that were able the most to benefit from CL opportunities in the LMD field (Arslan et al., 2016; Castillo et al., 2018; Frehe et al., 2017). On the managerial side, *Amazon Flex* is representative of the multi-parcel crowdsourcing logistics model addressed by this work, as it has all the peculiarities and the specificities of such a delivery solution. Besides, this initiative operates in many different countries worldwide (e.g., USA, UK, Spain), and it thus constitutes a well-established case, for which results may be easily generalised.

*Amazon Flex* was launched in Seattle, US, in September 2015. Due to its huge success, the implementation was immediately extended to Manhattan, Chicago, and seven other American cities. In the upcoming years, it also spread across Europe (entering the UK in 2016, Germany in 2017, Spain in 2018) and Asia (specifically Singapore in 2017). The main characteristics of *Amazon Flex* may be summarised as in the following. First, as it happens for the majority of CL initiatives, it has been finding application in – usually big – cities (i.e., urban environments), and this is true independently from the considered country. Second, the remuneration of riders is based on an hourly fee. It typically ranges from 18 to 25 $/hour in the US, from 12 to 15 £/hour in the UK, from 14 to 16 €/hour in other European countries (e.g., Spain and Germany). Third, riders may give their availability for time slots whose durations varies from 1 hour up to 4 hours. Fourth, riders are assigned a delivery tour in which they have to deliver different parcels to the customers' houses. These logics, which find application in the analytical model developed in this work, are better detailed in the following section (devoted to describing the model architecture).

### *4.2 The model architecture*

The architecture of the model (see Figure 1) is composed of four main building blocks.

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The "Input variables" are the variables describing the last-mile delivery problem.

- Delivery area and sub-areas – geographical area where the last-mile deliveries have to be performed; the area is divided into different sub-areas. As a matter of fact, the model is modular, and supports a multi-hub delivery option, in which each sub-area is served by a different warehouse.
- Number and location of warehouses – number and location (i.e., geographical coordinates) of the hubs serving the different delivery areas.
- Demand – total daily number of parcels to be delivered in the area.
- Time slots – number of time slots in which the daily delivery time is divided, and for which the scheduling of CL deliveries may be independently managed.
- Number of riders – dimension of the crowd, i.e., overall number of riders available to accomplish deliveries during the day. In line with different academic works investigating the implementation of CL to LMD (e.g., Seghezzi et al., 2020), the model relies on the assumption that there are enough riders to perform all the delivery tours. As a result, the available fleet dimension is found by increasing the number of delivery tours to be assigned (i.e., the minimum required number of riders) by a defined percentage.

- Distribution of riders per shift – percentage distribution of available riders over the different types of shift (shifts may differ in terms of duration). The model considers that – as it happens in real CL initiatives – riders may give their availability for different time windows (e.g., some may be willing to work for four hours, some may give their availability for just one hour).

The "Context data" describe those elements related to the specific context in which the LMD problem is applied (e.g., legal regulations).

- Daily deliveries distribution – percentage allocation of the orders to be delivered to the different time slots of the day (e.g., a higher number of deliveries may be scheduled during the afternoon/evening hours compared to morning hours).
- Duration of working shifts – duration of the possible working shifts offered to the crowd (i.e., options in terms of the number of consecutive hours for which riders may decide to apply).
- Riders' wage – hourly compensation paid to the riders. Based on the analysis of both literature and real initiatives, riders are paid depending on the expected time needed to accomplish the delivery tasks.
- Duration of stops – fixed time required for each stop, both at the customers' home for the delivery (to perform the needed activities, e.g. park the transport mode – i.e. the van for traditional LMD/the car for CL – ring the bell, deliver the parcel) and at the hub (at the beginning of the tour to load the parcels, and at the end of the tour to manage those parcels that have not been delivered due to the absence of the customer).
- Failure delivery rate – percentage of deliveries not successfully accomplished due to the absence of the customers at home. Based on both literature and interviews, the model considers different percentages depending on the time slots of the day in which deliveries are performed (i.e., lower failure rate in the afternoon/evening).

The "Output" is the set of results provided by the model. Aligned to the objective of the work, the main outcome is the average delivery cost per parcel (for both the multi-parcel CL and the traditional LMD options).

The model "Algorithm" is made of all the major steps and computations needed to achieve the output. It works according to six main stages:

(i) *Demand generation*: based on the overall daily number of orders to be delivered, on their distribution along the day, and on the delivery area, the model is initialised, generating the orders and associating them to the addresses of the customers (in terms of both latitude and longitude) (similarly to Arnold et al., 2018).

(ii) *Clusters creation*: depending on their geographical distribution over the delivery areas, the orders are then grouped into different clusters, each one representing a delivery tour assigned to one rider. Clusters are built based on the geographical distribution of addresses to maximise the delivery density per tour, leveraging on the centre of gravity principle. More in detail, the clustering algorithm works according to an iterative process including the following steps: N centroids (N being the number of clusters to be created) are generated; based on their position, the different delivery points are associated to the closest centroid (thus defining a first version of the clusters); new centroids are defined as gravity centres of the derived clusters. These two latter steps are repeated until the composition of the clusters is steady. For additional details concerning the centre of gravity-based clustering in the logistics field, please refer to Esnaf and Küçükdeniz (2009).

(iii) (iii) *Theoretical routings optimisation*: once the clusters have been created, the routing is optimised for each of them (i.e., for each delivery tour). A Vehicle Routing Problem (Laporte and Osman, 1995) is solved for each cluster to find the sequence of customers that minimises the overall travel time for the tour. In order to reduce the time needed for the computations, this first theoretical step is based on the rectilinear distances among the different destinations, which is estimated according to the following formula: $d_{i,j} = |x_i-x_j|-|y_i-y_j|$ (Taracena Sanz and Escobar Gómez, 2013). There seems to be an agreement among logistics scholars in recognising that this estimation is a good proxy of real distances to solve VRPs (Dandotiya, et al., 2011; Hsieh and Tien, 2004).

(iv) *Actual travel time computation*: based on the theoretical optimal sequence of customers for each delivery tour, the actual travel time needed to visit them is computed. During this step, the considered distances and the traffic conditions, are the real ones, which –

similarly to Rothfeld et al. (2019) – are integrated into the model through the Google Maps Distance Matrix API (Application Programming Interface). In addition to the travel time, the time needed to stop at both the warehouse and each customer's house is considered, and the overall duration of the tours is computed.

(v) *Allocation of delivery tours to riders*: based on the actual total time needed to perform the delivery tours, each tour is assigned to one available rider (Carbone et al., 2017). The allocation of each tour to the riders follows the "minimisation of the non-operative time" logic: among the riders whose availability time is higher than the time needed to perform the tour (i.e., the riders whose availability is sufficient to delivery all the parcels), the algorithm selects the candidate for which the availability time is the closest to the time needed (trying to saturate the time of the riders as much as possible).

(vi) *Delivery cost estimation*: based on the total number of assigned riders and on the duration of their working shifts, the average cost for performing the deliveries is computed for each time slot. First, the number of hours – associated with each rider – is multiplied by the hourly pay; second, the values referred to the different riders are summed up; third, the average cost to deliver a parcel in that slot is computed, allocating the total cost paid for the riders to the overall number of deliveries successfully accomplished in that slot (Mangiaracina et al., 2019). The overall daily average delivery cost per parcel in the CL option is then derived (please refer to the formula below) as the average of the delivery costs associated with the different time slots, weighted by the number of deliveries scheduled in each slot.

$$\text{Average CL Delivery Cost per Parcel} = \sum_{t=1}^{T} \left( D\%_t \cdot \frac{\sum_{r,t=r,1}^{Rt} SD_{r,t} \cdot W}{P_t} \right)$$

Where:

t = considered time slot;

T = overall number of time slots within the day;

$D\%_t$ = percentage of the total number of daily deliveries scheduled in time slot t;

r,t = r-th rider working during the time slot t;

Rt = total number of riders working during time slot t;

$SD_{r,t}$ = duration of the shift of the r-th rider working during time slot t;

$P_t$ = total number of parcels successfully delivered in time slot t;

W = hourly wage of the riders.

## 5. Model application

### *5.1 Base case*

After its development, the model is applied to a realistic context in Milan (Italy). The main goal of the model application is to evaluate the effect of multi-parcel crowdsourcing logistics on LMD cost, and compare it with the traditional delivery based on vans.

Milan is the second-largest city in Italy, and it has always been capturing the interest of logistics scholars, who have been selecting it as the implementation scenario for their studies (e.g. Akhavan et al., 2020). This is true especially if considering B2C e-commerce and crowdsourcing logistics (e.g., Seghezzi et al., 2020), due to the high adoption rate by Milan citizens (B2C eCommerce observatory). When referring to Milan, three different areas are traditionally identified (Croci and Rossi, 2014): the city centre (which is very small, i.e., 9 $Km^{2,}$), the outer part (which includes the surrounding areas and has as boundaries the beltway roads around the city) and the suburbs. Similarly to previous works (e.g., Seghezzi et al., 2020), the delivery area considered in this work includes the centre and the outer part, and is about 240 $Km^2$ large. As anticipated, the delivery area is divided into sub-areas, each served by a different warehouse. In line with the real cases of the leading express couriers operating in Milan, the sub-areas – and thus the hubs (whose coordinates are reported in Table 2) – are three, and their size is very similar (81, 77 and 82 $Km^2$ respectively). Demographical and geographical studies about Milan (e.g. Akhavan et al., 2020) show how the considered delivery area is urban – including both residential and office zones – and with a high population density (Pucci, 2016). These characteristics are maintained within the three zones considered in this study (which may be considered as comparable in terms of population density and geographical features). For additional details concerning the geography of Milan, the reader can refer to Akhavan et al. (2020) and Pucci (2016). Figure 2 (Google, n.d.) shows the overall delivery area, the three identified sub-areas and the three hubs (represented as black triangles). The positions of the hubs have been defined mainly based on the interviews with practitioners, who suggested to locate them within the delivery areas but in the outer part. When considering urban fulfilment environments, warehouses are typically placed in the outer part of the city to facilitate the inbound from major logistics hubs and find areas with lower renting/building costs and housing density (Klauenberg et al., 2018).

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The values needed to feed the model were defined based on assumptions and data coming from a twofold contribution. On the one hand, they were selected relying on literature and secondary sources (e.g., websites of express couriers or reports from consulting companies); on the other hand, they were discussed during the interviews with practitioners. More in detail, it is possible to distinguish between two main types of data (which mainly differ based on the role of practitioners in the collection process):

(i) Data coming from “Secondary sources + Interviews” – they underwent a two-stage process. First, different secondary sources were consulted, and a hypothesis about the associated value was made. Second, practitioners were interviewed about the reliability of the value, and they were asked to validate it.

(ii) Data coming from “Interviews” –the practitioners were individually asked to provide or suggest the values of the variables and parameters for which it was not possible to clearly define a value from secondary sources. In case they were aligned, i.e., at least three out of four practitioners indicated the same – in a range of minus/plus 10% – value (and this happened in 89% of the cases), it was selected. In case of disagreement (11% of the cases), the practitioners discussed the values together until an agreement was found.

The resulting values for all the input variables and context data presented in section 4.2 – and the associated source – are reported in Table 2 (for the crowdsourcing logistics case) and Table 3 (for the traditional by-van delivery option).

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Comparing the two delivery options, most of the values and hypotheses made for CL are the same, but some need to be adjusted if considering traditional LMD. They are:

- Time slots and Working shifts duration: while crowdsourcing logistics allows to organise the daily horizon in different independent time slots (and to schedule a different number of deliveries in the different time slots of the day), the traditional delivery shift of a van-driver lasts for the whole working day, i.e. 8 hours (Arnold et al., 2018).
- Availability of the driver: while for CL riders may decide whether to give their availability for a specific working shift, traditional deliveries are performed by drivers who are employees (Carbone et al., 2017). As a result, their availability is considered to be 100% for the whole working day.
- Daily deliveries distribution: both literature and interviews show how deliveries will most likely be successful if they are performed during the afternoon/evening, as the probability of customers being at home is greater (Lim et al., 2018). Accordingly, it is better to schedule more deliveries in the latter part of the day. This is possible in the CL option, since its operating mode allows to hire a higher number of riders in specific time slots (thus being able to deliver more orders). As a result, with CL, a higher percentage of deliveries is scheduled in the afternoon/evening (Macioszek, 2017), i.e., during the 16.00-20.00 time slot. This cannot happen in the traditional solution, for which deliveries need to be evenly distributed along the whole 8-hours shift of the van-driver.
- Cost for the courier: in the CL option, the cost associated with the delivery accomplishment is computed based on the riders' hourly wage and the number of working hours. On the contrary, in traditional LMD, the cost is assessed summing up two components: a fixed daily component tied to the "activation" of the mean of transport – which includes the cost for the daily shift of the rider – (Punakivi et al., 2002) and a variable component depending on the travelled distance, e.g., fuel (Mangiaracina et al., 2019).

The model has been applied considering the presented values. The results, i.e., the delivery cost per parcel – for both the CL and the traditional delivery cases – are shown in Table 4. It displays the average outcome considering the whole delivery area and the details for the three warehouses.

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These outcomes lead to three primary considerations.

First, the CL option is more efficient than the traditional delivery solution. The average CL delivery cost per parcel is € 2.56, while for the traditional LMD the cost is € 2.89 (about 11% saving). The main reason behind this benefit is the flexibility crowdsourcing logistics allows to achieve in managing deliveries over the day. In fact, on the one hand, deliveries may be scheduled considering shorter time slots (120 to 240 minutes) if compared to the daily delivery tour of vans in traditional LMD (480 minutes). On the other hand, crowdsourcing logistics allows allocating a higher number of deliveries to the afternoon/evening hours. As already mentioned, the success rate in these slots is higher (as a result, the number of deliveries on which the total cost may be spread increases).

Second, the savings for the different warehouses vary from about 10% to nearly 12%. The differences among the three scenarios (which are pretty low if considering the absolute values) are mainly linked to viability conditions: warehouse 3 is located in a central area, in which the travel time per km is higher, due to traffic and congestion.

Third, the model quantifies the economic benefits stemming from the implementation of crowdsourcing logistics in terms of delivery cost (i.e., cost of workforce and transport). However, it does not fully evaluate the positive effects of CL flexibility, which is twofold. Considering short-term flexibility, as previously stated, it is possible to rely on a higher number of riders, and this schedule more deliveries, in the afternoon/evening time slot. Nonetheless, the consequent increased delivery success rate does not only result in a lower delivery cost, but also in greater customer satisfaction (Vanelslander et al., 2013). Considering instead long-term flexibility, CL allows to more easily deal with demand peaks not only during the day, but also along the year. Seasonality strongly affects online purchases (e.g., Christmas peak), and being able to avoid adding vans to the fleet may entail great economic advantages (Mangiaracina et al., 2019).

### *5.2 Sensitivity analyses*

Besides the base case application, some sensitivity analyses are run in order to achieve a twofold objective. On the one side, testing the robustness of the model and the reliability of the outcomes of the base case application. On the other side, investigating the effect of potential variations in the inputs on the obtained outputs, i.e., understanding the impact of the main variables and parameters on the performances of multi-parcel CL. The evaluated parameters and variables are the demand, the riders' wage, the duration of the working shifts, the number of riders, and the failure delivery rate.

Two key considerations need to be outlined about the major decisions made concerning the sensitivity analyses. First, the reason behind the identification of the variables/parameters to be varied and the definition of the alternative values to be assigned to them. These choices are based on both literature (e.g. many scholars state that the wage of the riders is critical in determining the outcomes of a CL initiative (Qi et al., 2018)) and interviews with practitioners (e.g. the different failure delivery rates have been proposed by operators from express couriers, based on the experience of the drivers in delivering parcels). Second, the role of the demand. Since both academics (see, for instance, the work by Boyer et al. (2009)) and practitioners agree in recognising that the demand has a massive impact on last-mile delivery performances, this variable has been assigned a key role in the sensitivity analyses. More specifically, all the other sensitivity analyses are run for four different demand values, and not just for the reference value of the base case. For the sake of clarity, the results disclosed in the following part of this section are referred to the 20,000 daily parcels case. Nonetheless, the outcomes of all the other scenarios are aligned to those displayed, and the stemming conclusions are coherent.

***Demand***. Beside the base case (20,000 daily parcels) the considered demand values are: 10,000 / 30,000 / 40,000 daily parcels. The results of the first sensitivity analysis, in terms of CL delivery costs, are shown in Table 5.

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Please take in Table 5

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As expected, increasing the demand implies reducing the average CL delivery cost per parcel. As a matter of fact – aligned to what also happens in traditional home deliveries (Boyer et al., 2009) – the distance between two consecutive destinations (and thus the time needed to travel between two customers) decreases. Accordingly, the rider can accomplish more deliveries at the same time (i.e., in the same tour). The costs of a delivery tour (e.g., the salary of the rider) are consequently allocated to a higher number of deliveries. Based on these results, online players deciding to introduce CL as a delivery option should try to increase the adoption of such a solution by customers as much as possible. For this purpose, appropriate actions (e.g., lower delivery price paid by customers if opting for CL, CL implemented for all the free-delivery purchases) should be carefully designed and implemented.

***Riders' wage.*** Concerning the wage of the riders, both higher and lower values compared to the base case (i.e. 14 €/hour) are considered. More specifically, the additional values are: 12 / 13 / 15 €/h.

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Please take in Table 6

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Three main considerations may be derived from the stemming outcomes (Table 6). First, as it could be anticipated, an increase in the riders' salary results in a higher CL delivery cost per parcel. Second, these two increases (salary and delivery cost) are proportional; this is coherent with the type of compensation, which is hourly based (a higher cost is thus allocated to the same number of deliveries). Third, even in the worst – i.e., most expensive – case, CL is still cheaper than the traditional LMD option.

A clarification needs to be outlined about this sensitivity analysis: only the individual impact of the wage on the delivery cost is considered, while its potential indirect effects on the performances of such deliveries (e.g., higher availability of riders) are not investigated. These being the premises, players in charge of parcel sized home deliveries – e.g., express couriers – should carefully evaluate the relationship between a higher riders' wage and a lower availability, and the impact they could have on the average delivery cost.

***Duration of working shifts*.** The base case scenario contemplates three different types of shifts, whose duration is 120, 180, and 240 minutes respectively. Since one of the main advantages tied to CL – for both companies and riders – lies in the flexibility of the work organisation, two additional (and more flexible) configurations are evaluated. The first one includes four shifts (120 min / 160 min / 200 min / 240 min) and the second one includes 6 shifts (90 min / 120 min / 150 min / 180 min / 210 min / 240 min).

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Please take in Table 7

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Table 7 details the distribution of available riders for the different shifts (i.e., the percentage of riders offering their availability for each option).

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Please take in Table 8

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The results of this analysis (Table 8) show how increasing the number – and thus the flexibility – of the potential options in terms of duration of the shifts results in a lower average CL delivery cost per parcel. Also in this case, the outcome is tied to the logic behind the compensation scheme of riders. They are remunerated based on the entire duration of the delivery shifts they apply for (i.e., the expected time they should spend to perform the assigned deliveries), without considering the actual time needed to accomplish the tour. If the time to complete the deliveries is lower than the duration of the shift, they are also paid for the exceeding time in which they are not "active". As a result, practitioners should be aware that increasing the granularity of the duration of the shifts reduces the idle time of the riders, allowing to better adapt the overall paid time to the time actually spent to perform the deliveries.

***Number of riders***. In the base case scenario, the riders' availability is assumed to be always more than sufficient to accomplish all the deliveries. More in detail, the total number of available riders is defined increasing the number of delivery tours to be assigned (i.e., the minimum required number of riders) by 35%. It means that if 100 tours are necessary to fulfil the deliveries in a specific time slot, the algorithm selects the riders from an available fleet made of 135 people. This percentage, defined based on interviews with practitioners, is varied in this sensitivity analysis. More in detail, both a case with lower availability (+15% with respect to the number of tours) and a case with higher availability (+55% with respect to the number of tours) are evaluated (thus still granting the accomplishment of all the deliveries).

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Please take in Table 9

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Results (Table 9) show that a higher riders' availability is associated with lower CL delivery costs. As a matter of fact, as the fleet gets larger, the probability of being able to find a better match between the duration of riders' shift and the duration of delivery tours increases: a higher number of riders implies a higher probability to select those candidates whose shifts do not cause high inactivity time. On the contrary, if the number of eligible riders is low, it may be necessary, in case candidates offering shorter shifts have already been assigned to other tours, to employ candidates offering long shifts.

***Failure delivery rate*.** The failure rate is intended as the probability not to find the customer at home when delivering the parcel. As mentioned in section 5.1, two different situations have been modelled in the base case scenario, one for each delivery option (traditional and CL). In traditional deliveries, the failure rate has been set to 18%. Conversely, as crowdsourcing logistics allows to better manage the scheduling of the deliveries, two different average values have been defined for the failure rate in the CL option: 18 % for the first two time slots and 10 % for the evening one. These are the failure delivery rates on which the sensitivity analysis is run. More specifically, Table 10 displays the three alternative CL scenarios that are evaluated: one with no failed deliveries (average failure delivery rate: 0%), one with low failed delivery rate (average rate: 10%) and one with high failed delivery rate (average rate: 18%).

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Please take in Table 10

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The combination of these three scenarios allows, on the one hand, to evaluate the potential savings entailed by CL in case it could not benefit from the better delivery allocation, i.e., if the number of deliveries is the same independently from the time slot (18% case). On the other hand, it is possible to analyse how the advantages of CL could be boosted in case deliveries may be scheduled when customers are (almost) for sure at home.

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Please take in Table 11

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The outcomes (Table 11) show how the impact that the customers' no-show rate has on the delivery cost is crucial. Additionally, different considerations may be derived. First, despite the failure delivery rate is equal to 18 % – as per the traditional scenario – CL is still remarkably more efficient than traditional deliveries. The savings vary from 8.4 % of the delivery cost (for the first delivery area) to 6.6 % (for the third one), and it is 7.7 % on average (whole area). Second, as it could be expected, these savings are boosted in case the probability of incurring in failed deliveries for the CL case decreases. With a 10% average rate, the average saving for the whole area (CL vs. traditional delivery) is nearly 16 %; with a 0 % average failure rate, this benefit increases to around 24.4 %. Accordingly, online players should devote great effort in trying to maximise the delivery success rate, according to a twofold perspective. On the one hand, leveraging the efficiency improvement lead by the higher CL flexibility (i.e., scheduling a higher number of deliveries in the slots with low failed delivery probability). On the other hand – and to a greater extent for the slots associated with low success rates – notifying customers in advance about the moment in which their delivery will be performed (for instance, through alert messages). As a result, customers could know the deliveryman is coming with their parcel and manage to be at home (Zuccotti *et al.*, 2011).

Overall, the sensitivity analyses allow drawing some general conclusions. First, the results – concerning the comparison of the delivery cost for multi-parcel CL and traditional by-van LMD – are consistent with those obtained in the base case application. Independently from the variations of the inputs, multi-parcel CL is always more efficient than traditional LMD. Accordingly, it is possible to state that the developed model is reliable and that the outcomes are robust. Second, some considerations may be derived concerning the considered CL scenarios. The best configurations in terms of average delivery cost, among those that have been investigated, are the following: (i) 12 € / h wage and (ii) 0% CL failed delivery probability. In both these settings, the average delivery cost per parcel is € 2.19. Conversely, the least efficient configurations are (i) compensation equal to 15 € / h and (ii) overall daily demand set to 10,000 parcels (both resulting in a 2.74 € average delivery cost per parcel). Nonetheless, even in these worst-case scenarios, CL is still more economic than traditional deliveries (being traditional by-van LMD characterised by an average € 2.89 delivery cost per parcel). Finally, the sensitivity analyses allow evaluating the individual impact of variations in the input variables and context data on the outcomes. According to this perspective, the most significant factors affecting the delivery cost are the demand, the compensation of the riders, and the probability (not) to find the customer at home. As a result, these are the dimensions towards which operators should devote their attention.

## 6. Conclusions

Crowdsourcing logistics is a promising answer to the efficiency and effectiveness challenges posed by last-mile deliveries. Among the different CL configurations, a model that is gaining the interest of both academics and practitioners is the multi-parcel paradigm, in which each rider accomplishes different deliveries in the same tour. Despite its great potentialities – also due to the novelty of such a phenomenon – it is still under-investigated in literature.

This paper aims to compare the performances (in terms of delivery cost) of multi-parcel crowdsourcing logistics with those of the traditional van-based last-mile delivery option. To reach the defined research goal, three stages are performed. First, an analytical model is developed that estimates both CL and traditional LMD costs. Second, the model is applied to a representative case in Milan, Italy. Third, sensitivity analyses are run on key variables/parameters – i.e., the demand, the wage of riders, the duration of the working shifts, the availability of riders, and the failure delivery rate – to both investigate their impact on the delivery cost and to test the robustness of the model and the reliability of the outcomes.

This paper provides both academic and managerial implications. On the academic side, it contributes to the extant knowledge about crowdsourcing logistics for LMD, investigating the multi-parcel model through a quantitative-oriented multimethod approach. As a result, it allows gaining numerical insights about a CL paradigm that – even if identified as promising by both practitioners and academics – has been mainly addressed in literature employing high-level qualitative methodologies. On the managerial side, this work offers a useful tool to practitioners from the B2C e-commerce field, on which they may rely to evaluate the convenience of implementing multi-parcel CL in LMD (as an alternative to traditional solutions). Additionally, it allows to draw some considerations about the areas of action online players should prioritise in order to enhance the efficiency of multi-parcel CL (e.g., offering a higher number of options for the duration of the shifts; trying to increase the delivery success rate, both scheduling a higher number of deliveries during the afternoon/evening time slots and notifying customers in advance about the moment in which their delivery will be performed).

This work has some limitations, which could be overcome through further developments. First, the model relies on the assumption that the number of available riders is sufficient to deliver all the parcels, and this is not always true in real contexts. Future works could be aimed at evaluating the effects that the potential unavailability of riders may have on CL performances. In addition, instead of considering the dimension of the crowd as an independent input variable, efforts could be made to analytically model the relationship between the compensation offered to the riders and their availability (as the wage may influence the willingness of riders to perform a delivery task). Second, the only way this work quantifies the benefits stemming from the flexibility entailed by CL lies in a more efficient management of deliveries along the day (i.e., a higher number of deliveries scheduled in the afternoon/evening, thus implying a greater success rate). Future works could also quantify the impact (i.e., the savings) of the long-term CL flexibility, on which – as mentioned in the previous section – online players could leverage to cope with demand seasonality over the year. Finally, the sensitivity analyses are run considering one variable/parameter at a time. Additional developments could be aimed at evaluating the effect of combined variations of different items. Despite its limitations, the authors – also based on the interviews with practitioners – are confident that the obtained results are coherent with the reality and that the stemming conclusions are significant and consistent.

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| Crowd local delivery model | Main references | Crowd composition | Main advantages |
|---|---|---|---|
| For-free deliveries | Devari, Nikolaev, and He, 2017; Suh, Smith, and Linhoff, 2012 | Friends or acquaintances | Social, Environmental |
| Community deliveries | Kim, 2015; Paloheimo, Lettenmeier, and Waris, 2016 | Community members | Social, Environmental |
| Hybrid deliveries | Dahle, Andersson, and Christiansen 2017; Macrina et al. 2020 | Employees | Economic |
| Ad-hoc fleet deliveries | Chen, Mes, and Schutten, 2018; Kafle, Zou, and Lin, 2017 | Employees | Economic, Effectiveness |

*Table 1: Crowd local delivery models*

| | | | |
|---|---|---|---|
| Input parameters | Delivery area and sub-areas | 240.28 $Km^2$ divided into three areas (80.85 – 77.44 – 81.99 $Km^2$) | Interviews |
| | Number and locations of hubs | 3 warehouses. Coordinates: (45.522; 9.175) – (45.435; 9.1) – (45.435; 9.245) | Interviews |
| | Demand | 20,000 parcels/day | Secondary sources + Interviews |
| | Time slots | 8.00-12.00 – 12.00-16.00 – 16.00-20.00 | Secondary sources + Interviews |
| | Number of riders | Number of delivery tours to be assigned + 35% | Interviews |
| | Distribution of riders per shift | 30 % (120 min) – 35 % (180 min) – 35 % (240 min) | Interviews |
| Environmental parameters | Daily deliveries distribution | 25 % (8.00-12.00) – 30 % (12.00-16.00) – 45 % (16.00-20.00) | Interviews |
| | Working shifts duration | 120 min – 180 min – 240 min | Secondary sources + Interviews |
| | Riders' wage | 14 € / hour | Secondary sources + Interviews |
| | Stops duration | 4 min per customer – 5 min at hub | Secondary sources + Interviews |
| | Failure delivery rate | 18 % (8.00-12.00) – 18 % (12.00-16.00) – 10 % (16.00-20.00) | Interviews |

*Table 2: Crowdsourcing logistics case*

| | | | |
|---|---|---|---|
| Input | Time slots | 8.00-16.00 | Secondary sources + Interviews |
| | Availability of the driver | 100 % (480 min) | Secondary sources + Interviews |
| Environm | Daily deliveries distribution | 100 % (8.00-16.00) | Secondary sources + Interviews |
| | Working shifts duration | 480 min | Secondary sources + Interviews |

| | | | |
|---|---|---|---|
| | Cost for the courier | 150 € + 0.01 € * Travelled Km | Interviews |

*Table 3: Traditional delivery case*

| Cost per parcel | Crowdsourcing Logistics | Traditional LMD |
|---|---|---|
| Average (overall area) | 2.56 | 2.89 |
| Warehouse 1 | 2.52 | 2.86 |
| Warehouse 2 | 2.53 | 2.87 |
| Warehouse 3 | 2.63 | 2.93 |

*Table 4: Results of the model application*

| CL Delivery cost per parcel [€] | 10,000 parcels | 20,000 parcels | 30,000 parcels | 40,000 parcels |
|---|---|---|---|---|
| Average (overall area) | 2.74 | 2.56 | 2.52 | 2.47 |
| Warehouse 1 | 2.63 | 2.52 | 2.48 | 2.44 |
| Warehouse 2 | 2.77 | 2.53 | 2.51 | 2.43 |
| Warehouse 3 | 2.81 | 2.63 | 2.57 | 2.53 |

*Table 5: Results of the sensitivity analysis - Demand*

| Delivery cost per parcel [€] | CL | | | | Traditional LMD |
|---|---|---|---|---|---|
| | 12 €/h | 13 €/h | 14 €/h | 15 €/h | |
| Average (overall area) | 2.19 | 2.38 | 2.56 | 2.74 | 2.89 |
| Warehouse 1 | 2.16 | 2.34 | 2.52 | 2.70 | 2.86 |
| Warehouse 2 | 2.17 | 2.35 | 2.53 | 2.71 | 2.87 |
| Warehouse 3 | 2.25 | 2.44 | 2.63 | 2.81 | 2.93 |

*Table 6: Results of the sensitivity analysis – Riders' wage*

| Case | Shift [min] | Riders [%] |
|---|---|---|
| Base case (3 shifts) | 120 | 30 |
| | 180 | 35 |
| | 240 | 35 |
| Scenario 1 (4 shifts) | 120 | 30 |
| | 160 | 20 |
| | 200 | 25 |
| | 240 | 25 |
| Scenario 2 (6 shifts) | 90 | 10 |
| | 120 | 20 |
| | 150 | 15 |
| | 180 | 20 |

| | | |
|---|---|---|
| | 210 | 15 |
| | 240 | 20 |

*Table 7: Sensitivity analysis – Duration of working shifts*

| Delivery cost per parcel [€] | CL | | | Traditional LMD |
|---|---|---|---|---|
| | 3 shifts | 4 shifts | 6 shifts | |
| Average (overall area) | 2.56 | 2.44 | 2.36 | 2.89 |
| Warehouse 1 | 2.52 | 2.41 | 2.34 | 2.86 |
| Warehouse 2 | 2.53 | 2.41 | 2.31 | 2.87 |
| Warehouse 3 | 2.63 | 2.51 | 2.43 | 2.93 |

*Table 8: Results of the sensitivity analysis – Duration of working shifts*

| Delivery cost per parcel [€] | CL | | | Traditional LMD |
|---|---|---|---|---|
| | Availability +15% | Availability +35% | Availability +55% | |
| Average (overall area) | 2.66 | 2.56 | 2.51 | 2.89 |
| Warehouse 1 | 2.62 | 2.52 | 2.47 | 2.86 |
| Warehouse 2 | 2.63 | 2.53 | 2.48 | 2.87 |
| Warehouse 3 | 2.73 | 2.63 | 2.57 | 2.93 |

*Table 9: Results of the sensitivity analysis – Number of riders*

| Failure delivery rate in the considered time slot | 8:00-12:00 | 12:00-16:00 | 16:00-20:00 |
|---|---|---|---|
| Null | 0% | 0% | 0% |
| Low | 10% | 10% | 10% |
| Base case | 18% | 18% | 10% |
| High | 18% | 18% | 18% |

*Table 10: Sensitivity analysis – Failure delivery rates*

| Delivery cost per parcel [€] | CL | | | | Traditional LMD |
|---|---|---|---|---|---|
| | 0% | 10% | Base case | 18% | |
| Average (overall area) | 2.19 | 2.43 | 2.56 | 2.89 | 2.89 |
| Warehouse 1 | 2.15 | 2.39 | 2.52 | 2.53 | 2.86 |
| Warehouse 2 | 2.16 | 2.40 | 2.53 | 2.64 | 2.87 |
| Warehouse 3 | 2.24 | 2.49 | 2.63 | 2.74 | 2.93 |

*Table 11: Results of the sensitivity analysis – Failure delivery rate*

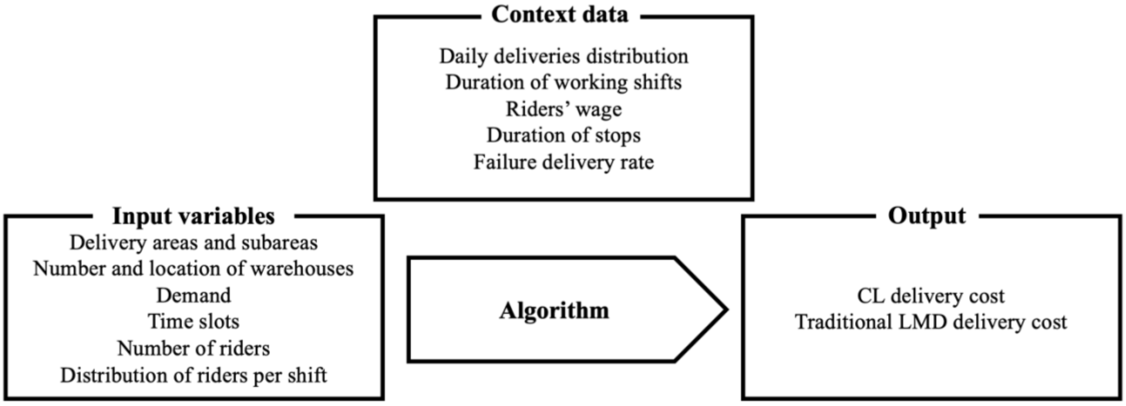


*Figure 1: The model architecture*

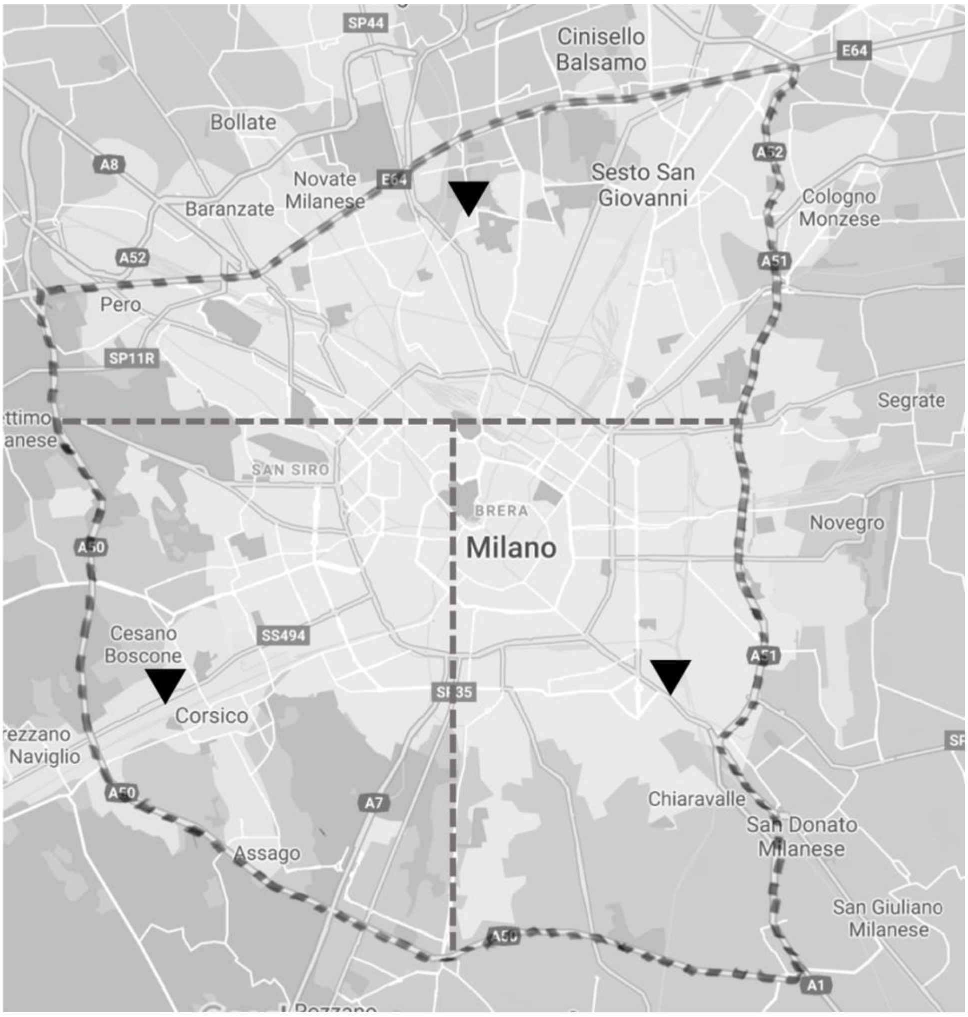


*Figure 2: The application context*