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Guido Perboli
Mariengela Rosano
Michael Saint-Guillain
Pietro Rizzo

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Bureaux de Montréal :
Université de Montréal
Pavillon André-Aisenstadt
C.P. 6128, succursale Centre-ville
Montréal (Québec)
Canada H3C 3J7
Téléphone : 514 343-7575
Télécopie : 514 343-7121

Bureaux de Québec :
Université Laval
Pavillon Palasis-Prince
2325, de la Terrasse, bureau 2642
Québec (Québec)
Canada G1V 0A6
Téléphone : 418 656-2073
Télécopie : 418 656-2624

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A Simulation-Optimization Framework for City Logistics. An Application on Multimodal Last-Mile Delivery.

Guido Perboli[1,2,*], Mariangela Rosano[2], Michael Saint-Guillain[3], Pietro Rizzo[2]

[1] Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation (CIRRELT)
[2] ICT for City Logistics and Enterprises, Politecnicò di Torino, Corso Duca degli Abruzzi, 24 - I-10129 Torino, Italy
[3] Université catholique de Louvain, Belgium and Institut National des Sciences de Lyon, France

Abstract. City Logistics has attracted considerable interest from the operations research and logistics communities during last decades. It resulted in a broad variety of promising approaches from different fields of combinatorial optimization. However, research on urban freight transportation is being currently slowing down due to two different lacks, limiting the exploratory capacity and compromise the technology transfer to the industry. First, the major part of the instances in the literature is based on artificial data, with results that cannot be directly evaluated in to real settings. Second, there is no standard way to mixing data gathered from different sources and generate instances in urban applications. This paper aims to overcome these issues, proposing a simulation-optimization framework for building instances and assess operational settings. To illustrate the usefulness of the framework, we use it to conduct a case study, in order to evaluate the impact of multimodal delivery options to face the demand from e-commerce, in an urban context as Turin (Italy). We investigate the impact of instance parameters on realistic scenarios and demonstrate that additional observations are obtained by following the proposed framework.

Keywords: Simulation-optimization framework, parcel delivery, online delivery, cargo bike, locker.

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* Corresponding author: Guido.Perboli@cirrelt.ca

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1 Introduction

Taniguchi et al. [19] define City Logistics as "the process for totally optimizing the logistics and transport activities by private companies with the support of advanced information systems in urban areas considering the traffic environment, its congestion, safety and energy savings within the framework of a market economy. In such settings, the transportation community has been recently devoting significant efforts to propose efficient and innovative approaches to address many types of City Logistics problems. On the other hand, a standard framework for simulating and studying the impact of optimization in City Logistics is currently missing, limiting the possibility to validate in real settings the technology transfer to industry. In particular, as highlighted by [10] and observed in section 2, there is an obvious lack of available realistic benchmark data set for the City Vehicle Routing Problem (VRP). Furthermore, in City Logistics the different categories of stakeholders all play an important role in urban applications, but they are rarely considered all together, leading the search to some local optimum [10].

In our opinion, the later issue is due to the following current limitations:

1. **unavailability of full data:** given a urban area, gathering the real data associated to all four stakeholders usually requires to much time and/or expertise to be actually implemented;

2. **difficulty of combining/reusing existing data:** whereas existing studies may provide realistic data involving one or more stakeholders, there is still no trivial way to combine such data from different sources.

The contribution of this paper is twofold. First, we propose to mitigate the two above-mentioned limitations by introducing a new standard optimization-simulation framework for City Logistics. Whereas the framework generalizes to many types of routing problems encountered in urban areas, its generality also allows to describe and combine requirements coming from different stakeholders.

Second, we apply our framework to a case study focused on the online urban freight distribution in the city of Turin (Italy). This study concerns the application of the proposed simulation-optimization framework to address the Dynamic and Stochastic Vehicle Routing Problem with Time Windows (DS-VRPTW) problem. We analyse how the solution quality in realistic urban scenarios is sensible to various stakeholder parameters, such as customers geographical distribution, the available types of vehicles and their limitations, the use of lockers for delivering part of the demand.

Our experimental plan leads to a broad variety of realistic benchmarks, each of these being specialized on a particular operational context in online urban collection of parcels. This portfolio of benchmarks is made available to the community under a simple common format, in order to reuse them in different case studies.

The papers is organized as follows. In section 2 we review the literature for vehicle routing case studies and applications in realistic urban areas. Section 3 describes the framework we propose in order to analyse realistic urban freight collection problems. Section 4 show how our framework can be exploited to realize a concrete case study of online freight collection in a realistic urban context. Conclusions and perspectives are discussed in section 5.

2 Literature review

We focus our review on realistic City Vehicle Routing Problem (VRP) related case studies one can find in the literature up to these days. The purpose of this section is primarily identify the scope of city VRP applications already addressed by the scientific community and secondly, identify the benchmark that are still currently available in that field. This review is initially based on the excellent work [10], which we restrain in order to focus on real case studies, in particular those for which the benchmarks are still available.

In [22], a real world problem of distributing pharmaceutical products in downtown Bologna (Italy) is considered and modelled as an asymmetric Capacitated Vehicle Routing Problem (CVRP). The test instances, involving up to 70 customers, are still available on the author's web page.

Variability in vehicle travel times have been studied from several aspects. In particular, in [11] the authors worked on shortest paths under dynamic travel times in a downtown area in Shanghai. The raw data (1 month of taxi GPS data, 3 months of bus GPS data in Shanghai during year 2007) are still currently available on demand to the authors.

Multi-level vehicle routing problems, such as the Two-Echelon VRP (2E-VRP) introduced by [15], have also received recent interest in urban context. In [6], the authors present a real world case study involving a time dependent VRPTW in Zaragoza (Spain), in which customers can be either directly delivered from the classical depot or by mean of green vehicles by using intermediate urban depots.

Vehicle breakdowns have been considered in [13]. Whenever a breakdown occurs, the re-planning problem is modeled as a modified Team Orienteering Problem (TOP) over the remaining customers and vehicles. They validate their heuristic method on real data from a food distribution company in Attica (Greece). Note that their benchmark is still available on demand.

Environmental-friendly decision systems in the context of (City) VRPs are being increasingly studied nowadays under various names: Green Vehicle Routing Problem (GVRP), Pollution-Routing Problem (PRP), Emissions Vehicle Routing Problem (EVRP), etc. Alternative fuel vehicles are considered in [5] by means of the GVRP. The objective is to minimize the total routing cost given limited refueling stations. Numerical experiments are conducted based on data from a medical textile supply company in Virginia. These data are still available under demand. In [1], a realistically generated benchmark is used in order to illustrate the PRP over a set of cities in United Kingdoms. The later benchmark is still available. A number of similar studies have been conducted on artificially generated benchmarks, many of them based on Solomon's instances. More recently, [12] provided a realistic benchmark for the Multi-path TSP with stochastic travel costs ([17]) applied to electric and hybrid vehicles in freight distribution. In particular, [12] propose a first example of instance generator. However, it was in a prototype form and strictly dependent on the application, lacking of a global vision.

Our literature review highlights that the City VRP contributions contain very few real-world based applications and the results are normally based on academic (and unrealistic) datasets. Up to our knowledge, among those studies that are based on realistic data, the corresponding benchmarks are still currently available for only 6 papers ([1, 5, 11–13, 22]). Moreover, these applications lack of a global vision and they are scarcely repeatable in different context. Thus, in the next section, we introduce our simulation-optimization framework, proposed to overcome these issues. Recently, the DATA2MOVE initiative started to collect data from different sources for Logistics ans Supply Chain applications, but the project is still at an early stage [21]. A lack emerging from the literature is the identification of the main sources types, how to mix and how to interface them with one or more simulation and optimization module in order to give flexible solutions to the stakeholders and the users.

3 A simulation-optimization framework for VRP in urban areas

The simulation-optimization framework proposed in this paper is depicted in Figure 1. According to [4], this framework applies a sequential simulation-optimization, where the simulations are numerical and based on the Monte-Carlo method. The simulation is implemented in Python, while the optimization modules can be defined directly in Python by the Pyomo modelling tool, including the PySP library for Stochastic Programming problems [8, 23] or can be integrated as external modules.

Thus, the framework is composed by the following modules:

1. Data fusion and operational context description. First phase of the framework consists in describing both the problem studied and the operational context, which may consider different types of data sources. We define the operational context using the following five sources of information: city network graph, vehicles and travel times, behavioural data (e.g., users choice preferences), socio-demographical data and city constraints (e.g., limited traffic zones, specific restrictions for certain vehicles, etc.) and problem objectives and constraints. Some data may be stochastic, i.e., they can be described by random variables, whenever some component of the operational context is uncertain (e.g., service or travel times, customer demand or presence, etc.). The problem is then fully defined by the problem objectives and constraints data type. The framework requires as input a problem (or operational context) description consisting in five types of data:

    - City network graph and maps. They are represented by complete directed graphs over a set of depots and customers. Ideally, vertices should be associated geographical coordinates so that to be visualized on real maps. The city network graph is usually obtained using raw data from cartography and the companies, including maps and empirical distributions of customers and depots. Amongst the four main stakeholders identified by [10] (residents, carriers, shippers and local administrators), the city network graph explains the baseline geographical attributes and means of the residents (customer locations), the shippers (the location of the depots) and the carriers (the available road network).

- Vehicle fleet and travel times. They include the specificities of the vehicle types, as capacity, speed, fuel consumption, etc., as well as their respective travel times and costs matrices. Vehicle fleet and travel times captures the means supplied by the shippers. In practice, these are provided by the company and possibly combined with data from external sources (such as sensors spread over the city network). Time dependence and/or uncertainty in the travel times/costs, if any, may also be described here together with other uncertainties (e.g., vehicle breakdown probability distributions).
- Behavioural and socio-demographic data. They include information concerning the density and the purchasing behaviours of final customers for a specific market. Thus, they clearly describe the residents stakeholders in all of their possible attributes. In a static context, these capture the customers constraints (e.g., time windows, demands, origin-destination matrices, etc.). In dynamic applications, any stochastic knowledge about the customer habits can be described here (e.g., demand or service time probability distributions, etc.).
- City constraints. Regulations imposed by the local administrators, such as access time windows (e.g., forbidding trucks during rush hours), vehicle weight restrictions (e.g., no heavy truck in the city centre), etc. City constraints clearly represent the administrators in all the regulations that could be imposed to the other stakeholders (e.g., the carriers).
- Problem objectives and constraints. Describe the problem itself in terms of constraints, preferences, as well as the objective function to be optimized. They can be defined by declaring the specific optimization module including its interface with the scenarios, or using a MIP solver by the Pyomo modelling tool.

This partitioning of the data into five distinct types allows to easily study the impact of modify a specific aspect of the operational context. Furthermore, it provides the possibility of combining/reusing data from existing case studies, hence alleviating the full data unavailability issue discussed in section 1. For instance, provided a real-world case study on a classical CVRP, modifying only components d and e of the problem allows to study the impact on the total carbon emissions of restricting the access of the city centre to green vehicles. Furthermore, filling component c with customer demand probability distributions permits to study Stochastic VRPs, whereas updating component b could allow to study the impact of taking travel time variability into account, as well as to use empirical distributions coming from other studies, letting to anonymize industrial data.

2. Scenario generation and Simulation. Once both the problem and the operational context are well defined, a broad set of scenarios is generated by using a high-level scenario generator, which allows the researchers to develop specific scenarios for different frameworks. Each scenario represents a particular realization of all the random variables involved in the problem data. In other words, each scenario is the description of a particular operational day. If the problem and operational day description contains no uncertain data, the only scenario is the description itself. Otherwise, a set of instances are generated using Monte-Carlo sampling. The framework let the user to define deterministic operational scenarios or stochastic ones with associated a scenario tree to each simulation scenario.

   The present version of the simulator implements a Monte Carlo method, a module for georeferencing the data and a post-optimization software. In more detail, the method works as follows:

   - The Monte Carlo simulation module repeats the following process for a given number $|I|$ of iterations.
     - Given the different data of the operational context as well as eventual distributions of the data themselves, the simulator generates a series of city scenarios.
     - The chosen optimization module is executed on each scenario.
     - A first statistical analysis on the aggregate results of the scenario-based optimization of a single iteration of the Monte Carlo simulation is performed. These data are used in order to check if one or more unrealistic or extreme situations have been introduced in the simulation itself.
     - In order to make a more accurate definition of travel times and cost matrices, the georeference module is used. The georeference feature is implemented by means of Google Earth

APIs and it is also used to graphically represent the results of the simulation itself.

- The distribution of the simulation-based optimization solutions is computed and a series of statistical data are collected.
- A post-optimization software module is devoted to compute additional Key Performance Indicators (e.g., CO2 and NOx emissions, stop per working hour, service and travel times).

3. Optimization. During this phase, each scenario is solved using a dedicated optimization algorithm that we consider here as a black box. Provided that the solver outputs the Key Performance Indicators required by the case study into consideration, post-optimization analysis are conducted. In order to cope with different contexts in urban areas, this simulation-optimization framework is composed by different building elements addressing the following problems:

   - Mathematical model generated by the Pyomo modelling tool;
   - VRPTW combined with the load balancing;
   - Stochastic TSP;
   - Dynamic Stochastic VRPTW solved by the optimization algorithm proposed by [16].

4. Context modification. Eventually, the structure of the operational context description makes it easily modifiable. During this phase, some properties of the description are modified, leading to a new operational context to be analysed by reiterating through phases 2 to 4.

4 Case study: online urban freight collection in Turin (Italy)

In order to demonstrate the potentialities of the proposed simulation-optimization framework, we adopt it in the case study of the city of Turin (Italy). Our aim is twofold:

- analyse the impact of multimodal delivery options to face the demand generated by the e-commerce.

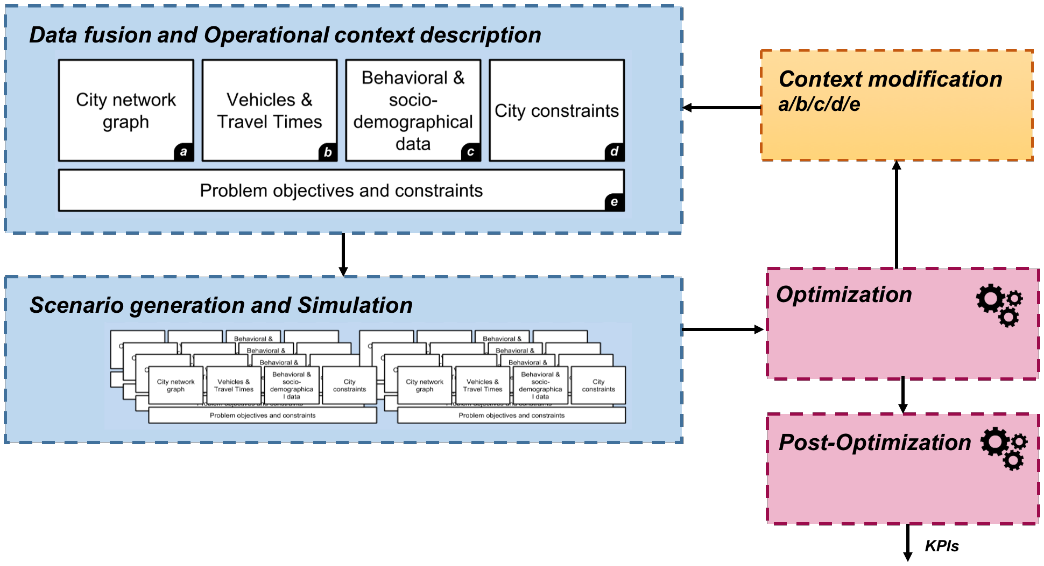

Figure 1: The simulation-optimization framework

- highlight the importance of considering real benchmark data set for DS-VRPTW coming from different sources and stakeholders.

Operational contexts and benchmark generation

Online shopping is rapidly increasing the freight flows which transit into the urban areas. According to [2, 3, 7], while the business to consumer (B2C) segment of e-commerce represents around 30% of the e-commerce turnover, they generate 56% of the all e-commerce shipments. Moreover, e-commerce involves individual fragmented and time sensitive orders of generally small-sized items, leading to more traffic in urban areas and negative externalities on the environment [18]. These are challenging factors for City Logistics applications, which are more and more focused on the integration of different delivery options (e.g., cargo bikes, drones, lockers, etc). In fact, our paper addresses this topic, considering the following four benchmarks:

- Benchmark 1 (B1). Only traditional vehicles (i.e., fossil fuelled vans) are used to manage the parcel delivery in urban areas.
- Benchmark 2 (B2). Outsourcing of classes of parcels to green carrier

subcontractors (i.e., they use bikes and cargo bikes) is a common practice to obtain operational and economic efficiency and customer proximity, while reducing the environmental impact of logistics activities [14]. Thus, in the B2 we consider that a green subcontractor delivers the parcels up to 6 kg in the central and semi-central areas of Turin. On the contrary, the traditional carrier manages all remaining parcels.

- Benchmark 3 (B3). We consider the adoption of delivery lockers. They represent self-service delivery location, in which the customer can pick up or return its parcel, according to the best and convenient time for him. In practice, these can be seen as special "super-customers" that aggregate the daily demands of a subsets of actual customers.

- Benchmark 4 (B4). In this benchmark, we consider the integration of the vans with both bikes and lockers.

These specific benchmarks derive from the combination of three parameters defined "a priori": the size of the traditional vehicles' fleet, the size of the green vehicles' fleet and the number of lockers. These data are provided by an international parcel delivery companies and an international e-commerce operator, which acting in Turin. Other input data considered in the DS-VRPTW are:

- City network graph and maps. We consider a 2.805 x 2.447 km area in Turin, which includes the centre of the city and a semi-central area, as in [14] (see Figure 2). Moreover, the list of the depots, the locations of lockers and of the potential customers inside the selected area are considered. Concerning the depots, we contemplate a distribution centre located on the outskirts of the urban zone and a mobile depot in the city centre. The former supplies the traditional carrier, while the second represents a satellite facility for the green carrier. In addition, the list of all the roads inside the city area is also required. Such list is arranged as a network of road-segments, each road-segment is defined as a sequence of two connected points, i.e., the crossroads. The information concerning the roads was extracted from the shape files made available by the local public authority in Turin. For each road-segment the average daily speed is measured by speed-sensors. Each element of the mentioned lists is defined with an unique identification number and its real GPS coordinates.

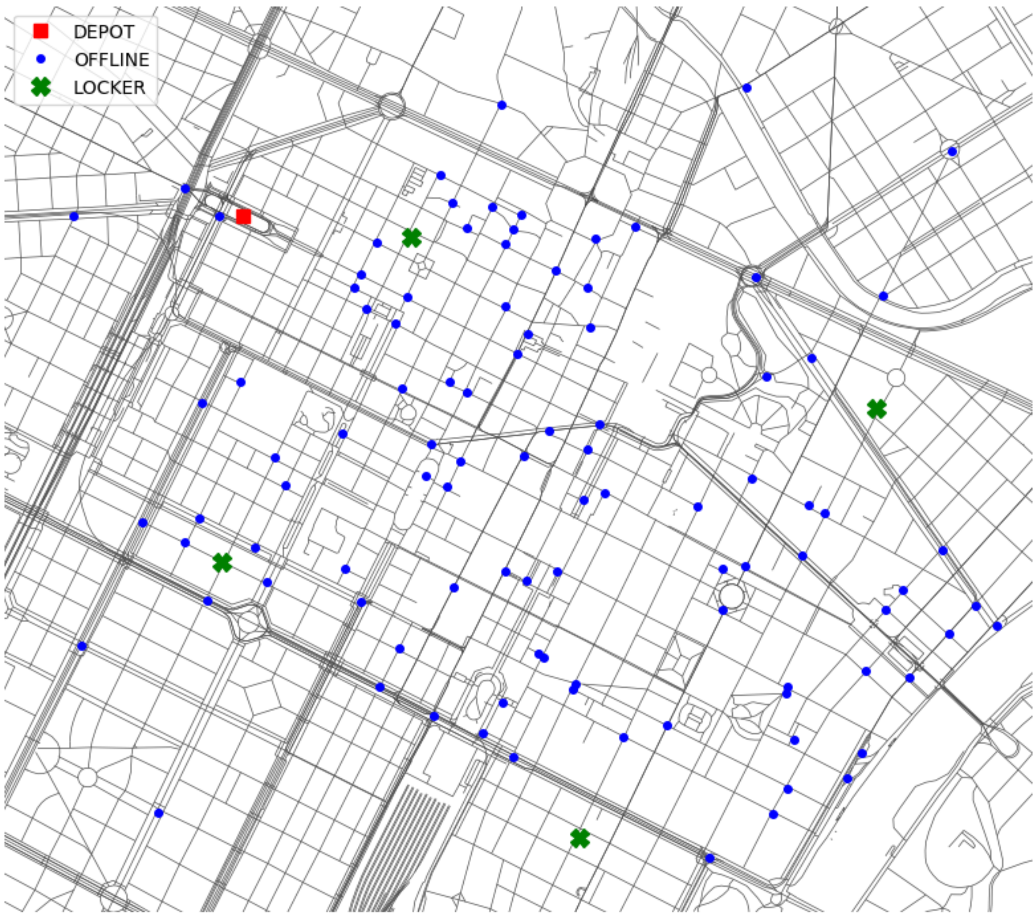

Figure 2: Area considered in the case study. Note that in the figure the mobile depot (square) and a set of offline customers (circles) and lockers (crosses) are represented.

- Vehicle fleet and travel times. As mentioned above, we consider two type of vehicle fleets: vans and cargo bikes. The parcel delivery company interviewed provides the characteristics of vehicle fleets (e.g., capacity, service time, speed). The service-time is a vector containing the information for each type of parcel handled, for the upload from the depot and for the unload into the locker. According to [14], we consider three classes of parcels: mailers (i.e., parcel with a weight up to 3 kg) small parcels (i.e., parcel with a weight between 3 and 6 kg) and large deliveries (i.e., parcel with a weight over 6 kg). The expected number of parcels for each class, expressed as a percentage of the total number of parcels delivered are shown in the Table 1.

- Behavioural and socio-demographic data. The horizon size is given here. We consider an 8-hours working day, from 9:00 to 17:00. The time-unit considered is 1 minute and the time-horizon is split into four time-buckets with the same length. For each potential customer, the demand expressed as parcel's volume is provided, together with the time-window for the service. The time-windows are assigned considering the percentage of prime members (i.e., those whose requests are prioritized restricting the time-window to the first two time-buckets). Then, the expected behaviour of each potential customer of the DS-VRPTW is described. It gives the probability that, for each customer location i and each time-unit t of the time-horizon, an online request (i.e., picking-up a parcel) appears at time t for location i.

- City constraints. We do not consider any specific city constraint.

- Problem objectives and constraints. The objective is first to maximize the (expected) number of online requests satisfied by the end of the horizon, and second minimize the total distance travelled by the vehicles.

The operational context defines the number of potential customers in the city map, the number of offline customers selected among the potential ones and the percentage of prime members. In this simulation, we generate three different-sized operational contexts with respectively 500, 250 and 100 potential customers. Each context contains 70% of offline customers and 25% of prime members. These potential customers are randomly picked from the pool of potential customers listed in the input data, and then anonymized for confidentiality matters, by offsetting the Cartesian coordinate system. Once the potential customers are defined, it is possible to compute the matrix of the mutual distances among the customers and the depots in the map. Such distances are computed applying the Dijkstra's shortest path to the network of road-segments specified in the input data. The high level of detail in the network, coupled with the haversine formula used to estimate the distance between each pair of points that compose a road-segment, provide us an outcome, which is much more accurate than a simple application of the Manhattan distance. The obtained results are in line with the once provided by the most common web-mapping service Google Maps. From the matrix of distances is then possible to compute the travel-times between pairs of locations, by using the measured road-segments' speeds available in the input data. The set of online requests appearing during the daily time-horizon is defined by considering three different degree of dynamism: 15%, 30% and 45%. Three sub-contexts are thus defined for each operational context, according to the degree of dynamism assignation. For each sub-context, a set of n instances is sampled by generating n Poisson Random Variates (PRVs) with parameter λ dependent on the degree of dynamism considered. Each PRV i represents the effective number of online requests that appear in the Instance i. The accorded set of online customers is finally randomly selected from the list of potential ones, allowing multiple requests for the same customers, but provided that they appear at different moments (i.e., time units). Each scenario, which in the case of DS-VRPTW corresponds to a sequence of revealed online requests along the day together with their specific reveal times and locations, is then independently solved by the optimizer. All the instances are generated and classified in classes (i.e., the benchmarks presented above), depending on the operational context, as described in section 3. The benchmarks are available online on the following git repository [9].

Table 1 resumes the values of the input data considered in our analysis. These information derive from interviews to Chief Executive Officer (CEO) and logistic director of an international parcel delivery company and of an e-commerce company operating in Turin. For further information about these data, the interested reader could refer to [14]. Moreover, the tests are conducted using real data concerning the customer distribution and daily volumes of deliveries in Turin between 2014 and 2015, provided by the international parcel delivery company that operates in Italy and is involved in the URBan Electronic LOGistics (URBeLOG) [20].

Table 1: Input data

Classes of parcel			
Class	*Weight range*	*% on total parcels*	
Mailer	0-3 kg	57%	
Small delivery	3-6 kg	13%	
Large delivery	¿ 6 kg	30%	
Capacity			
Vehicle	*Parcel size max*	*Capacity*	*Coverage*
Locker	6 kg	20* *parcels*	1 km
Van	70 kg	700 kg	NA
Cargo bike	6 kg	70 kg	NA
Speed in urban area		**Setup time**	
Vehicle	*Speed*	Load locker	15 min
Van	40 km/h	Load bikes at mobile depot	15 min
Cargo bike	20 km/h		
Service time to deliver each class of parcels			
Vehicle	*Mailer*	*Small delivery*	*Large delivery*
Van	4 min	4 min	5 min
Cargo bike	2 min	2 min	NA

* max number of parcel per day. Note that part of the locker is actually filled with the parcels of the previous three days

Specific optimization problem definition

As introduced above, in this paper we adopt the proposed simulation-optimization framework to address the DS-VRPTW problem that we define as follows. Given a discrete horizon of length h, a depot location and a set of n customer locations, we define the set $R = \{1, \ldots, n\} \times \{1, \ldots, h\}$ of potential requests, that is, one potential request at each time unit for each customer location. We assume the probability of each potential request to appear to be known, together with its own demand, service time and time window in case it actually appears. Whenever it happens and by the end of the current time unit, the request must be either *accepted* or *rejected*. In case it is accepted, the request must be guaranteed to be satisfied according to its time window and the vehicles capacity constraints. A function $c : R \rightarrow \mathbb{R}_+$ defines the penalty cost inquired whenever a request $r \in R$ is rejected. Provided finite set of capacitated vehicles, the asymmetric travel times matrix between all pairs of locations and the set of potential requests, the goal (at each time unit) is to operate the fleet of vehicles such that the expected total penalty cost is minimized by the end of the horizon.

Generally speaking, VRPs aims at modelling and solving a real-life common operational problem, in which a known set of geographically distributed customer (pickup) demands must be satisfied using a fleet of capacitated vehicles. The VRPTW introduces a time dimension by restricting each customer visit in a predefined interval. The objective is to find an optimal feasible solution, where optimality is classically defined in terms of travel costs. In urban applications, some additional characteristics must be taken into account: the *dynamic of the customers*, i.e., the customer requests are not known in advance, but are instead revealed as the operations go and the *stochastic nature of some parameters*, i.e., some attributes are random variables. For the aforementioned reasons, we incorporate as optimization model the Dynamic Stochastic VRP with Time windows (DS-VRPTW) solved by the algorithm described in [16]. Based on Monte Carlo sampling, the main idea of the Global Stochastic Assessment (GSA) algorithm aims at maintaining an unique feasible current solution being continuously optimized with respect to a restricted pool of sampled scenarios, while preserving nonanticipativity constraints in the evaluation function. A classical local search approach is used to that extend, exploiting well-known VRP neighbourhood operators such as relocate, swap, inverted 2-opt and cross-exchange to construct neighbouring solutions. A diversification mechanism is provided by regularly renewing the scenario pool, hence modifying the shape of the evaluation function, making needless the use of any other meta-heuristic. Note that the algorithm implements a relocation strategy, allowing the vehicles to anticipatively travel and possibly wait at promising strategical (customer) locations, even when these do not require a service (yet, if any).

Numerical analysis

In this section, computational tests of the simulation-optimization framework on the DS-VRPTW are described. The experimental plan is composed by a set of randomly generated test problems. For each benchmark and each operational context we performed 10 independent runs. Thus, we obtained totally 360 instances, which were independently solved by the optimizer.

To evaluate the results we measured different Key Performance Indicators (KPIs), according to the following standpoints:

- Economic Sustainability. As defined in [14], the carrier incurs in operating costs related to feet management and maintenance, and personnel costs. These costs are increased by a margin equal to 15% when the fleet is managed by an external firm subcontractor. Moreover, typical contract scheme in the parcel delivery industry imposes the conversion from a cost per kilometre to a cost per stops. Thus, the KPI measured are:

  - Cost per stop (internal fleet), in the case in which the fleet of vehicles is owned by the carrier (CpsI).
  - Cost per stop (external fleet) in the case in which the fleet of vehicles is owned by the subcontractor (CpsE).

  For further details about the computation of operating costs and each cost item see [14].

- Environmental Sustainability. In order to evaluate the impact of the adoption of green delivery means on the environment, we computed the CO2 savings (CO2EMsav) as the kilograms of CO2 not emitted in the B2, B3 and B4. Moreover, as the externalities have a social cost that impacts on the economic efficiency of the logistics operator, we express the emissions saved (compared with the B1) in monetary terms by applying the carbon tax, based on the average price paid for CO2 emissions [14]. This KPI is the environmental costs saving (CO2CSsav). Note that according to the regulation ISO/TS 14067:2013 we consider the total amount and costs of Green Houses Gas (GHG) emitted directly or indirectly by the overall parcel delivery chain.

- Operational Sustainability. It is referred to the operative performance and efficiency of each operators involved in the urban parcel distribution. Generally, it is expressed in terms of number of parcels delivered per hour (nD/h)
- Social Sustainability. It is strictly related to the operational sustainability, as the fulfilment of the increasing demand of time sensitive and online deliveries and the high service quality required by the final customers affect the working conditions of the drivers.

To provide the reader an easier understanding of the results, we computed the percentage of each KPI compared with the reference benchmark B1, as shown in Figure 3. Thus, Figure 3 depicts the performance of the traditional courier in the B2, B3 and B4. The values are computed as percentage variation of each KPI with respect to the value of the same KPI in the Benchmark $B1$. In particular, the Δoperating costs and Δenvironmental costs show the percentages of costs savings, both operating and environmental, that the traditional carrier obtains when the parcels up to 6 kg are outsourced to green carrier or delivered by means of the lockers. While, the item Δefficiency represents the loss of efficiency that affects the traditional carrier due to the reduced number of deliveries and the high saturation of vans, particularly in B2.

Figure 3 highlights an improvement of both economic and environmental sustainability, when green delivery options (cargo bikes and lockers) are introduced. In particular, in B2 the adoption of cargo bikes and the optimization of routes lead to a reduction of the vans used of about 32% and of the kilometres travelled, with consequent benefits in terms of reduction of operating costs (-37%). At the same time a reduction of the CO2 emission on average of 303 kg, is registered, which correspond to a decrease of 40% in the environmental costs.

Figure 4 reports the number of deliveries per hour of traditional vans and green vehicles in the different operational contexts, segmenting the results according to the number of customers in the scenarios and the the degree of dynamism. For the operational context $B1$ the green carrier has no bar

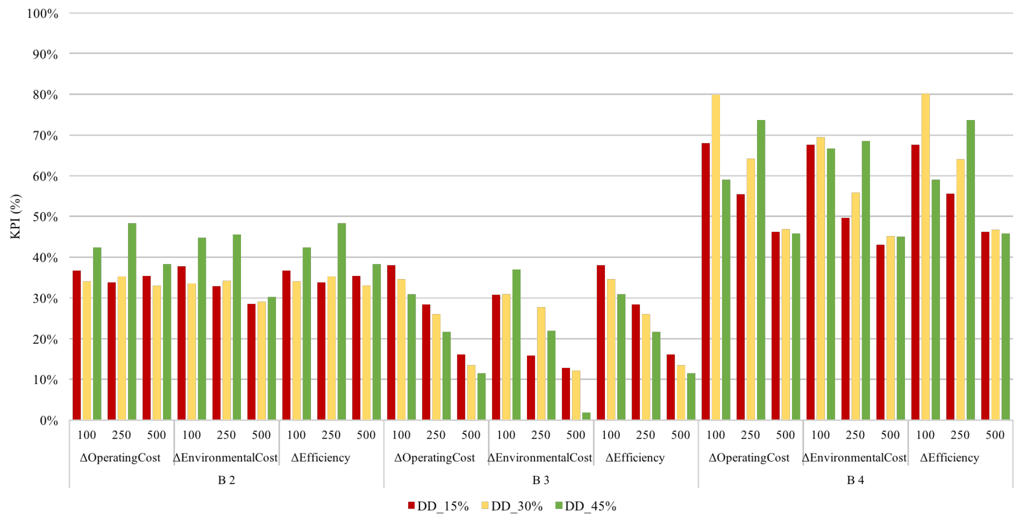

Figure 3: Performance of the traditional carrier, when cargo bikes and lockers are adopted.

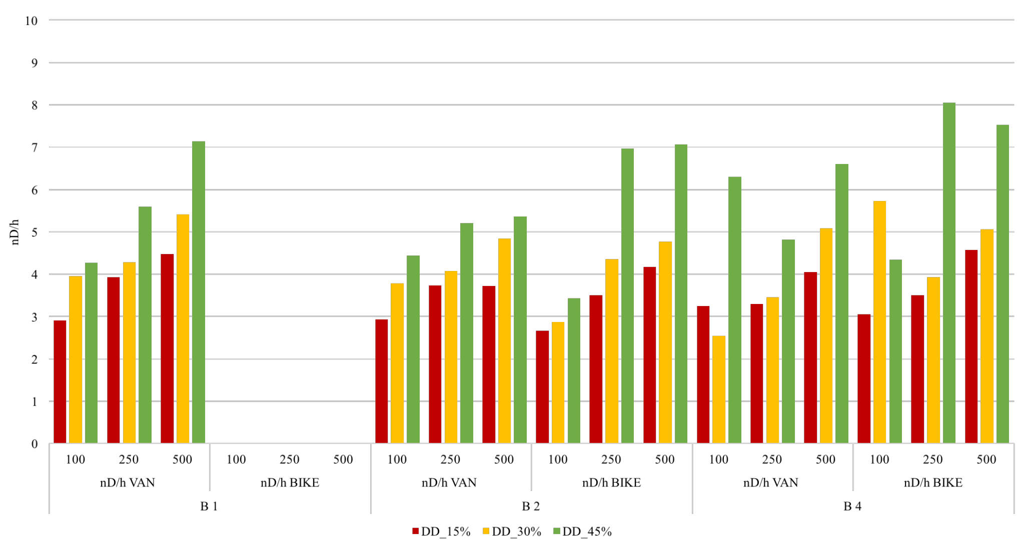

Figure 4: Performance of the green carrier. $B3$ is not reported, not involving any green vehicle for the delivery.

because it is not present in it. Thus, the number of deliveries per hour (nD/h) are given for the traditional vans only. They are reported in order to provide a value while comparing the results in the operational contexts $B2$ and $B4$. The values of $B3$ are not given because no green vehicle is usable in this operation context. As figured out in [14], the outsourcing of the small parcels (mailers and small deliveries) to the green carrier, the traditional one incurs in a reduction of efficiency of 80% at maximum. This means, for example, a reduction of the number of deliveries per hour from 126 to 25 in 10 working days when there are 100 customers locations and 30% of dynamism. Figure 4 shows how the green carrier reaches the highest number of parcels delivered when the degree of dynamism is equal to 45%. Similarly, when the deliveries are managed by means of lockers, there is an improvement of the economic and environmental sustainability. However, here the reduction of the costs, both operative (-25%) and environmental (-21%), is lower than B2. The reason is that, although there is a reduction in the kilometres travelled by the vans to serve the home deliveries directly to the customers, these vehicles are still adopted to reach and supply the lockers. When the number of customers to serve and the degree of dynamism are both to a low level, the adoption of lockers leads the highest decrease of the number of deliveries managed by the traditional carrier (-38%). This impact on the efficiency corresponds to costs savings of the same order. On the contrary, although the presence of the lockers, when the degree of dynamism is high and, i.e., the online requests increase, they are served by the traditional carrier. In fact, when the class of customers locations and the degree of dynamism are of respectively 500 and 45%, the loss of efficiency for the traditional carrier reaches the minimum value (-12%). An important finding is that, combining all the delivery options (B4), the highest reduction of emissions and operating costs is reached. In particular, this reduction becomes more evident when there is a low number of customers. Thus, they are served by environmental-friendly delivery modes, while a very few number of parcels is delivered by the traditional carrier. On the contrary, when we consider 500 customers, the performance of the traditional and the green carriers in terms of efficiency are similar to those achieved in the B2. This means that in case of high demand the lockers saturate quickly. Thus, bikes and vans (particularly) are used to cope the great part of the deliveries, as more flexible.

The results obtained figured out that by adopting the optimization solver we can minimize the number of rejected requests. In fact, only 1, 2 and 9 requests are rejected respectively in B2, B3 and B4. This rejection happens when the classes of customer locations and/or the degree of dynamism are medium-high. On the contrary, in the other instances all the online requests are fulfilled.

As mentioned above, the operational sustainability is strictly related to the social sustainability. The integration of traditional delivery mode with the two new options (i.e., bikes and lockers) could have a positive impact on the social sustainability. In fact, at the present, the drivers are hard-pressed to face the high demand of home-deliveries, respecting the time windows. Moreover, their working conditions are affected by a broad range of issues, as traffic and congestion, unavailability of loading/unloading zone, as well as second-time deliveries because the customer is not at home. All these problems make difficult in a regular working shift the achievement of the 80 deliveries per day imposed by the common practice in the industry [14]. Thus, considering the revenues based on the number of deliveries and the penalties in case of not fulfilment, these problems impose pressure to the drivers of the traditional carrier company. On the contrary, the reduction of the number of parcels that the traditional carrier have to deliver, combined with the optimization of the routes and the reduction of vehicles on road, lead to a less and more balanced workload and the improvement of the working conditions. However, a fundamental necessary condition is that this integration must be made in a reasonable manner. In fact, as stated in [14], the loss of efficiency for the traditional carrier must be contained and balanced by an increase in service quality led by the bikes and lockers and by a continuous process of optimization and monitoring of the activities in the overall last-mile chain.

5 Conclusions and perspectives

In this paper we presented a new simulation-optimization framework for building instances and assess operational settings. This research topic arose from the emerged lack of available realistic benchmark for VRP in City Logistics applications. We illustrated the proposed framework by applying it to a online parcel delivery problem in the medium-sized city of Turin (Italy). The novelty of our contribution is that the realism of case study is guaranteed by introduction in our framework of different real data sources and stakeholder requirements. In addition, we considered the integration of different deliveries modes (i.e., cargo bikes and lockers), reflecting the current practices in the city, which are devoted to the adoption of green delivery options. The experimental plan conducted highlighted that the switch to vehicles with a low environmental impact and to lockers, could lead an improvement in the economic efficiency of the business model of the traditional carrier and in the working conditions of the drivers. Moreover, the bikes represent the most suitable vehicles to face the online requests of deliveries, due to their high flexibility. Furthermore, the adoption of environmental-friendly vehicles could result in benefits in terms of CO2 emissions reduction. At the same time, this integration of different deliveries options could cause a loss of efficiency for traditional carriers. An important outcome obtained is that a multimodal last-mile delivery achieved by means the integration of all the delivery options considered, allows to reach the lowest levels of emissions when the number of customer is low/medium. On the contrary, vans and bikes represent the most appropriate means to deal with a high demand, while still pursuing environmental benefits.

Future development will be the usage of the simulation-optimization tool to validate a new system of two-echelon neighbourhood exchange points integrating more types of delivery options, as well as integrate in the simulation module a discrete event simulator.

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