Impact of lockerboxes location on routing planning in last mile delivery with uncertainty in demand and capacity availability

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1 INTRODUCTION

In the last years we have observed an exponential growth of e-commerce. The number of customers choosing to perform purchases online increases constantly. The current pandemic situation, which implied long lockdown periods for physical shops, further accelerated this phenomenon. The huge number of requests that have to be fulfilled every day, makes last-mile delivery a very critical issue for logistic companies. In Barenji *et al.* (2019), is reported that, in a last-mile delivery context, distribution can cost up to 40% of the price of a product. Furthermore, due to the high number of delivery requests, the companies cannot ensure customers to be served in their preferred time window, and since the delivery time is not known in advance, the delivery attempt can fail due to customer absence. According to Morganti *et al.* (2014), up to 40% of deliveries are unsuccessful. This could result in a huge extra cost for the company. To overcome this issue, an unattended delivery system has been established. This system involves deliveries to shared locations, particularly to lockers. Such facilities are generally located in widely accessible sites, such as supermarkets, refueling stations, train stations or other places with very long opening hours. Customers can pick their parcels from the lockers when it is most convenient for them. Not all orders are suitable for this delivery option, due to the size (or the value) of the parcel or to customers willingness. In fact, customers are well-disposed to accept this option only if the delivery is performed to a locker not too far from their home (or office etc.), otherwise they request home delivery (Mancini & Gansterer, 2021). Consequently, the location of the lockers may significantly affect the percentage of customers willing to accept this option. Shared delivery locations offer another great advantage, which is the possibility to strongly reduce the number of delivery points, and, consequently, the routing costs. Indeed, several customers can be simultaneously served at the same location, where lockers are installed. Hence, every home delivery avoided can yield to a potential large saving in terms of routing costs. While lockers location planning is a tactical decision, routing plans are operational decisions, since they are made daily based on the set of requests to fulfill. Location decision do strongly impact the routing plans for several months, therefore they are a crucial issue for logistic companies. Since the set of requests can vary from day to day, demand is uncertain but scenarios can be designed based on historical data. Lockers are composed of a certain number of lockerboxes, but some of them can be temporarily unavailable because they are out of order, they have been damaged, or because a customer served the day(s) before, did not pick up her parcel yet. This unavailability can affect the number of customers that can be assigned to the locker and, consequently, the number of home deliveries to perform. Hence, both customer demand and also unavailability of lockerboxes must be treated as uncertain parameters. The goal of our work is to study the impact of locker location planning on routing in last mile delivery. We define the problem as a capacitated facility location problem with uncertain demand and uncertain capacity availability (CFLP-UDC), where the goal is to firstly maximize the number of customers served through facilities, and in case of a tie, to maximize a service quality level assuming values between 0 and 1, where a higher value corresponds to a better service for the customers. The quality of service is proportional to the average distance to be covered by customers to pick up their parcel. To the best of our knowledge, this is the first study where both of these features are considered simultaneously. Many papers in the literature on stochastic facility location consider facility disruption, where the facility is fully operative with a probability p or is completely unavailable with probability 1-p. There are several applications in the military field or in emergency facility location for disaster preparedness. The first paper considering that a facility can be partially operative, is Cheng *et al.* (2021), where a robust optimization approach is proposed. Differently from our work, their goal is to minimize the total costs, given by the sum of facilities opened, customers assignment and costs for unsatisfied demands. Furthermore, while Cheng *et al.* (2021) consider the number of open facilities to be a decision variable, we use it as a exogenous given parameter. To solve the CFLP-UDC, we propose an integer programming formulation and a consensus-based matheuristic. We study how different parameters influence computational performance of both methods. Finally, we provide insights about the expected value of perfect information (EVPI) and the value of the stochastic solution (VSS), as well as the impact on the number of home deliveries avoided. Results on a real life scenario arising in the city of Turin, in Italy, will be discussed at the conference.

2 PROBLEM DESCRIPTION

The problem aims at determining the best location for a fixed number of facilities, P, chosen among a set of candidate locations J. Facilities have identical capacity C. A set of demand scenarios S is considered. In each scenario s, a set of potential customers I^s out of the set of all customers I has to be served. A customer may be accepted or rejected. If rejected, it has to be served by home delivery. If accepted, it must be assigned to a compatible open facility, j. Only facilities within a radius ρ from the customer location are considered compatible. The term ϕ_{ij} represents compatibility between customer i and facility j, where ϕ_{ij}=1 indicates that they are compatible and ϕ_{ij}=0 that they are not compatible. The number of customers assigned to a facility, within the same demand scenario, cannot exceed facility's capacity. A set of capacity reduction scenarios Ω is defined. In each scenario, the capacity of each open facility is reduced by a quantity δ_j^ω in interval $[0, \Delta]$. This reduction, represents a temporal unavailability of a portion of the capacity of the facility. The goal of the problem is to determine the location of facilities which maximize the average number of customers assigned to these facilities over all the demand and capacity availability scenarios. A secondary objective, which intervenes only in case of a tie, aims at minimizing the average covered distance from a customer's location to the facility to which it has been assigned.

For the mathematical formulation, the following decision variables are needed.

Y_{ij}^{ω}: binary variable indicating whether customer i is assigned to facility j or not
Z_j: binary variable indicating whether facility j is open or not

The stochastic programming (SP) model is formulated as follows.

$$\max \sum_{\omega \in \Omega} \sum_{i \in I} \sum_{j \in J} Y_{ij}^{\omega} + \sum_{\omega \in \Omega} \sum_{i \in I} \sum_{j \in J} \frac{d_{min}}{d_{ij}} Y_{ij}^{\omega} \frac{1}{|I||\Omega|} \tag{1}$$

$$\sum_{i \in I_s} Y_{ij}^{\omega} \leq C - \delta_j^{\omega} \quad \forall \omega \in \Omega \;\; \forall s \in S \;\; \forall j \in J \tag{2}$$

$$\sum_{j \in J} Y_{ij}^{\omega} \leq 1 \quad \forall i \in I \;\; \forall \omega \in \Omega \tag{3}$$

$$Y_{ij}^{\omega} = 0 \quad \forall \omega \in \Omega \;\; \forall i \in I \;\; \forall j \in J | \phi_{ij} = 0 \tag{4}$$

$$\sum_{\omega \in \Omega} \sum_{i \in I} Y_{ij}^{\omega} \leq |I||\Omega| Z_j \quad \forall j \in J \tag{5}$$

$$\sum_{j \in J} Z_j = P \tag{6}$$

The hierarchical objective function is reported in (1). It aims firstly at maximizing the number of customers assigned to a facility, and secondly, to maximize the customers' level of satisfaction. The latter is measured in terms of average distance between customer's location and the locker station, where the parcel has to be picked up. The secondary objective is formulated such that it takes values between 0 and 1 by integrating the overall minimum distance d_{min} and the distance d_{ij} between customer i and locker station j. Since the primary objective can assume only integer values, the secondary one intervenes only in case of a tie on the primary objective. Constraints (2) ensure that facilities' capacities is respected in all scenarios. A customer can be assigned to at most one facility, as expressed in constraints (3). Furthermore, customers can be assigned only to compatible facilities as ensured by constraints (4). Constraints (5) imply that customers can be assigned only to open facilities. Finally, the number of facilities to open is expressed in (6). All the variables included in the model are binary.

3 METHODOLOGY

To efficiently solve large and challenging instances, we propose a matheuristic based on the search of consensus among scenarios. The algorithm is described in the sequel. Firstly, we solve separately each capacity scenario ω, obtaining an *ideal* solution for the scenario (F_ω). Combining all the ideal solutions may yield to an infeasible global solution since more facilities than the maximum number allowed have to be opened. If it is not the case, we already achieved a global consensus and the solution is optimal. Otherwise we search for consensus among scenarios. We compute a score for each facility j, as the sum of the number of scenarios in which it is open plus the isolation degree, which is a parameter taking value between 0 and 1. The higher the minimum distance between j and another facility, the greater the value of isolation. Solutions with a high degree of isolation are most difficult to replace, therefore they are more likely to stay in the optimal solution. We create an initial *core* of facilities to open, picking the P facilities with the highest score. We also calculate a score for the interchangeability of each closed facility for each scenario ω. This interchangeability parameter is denoted as γ. It can take a value between 0 and 1, which measures the proximity of j to the nearest open facility in F_ω. To generate a first feasible solution, We solve the original problem by opening only the facilities in the initial core. Then the improvement phase starts and at each iteration we compute the level of "satisfaction" for each scenario, as the sum of customers served in that scenario minus the average percentage increment of distance between a customer location and the facility to which it has been assigned, respect to the nearest facility. The scenario with the lowest satisfaction, denoted as ω_{worst} is further investigated. The fist facility in the γ-based preference list, which has not been marked as *tested* yet, is marked as tested and is added to the core. The problem is solved again with the updated core. Since at most P facilities can be used but the core contains $P + 1$ facilities, one of them will be discarded by the model. This facility is removed from the core. Every time an improvement is found, all the tested facilities are marked again as untested. The algorithm terminates after a maximum number of iterations is reached or in case all the facilities, not belonging to the current core, are already marked as tested (i.e., if no more improvements are possible).

	MODEL		MH	
SCENARIO	OF	TIME	OF	TIME
S1	493.371	70.92	493.270	20.99
S2	981.988	454.01	980.788	40.89
S3	1960.831	1944.72	1959.333	80.39

Table 1 – *Comparison of MODEL and MH performances in solving the SP.*

SET	SP	EVPI	U^{EVPI}	VSS	U^{VSS}
S1	493.371	0.51%	2.5	1.63%	7.8
S2	981.988	0.29%	2.8	2.12%	19.6
S3	1960.831	0.34%	6.6	1.96%	37.2

Table 2 – *Comparison of stochastic indicators for different sets of instances*

4 RESULTS AND DISCUSSION

We discuss here some preliminary results, while an extended computational campaign will be presented at the conference. We analyze three set of instances, S1, S2, and S3, containing 10 instances each. Some parameters are fixed for all instances: 20 customers per demand scenario, 5 capacity scenarios, 5 facilities to open, 30 potential locations, 5 lockers per facility, and the probability of unavailability for each lockerbox: 10%. The varying parameter is the number of demand scenarios, which is equal to 5, 10, and 20 in S1, S2, and S3, respectively. In Table 1 we report the comparison between the mathematical model (MODEL), executed with a time limit of 3600 seconds and the matheuristitc (MH). As clearly shown in the table, MH is able to provide near optimal solutions for all the three sets of instances. Furthermore, while times required by the exact approach grows exponentially with increasing number of scenarios, MH experiences a linear growth.

In Table 2, we report the average solution of the stochastic problem (SP) as well as two classical stochastic parameters, Expected Value of Perfect Information (EVPI) and the Value of the Stochastic Solution (VSS), and two problem specific parameters U^{EVPI} and U^{VSS}. The first one, U^{EVPI}, represents the number of home deliveries that could be avoided having perfect information on the capacity availability. This gives us a measure of the impact of uncertainty. The second one, represents the number of home deliveries that can be avoided if the stochastic nature of the problem is taken into account. For this, we calculate a benchmark solution, where we first solve a deterministic problem assuming full availability of lockerboxes. Then we perform, for each capacity scenario, the assignment of customers to facilities taking into account the eventual unavailability related to the scenario. This could be seen as the cost of ignoring uncertainty. Despite the rather small values of EVPI and VSS (which represent relative differences), U^{EVPI} and U^{VSS} show considerable impact of uncertainty. This especially holds for the larger instances (S3). This means that uncertainty plays a very important role and, therefore, cannot be ignored. In fact, in S3 considering the uncertainty in capacity availability will help us to save on average 37 home deliveries over a total of 77, which indicates a huge saving in routing costs.

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