Design of 2-level city logistic infrastructures parcel delivery with electric vehicles.

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Abstract: Over the last decade, the increase in demand for B2C e-commerce has generated a higher request for urban transport services, thus causing a substantial environmental and social impact. To counteract such a situation, the involved institutions have issued restrictive regulations mandating logistic companies to implement new and more sustainable transport solutions for city logistics. The introduction of e-mobility in urban transport has represented in such regard a fundamental step towards more sustainable logistics systems for smart cities and communities. The implementation of such systems however requires a substantial re-thinking and redesign of the logistic networks, considering the different technical features of electric vehicles in comparison with traditional fossil fueled vehicles. In particular this research discusses the design of a city logistic system based upon proximity depots and short-distance zero emission vehicles (ZEV) such as cargo bikes, e-scooters, etc. A methodology is presented for dimensioning such a city logistic system, considering a 2-level network constituted by parcel delivery network and the depot replenishment routes. The approach proposed is based upon a mixed cluster-first and route second scheme and takes into account the specific elements of the operating context such as the population density and forecasted the daily request of delivery services. The approach is validated against a real case study referred to the city of Palermo, and the results obtained demonstrate the effectiveness of the approach proposed, and the viability of electric solutions for urban logistics with adequate logistic networks.

Keywords: WtW analysis; electrical vehicles; VRP.

1.Introduction

In the last decade, the exponential growth of e-commerce has substantially increased the request of logistic services in urban areas, fostering the birth of new business models for better responding to the customers' requests. In addition, the increased market competition is forcing logistics operators to provide not only a quick and cost-effective service, but also a higher flexibility in delivery options. Furthermore, the compliance with the sustainable development goals of modern cities and the tightening of environmental regulations require a substantial re-thinking and reorganization of urban logistic services, with zero emission vehicles replacing traditional fossil-fuel delivery trucks.

In such context, urban two-level logistics systems involving proximity depots and short-distance delivery vehicles appear a promising solution from both economic and environmental perspectives. These systems are structured in two phases. A first distribution level involves electric trucks to refill the proximity hubs, named Urban Consolidation Centers (UCC), from a distribution center generally located out of town. A second delivery level, involves small vehicles such as minivans, and cargo bikes, performing the final delivery to the customers in the city center. To apply these systems, managers must not only decide the number and type of vehicles to use, but also specify which customers are served by which vehicle and which sequence to follow to minimize the total distance travelled by the vehicles. Therefore, each vehicle route must begin and end at the assigned terminal and both capacity and working time constraints must be respected. This logistic problem falls in the broad class the vehicle routing problems (VRP) and its goal is to minimize the overall distance travelled by vehicles while serving all customers. Furthermore, each customer must be served by exactly one vehicle as split demand is not permitted. VRP are well known NP-Hard combinatorial optimization problems difficult to solve in practical applications. Since the goal of this work is to solve an electric vehicle routing problem on a real- case, a cluster-first -route second solution scheme will be applied to locate the decentralized proximity hubs and then to calculate the optimal routes. The objective is to minimize the total distance travelled by the trucks from the distribution center to the UCCs and to calculate the environmental impact through the Well to Wheel method.

The paper is divided 5 sections. Section 2 is the literature review, Section 3 discusses the methodology proposed, section 4 reports the numerical application and the results obtained, while in section 5 the conclusions are drawn.

2.Literature review

The Vehicle Routing Problem (VRP) is one of the most difficult optimization problems faced by logistics companies and transport operators. Researchers have studied vehicle routing and delivery scheduling since the fifties, when Dantzig and Ramser (1959) first introduced the basic truck dispatching problem. Since then, the problem formulation has enriched with several new elements, such as vehicle capacity, time windows and multiple depots. A further element of complication of the VRP, emerged in the last decade, derives from the introduction of electric vehicles. Joo and Lim (2019) analysed and compared electric and conventional vehicles, highlighting the necessity to use meta-heuristic algorithms to optimize the use of electric vehicles. Zhao and Lu (2019) proposed a mathematical model based on the Adaptive Large Neighborhood Search (ALNS) algorithm for electric vehicle routing, considering homogeneous vehicles and a time windows for deliveries. Rezgui et al. (2019) studied EV routing based on variable neighbourhood search (VNS) to minimize freight delivery and charging costs. Almouhanna et al. (2020) combined warehouse location and EV routing problems using the Tillman heuristic method and the VNS meta-heuristic algorithm. While Pelusi et al. (2020) presented an improved heuristic approach considering a hybrid phase between exploration and exploitation. Lin et al. (2020) provided a hybrid method based on a moth flame algorithm and a support vector machine to predict photovoltaic power generation. Other researchers, however, to reduce the number of variables that arise in a real case of vehicle route optimization, apply CluVRP which consists of dividing the problem into 2 parts, in the first part the customers are grouped based on the distance from a centroid, while in the second part the optimal routes are determined. Several researchers have adopted the k-means clustering method to solve the capacity vehicle routing problem (CVRP), such as Mostafa and Eltawil (2017) who used k-means clustering to assign customers to a heterogeneous fleet of vehicles before solving the TSP for each vehicle using mixed integer programming (MIP) with the aim of accelerating calculation times. Similarly, Singanamala, Reddy, and Venkataramaiah (2018) used k-means clustering as the first step of an assignment and path approach in solving multi-depot VRPs. This solution technique, known as Cluster-First Route-Second Method (CFRS), first divides customers into clusters and then solves an independent TSP on each cluster. As mentioned before, an additional source of complication in modern urban logistic systems originates from the introduction of electric mobility. The technical limitations of electric vehicles, related to their reduced load capacity, long charging times and limited operational range, currently limit their spread in city logistics. To overcome this problem a viable approach is to design a two-level logistics distribution system in order to reduce the load and distance travelled by the vehicles, thus facilitating the implementation of electric vehicles and bringing environmental benefits along the entire supply chain. These models have been recently studied and implemented by several researchers, such as Grangier et al (2016), who addressed a variant of the 2E-VRP involving time window constraints, synchronization constraints and multiple trips at the second level. Cattaruzza et al (2017), identified the main scientific challenges such as time-dependency, multi-level and multi-trip, organization of distribution, and then analyse them individually and capture the main difficulties. Esmaili et al. (2017) addressed the two-level vehicle routing problem by applying simple additive weighting (SAW) method considering customer satisfaction and environmental issues.

The approach proposed in this paper focuses on calculating the polluting emissions generated by the use of electric vehicles, in order to obtain a complete representation of how the implementation of BEVs affects the logistics chain. Furthermore, another important element to consider in the calculation of the polluting emissions, is that electric vehicles do not produce emissions during their use. It is thus advisable to use specific models that allow for the calculation of the emissions generated throughout the life cycle of the fuel. In such regard, an index used by several researchers (Torchio et al. 2010, Liu et al. 2020) is the Well to Wheel method which allows to carry out a complete analysis of the environmental impact and greenhouse gas emissions in two different phases, the first Well-to-Tank (WtT) which allows us to calculate the emissions generated during the energy production phase, while the second Tank-to-Wheel (TtW) analyses the pollutants produced during the use phase of the vehicle.

3.Methodology

This section discusses the methodology that allows solving a routing problem in the city of Palermo. In particular, the application of a VRP on a real case is troublesome due to the dimensions of the problems. An effective approach to reduce the complexity of the problem is thus to apply a two steps cluster-first and route-second model, which allows to break the problem down into two phases. In the first phase we will focus on data clustering through k-means which allows us to reduce the amount of data and find the positioning of the proximity hubs, while in the second phase we will solve the routing problem with the aim of reducing the overall distance travelled. It assumed that trucks are serving the peripheral depots from a central distribution centre and e-cargo bikes performing the final delivery.

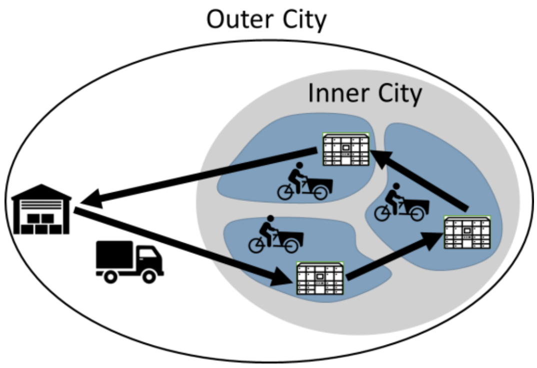

Figure 1: Two tier system distribution

Before proceeding with the identification of the location of the hubs, the city is divided into districts and the average number of daily deliveries (see table 1) is calculated using eq. 1 (Briest et al 2019). This formula allows us to approximately calculate the number of parcels considering the area to be served (A), the population density (D) and the average frequency of orders per person (f).

$$N = D \times f \times A \qquad (1)$$

Subsequently the number of vehicles/clusters required to satisfy the demand, is calculated based on the payload of the cargo bikes, in particular, considering that each bicycle has a volume of approximately 0.28 m^3 and a maximum payload of 500 kg (including the driver) and assuming a maximum number of 50 packs can be delivered at each run. Therefore the number of clusters that we have set a priori to cluster the data is equal to the ratio between the number of parcels in each district and the number of parcels that each cargo bike can deliver.

$$N_c = \frac{N}{Packs_{c-bike}} \quad (2)$$

After calculating the number of vehicles required for performing all the required deliveries, the clustering step is performed to identify the centroids representing the locations of the UCCs. The centroids are identified according to the k-means clustering procedure, considering an initial random location and. Each delivery point is then assigned to one of the clusters based on its minimum Euclidean distance from the centroids, thus creating an initial grouping. Subsequently, the position of the centroids is updated and the process is iterated until convergence.

After determining the location of the decentralized proximity hubs the VRP is solved with the aim of minimizing the total distance travelled by the vehicles satisfying all customer requests. Therefore, considering that the binary variable x_{ijk} is equal to *1* if the arc (i,j) is travelled by the cargo bike *k*, *0* otherwise, the objective function can be expressed as follows:

$$Min \sum_{k=1}^{p} \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} x_{ijk} \quad (5)$$

Where the parameter d_{ij} is the distance from node *i* to node *j*,. The constraints 3 and 4 imply that the truck cannot pass through the same node we will have:

$$x_{ijk} \in \{0,1\} \quad \forall k \in \{1, \dots, p\}, i, j \in \{1, \dots, n\} \quad (3)$$

$$x_{ijk} = 0 \quad \forall k \in \{1, \dots, p\}, i \in \{1, \dots, n\} \quad (4)$$

Where p is the number of available trucks and n is the number of nodes to be visited.

Furthermore, each node should be entered and released once and by the same vehicle (7-8). The deposit should be left and entered once by each vehicle (9). q_1 describes the demand of each customer and *Q* is the capacity of the vehicles. The sum of requests from all customers that vehicle k will serve should not exceed the capacity of the vehicle (10).

$$\sum_{k=1}^{p} x_{ijk} = \sum_{i=1}^{n} x_{ijk} \; \forall j \in \{1, \dots, n\}, k \in \{1, \dots, p\} \quad (6)$$

$$\sum_{k=1}^{p} \sum_{i=1}^{n} x_{ijk} = 1 \quad \forall j \in \{2, \dots, n\} \quad (7)$$

$$\sum_{j=2}^{n} x_{1jk} = 1 \quad \forall k \in \{1, \dots, p\} \quad (8)$$

$$\sum_{i=1}^{n} \sum_{j=2}^{n} q_j x_{ijk} \leq Q \; \forall k \in \{1, \dots, p\} \quad (9)$$

Finally, after determining the optimal routes, the environmental impact is calculated, considering that electric cargo bikes do not produce emissions during their use, the Weel-to-Wheel (WtW) analysis is applied which takes into account the environmental impact related to the energy production process. In particular, the WtW analysis (equ.10) is given by the sum of two sub-indexes Weel-to-Tank (WtT) and Tank-to-Wheel (TtW), where the WTT emission index (equ.11) holds account of the mass of pollutant emitted (mp) in the extraction, chemical processing and transport processes, while the TTW index (equ.12) takes into account the mass of pollutant emitted (mp) during use of the vehicle by relating it to the distance traveled (D).

$$WtW_p \left[\frac{g}{km}\right] = WtT_p \left[\frac{g}{km}\right] + TtW_p \left[\frac{g}{km}\right] \quad (10)$$

$$WtT_p = \frac{m_{p-WtT}}{D} \left[\frac{g}{km}\right] \quad (11)$$

$$TtW_p = \frac{m_{p-TtW}}{D} \left[\frac{g}{km}\right] \quad (12)$$

4.Applications and results

The model previously described was applied to the real case referring to the city of Palermo in order to determine the optimal routes from a central depot to the proximity hubs. Before proceeding with the application of the model it is appropriate to describe the distribution system that we are taking into consideration and the choice of means that are adopted. In particular, this research focused on the choice of vehicles with low environmental impact, to try to minimize the emissions generated along the supply chain, but this choice generates problems at a logistical level as these vehicles have a much shorter operational range compared to traditional vehicles. For this reason it was appropriate to implement a two-level logistics model taking into account such shortcomings. Concerning the vehicles used, e-cargo bikes have been considered for last mile deliveries while eVans for serving the UCCs from the central depot. As for the locations of the delivery points, they were randomly generated for each district according to eq. 1, considering the area of the district and the corresponding population density, and considering an order frequency equal to 0.0055 orders per person per day (Briest et al. 2019). This led to a total of 3,383 delivery points distributed across the 7 city districts.

Table 1: Number of packs for each district

Districts	Area	Density	N.Packs
1	21.39	3290	387
2	20.34	3572	399
3	26.16	3783	544
4	17.53	6274	604
5	23.9	2953	388
6	32.95	2300	416
7	15.32	7662	645

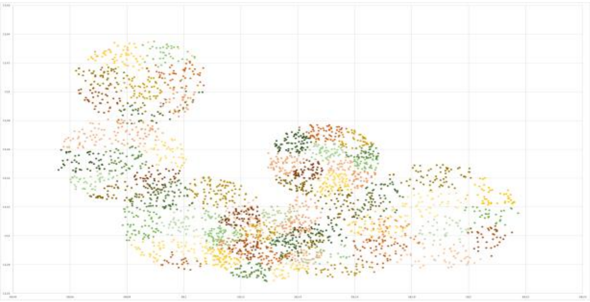

Figure 2: clustering of the delivery points

Figure 2 shows us the clusters that were generated through equation 2, considering the maximum capacity that a small electric or pedal-assisted vehicle (e-cargo-bike) can transport. In particular, the maximum capacity was calculated considering a loading space of the cycle equal to 0.28 m^3 and a mix of packages including envelopes, envelopes and boxes with a percentage of the total packages equal to 30%, 50% and 20%.

Furthermore, the clustering procedure also allows to identify the centroids of each cluster, which represent the positions of the UCCs and the central depot (fig. 3).

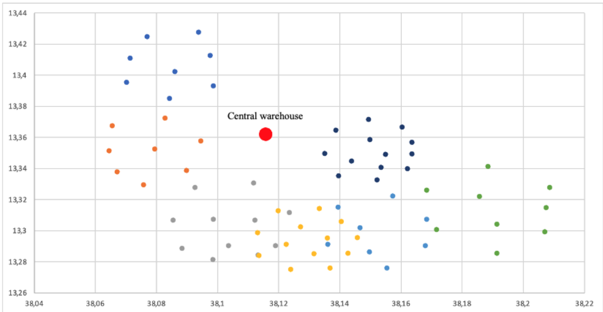

Figure 3: UCC for each district

After the UCCs have been located and before proceeding with the solution of the VRP, the FUSO 8.55 T eCanter 6S15E commercial electric truck was chosen for replenishing the UCCs. Such vehicle allows for a maximum payload of 2930 kg or 1362 packages assuming an average weight of 2.15 kg per package. A further assumption has been made on the weight of the package associated to each delivery point which has been determined considering packages are categorized in parcels, envelopes and boxes (Table 2) with a percentage of 30%, 50% and 20% respectively.

Table 2: Numbers and weights of the packs

	Kg	Package type (%)	Tot. number (pcs)	Number of packs	Weight (kg)
Envelope	0.5	0.3	3383	1015	507.45
Pack	2	0.5	3383	1692	3383
Box	5	0.2	3383	677	3383

Table 3: Pack categories considered

	Total number (pcs)	Total weight (kg)	Average weight (Kg)	Numb. Packs for vehicle
Packs	3383	7273.45	2.15	1362

Based on such assumptions, the capacitated VRP was solved.

Once the load capacity of the vehicle has been calculated, which represents one of the constraints for the application of the CVRP, the model described previously is applied. in the appendix you can find table 4 which shows the locations of the UCCs, with which the VRP was applied. After evaluating the service requests of the UCCs, the optimum feeding routes were determined by solving the capacitated VRP.

According to the final results obtained, depicted in Fig.4, it is possible feed all the UCCs implementing 3 routes, with an overall distance travelled by the trucks equal to approx. 90 km to deliver all the 3383 parcels.

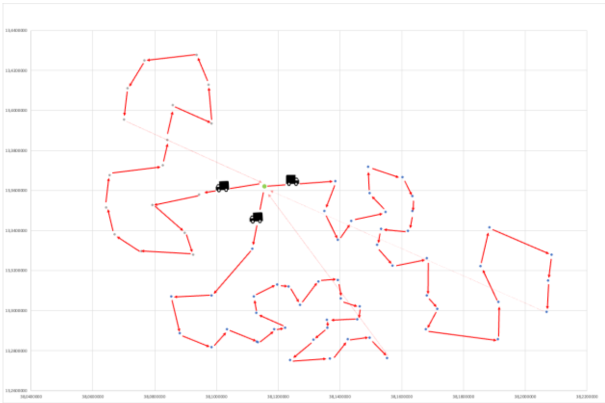

Figure 4: Vehicle routing to minimize the total distance

Finally, after calculating the minimum traveled to satisfy all the service requests, the overall environmental impact has been calculated in terms of WtW referring to the Italian energy production mix (Torchio et al., 2010) in terms of GHG, NOX, PM and SOX emissions, as a function of the energy consumption over distance travelled, assuming the current Italian energy production mix. The results obtained are shown in figure 5.

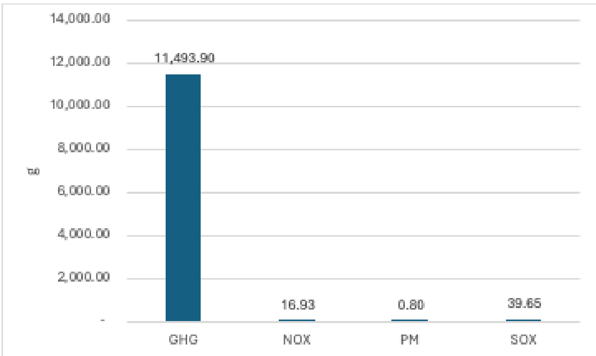

Figure 5: Total emission considering the total distance delivered

5.Conclusion

With the advent of B2C e-commerce, the impact of urban distribution activities on the quality of life of residents has become a critical issue. In this article we provide a clear picture of how the use of urban electric mobility systems can reduce transport externalities, thus improving both the quality of transport services and the livability of the urban environment. In particular, this research stands out compared to the articles found in the literature as the adoption of these vehicles was applied in a real context and despite the complexity of the resolution of the VRP, the results obtained demonstrate that an accurate design and implementation of a two-level system, based on the use of e-Vans and cargo-bikes, may be the best choice to substantially reduce the level of congestion and the environmental impact linked to city distribution. In the specific case of the city of Palermo, the use of electric vehicles allows, for the same kilometers travelled, to reduce polluting emissions by 17% compared to traditional internal combustion vehicles. This result highlights the significant potential of electric vehicles in reducing urban congestion and the environmental impact associated with city distribution. Therefore, the adoption of such solutions represents a fundamental step towards creating more sustainable and livable cities.

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Appendix A. FIRST APPENDIX

Table 4: Geographical coordinates of delivery points for each UCC

UCC	Latitude	Longitude
1	38.070267	13.3953656
2	38.0713626	13.4110073
3	38.0842466	13.3850532
4	38.0986214	13.3931836
5	38.0769145	13.4248905
6	38.0937802	13.4275204
7	38.0975508	13.4125836

8	38.0859934	13.402358
9	38.0794443	13.3525695
10	38.0655128	13.3675779
11	38.0945481	13.3578113
12	38.0671174	13.3378501
13	38.0898405	13.3386582
14	38.0758316	13.3294551
15	38.064433	13.3513735
16	38.0827913	13.3723727
17	38.0883552	13.2885347
18	38.1122122	13.3068572
19	38.098509	13.2816123
20	38.1117498	13.3307293
21	38.0925827	13.3277495
22	38.1234624	13.3117439
23	38.1035987	13.2904078
24	38.098577	13.3074611
25	38.1188975	13.2904209
26	38.1132743	13.284296
27	38.0854785	13.3067834
28	38.122397	13.2912851
29	38.1457613	13.295571
30	38.1359469	13.295258
31	38.1404509	13.3058435
32	38.1134985	13.2840442
33	38.1130903	13.2987293
34	38.1315168	13.2852815
35	38.1271944	13.3026156
36	38.1239721	13.2750179
37	38.1426715	13.285487
38	38.1368303	13.2758885
39	38.1332434	13.3143779
40	38.119867	13.3128785
41	38.1572403	13.3222313
42	38.1466068	13.3020242
43	38.1394215	13.3150977
44	38.1683466	13.307367
45	38.149717	13.2862809
46	38.1679074	13.2904619
47	38.155375	13.2761052
48	38.1360898	13.2913135
49	38.1913371	13.2855705
50	38.1856191	13.3219153
51	38.1914474	13.3042568
52	38.1716754	13.3006385
53	38.2086234	13.3278164
54	38.2075001	13.3148594
55	38.2070408	13.2992996
56	38.1884781	13.341338
57	38.1683434	13.3261095
58	38.1621063	13.3397492
59	38.1521889	13.3327849
60	38.163558	13.3494672
61	38.149309	13.3716329
62	38.1603467	13.3665303
63	38.1636139	13.3569743
64	38.15492	13.3490717
65	38.1534124	13.340707
66	38.1498021	13.3586432
67	38.1438033	13.3446527
68	38.1395326	13.3351747
69	38.138709	13.364608
70	38.1350812	13.3495999