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Agent-based modelling and simulation for hub and electric last mile distribution in Vienna

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Abstract

With the rise of e-commerce and door-to-door sales, last-mile deliveries are gaining more and more importance. As a result, last-mile distribution has become one of the most sensitive logistics processes due to its uniqueness, difficulties in meeting schedules, and high costs. Therefore, this work explores the use of urban consolidation centers to ease these last-mile difficulties. For that purpose, a hub in the city center of Vienna has been selected to deliver up to 150 clients disseminated by the city. This suitability is assessed by defining convenient simulation settings in order to replicate parcel demands in the city. Experiments are based in different hub-based fleets (traditional internal combustion vehicles or electric cargo bikes), demand patterns, and delivery frequency strategies by means of a biased randomization vehicle routing optimization heuristic. Results quantify the effects of having an urban consolidation center and highlight the use of electric cargo bikes for the last-mile distribution.

Keywords: Last-Mile Distribution; Logistics; Simulation; Optimization; Heuristics

1. Introduction

Logistics activities are a challenge all around the world. Hospitals need their medicines daily; supermarkets need to fulfill their shelves daily; small shops need to replenish their stocks with a certain periodicity; and so on. For all of these activities, such a complex network capable of meeting all needs is available. However, the continuous increase in transportation demand for passengers and freight, often means a significant increase in costs and times. This is particularly the case of last-mile freight urban distribution [6].

Thus, the increment in the number of parcels delivered daily, [18] leads to an even bigger number of vehicles, sometimes half-empty, driving for long distances. Additionally, this leads to a growth in urban freight vehicles, which

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congest city centers and produce such an amount of noise and air pollutions. Therefore, urban consolidation centers or city freight hubs arise as an appropriate mitigator of those problems [1]. Urban hubs are warehousing centers located at key points in cities that speed up the entire process of delivering packages to retailers and online customers. Thanks to this type of solution, it is possible to meet ultra-fast delivery services at the time delivery operations gain efficiency as freight consolidation occurs.

Hence, this article explores the use of urban hubs in the city center of Vienna (Austria) [1, 6] and the use of hub-based electric-powered vehicles for the final deliveries in the hub influence zone. Moreover, a simulation-optimization model is designed and implemented to run the computational experiments. In this respect, Section 2 reviews related literature on the topic. Section 3 introduces the methodology, *i.e.*, the simulation and the heuristic optimization algorithm. Finally, Section 4 describes the case study in Vienna and shows the main findings whereas Section 5 concludes the paper.

2. Related literature

Last-mile distribution is a key point in nowadays society. Particularly, home deliveries coming from online shopping are continuously increasing [17]. This situation has been boosted during lock-downs in the COVID-19 pandemic, and does not seem to come back to pre-pandemic levels. This results in a steady flow of delivery vehicles going from the customers to the depots, contributing to traffic congestion, scarcity of parking spaces, and pollution [4]. Actually, according to [3], traditional retailing channels reduce CO_2 emissions by 84% compared to ultra-fast delivery systems.

Similarly, [15] state that the most important constraints in last-mile distribution are fast-delivery options, hard time windows, and no-show-up customers. All of them can be solved by using automated parcel lockers in which the delivery company deposits the parcel and the customer goes there whenever they want to take it. This way, much of the traffic generated by delivery vehicles will be concentrated in certain areas that can be designed beforehand in order to disturb as little as possible to other activities and citizens. The use of urban hubs is, therefore, seen as a way of mitigating some of the aforementioned problems as described in [2, 8, 16, 19].

Once orders are collected, the delivery process has to be performed resulting in the design of routes. This leads to the Vehicle Routing Problem (VRP) [13] and its solution techniques [11]. This article includes a biased-randomization Clarke and Wright savings heuristic to deal with the routing part.

3. Methods

3.1. The simulation model

The agent-based simulation model is based on customer, hub, and vehicle agents. Additionally, a order agent is considered, as well as the heuristic agent that is explained in the Subsection 3.2. Thus, customer agents are characterised by a demand and a ordering trigger probability. On the other hand, the hub agent considers a parcel capacity and a schedule for doing the deliveries. Similarly, vehicles fleet are hub-based with a given capacity. In this regard, we consider an homogeneous fleet with same capacity. Figure 1 illustrates the work flow diagram of the simulation model.

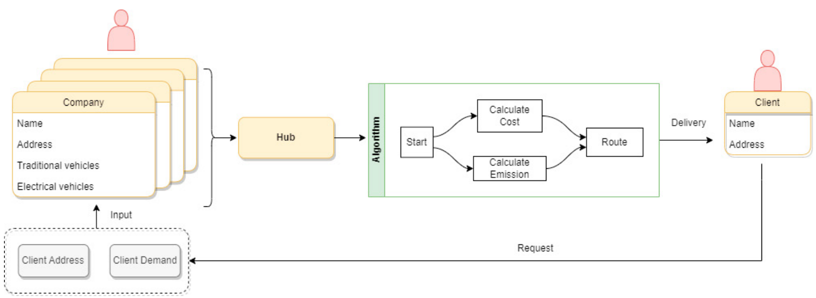

Fig. 1. Work flow diagram of the simulation model

The method is based on simulating routing to estimate the delivery costs and CO_2 emissions for parcel delivery using traditional fuel-based engine vans and electric-powered cargo bikes in two periods during one week. The first period is the regular days, and the second is the peak seasons. In each period, we have assumed two ways of parcel delivery; the first one is to deliver them daily. The second one is accumulating all orders during the week and delivering them in a day. The simulation is repeated 100 times for each scenario to obtain an average value of delivery costs and CO_2 emissions. The emissions are calculated based on the EcoTransit methodology proposed by [10].

3.2. The VRP heuristic

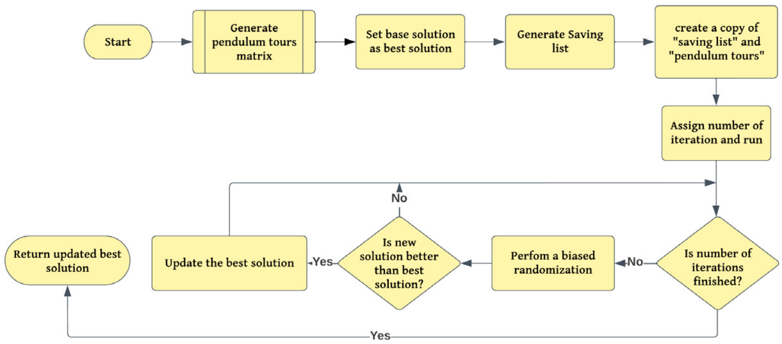

Fig. 2. Flowchart diagram of the method

In order to solve our VRP, calculate delivery costs, and measure CO_2 emissions; a biased-randomized solution procedure [7] was implemented on the basis of the concepts presented in [9]. These studies demonstrate that the biased randomization Clarke and Wright savings VRP heuristic is effective in finding high-quality solutions (often optimal) in a short amount of time.Our approach depends in its work on the implementation of a set of steps in order to reach a good solution.The first step is calculating the cost of serving each customer individually with a vehicle; in our case, we named it pendulum tours. The cost in this step represents the total cost for each round trip from the depot to each customer separately.

The generated pendulum tours matrix represents the initial base routing solution, where we have assumed/assigned it at this phase as the "best solution" to compare it later with other solutions that will be found. The next step is to generate the saving list by performing Clarke and Wright Savings heuristic on the pendulum tours matrix. Both, the provisional best solution and saving list have stored in temporary variables, so we do not lose them and keep them as a reference to compare with generated solutions. After all, the required parameters have been set, we have assigned a number of iterations in order to perform an iterative biased-randomized saving heuristic procedure.

Every solution obtained is compared to the "best solution" in each iteration cycle. The "best solution" is updated if the obtained solution is better. Afterward, the best-found solution is taken to evaluate its setting. Figure 2 illustrates the flowchart diagram of the heuristic.

4. Results

4.1. Problem description

Large cities such as Vienna have a special interest in solving the problems generated by last mile logistics. Thus, our experiment is based on a third party entity (public or not) that operates an hypothetical urban hub placed in an existing infrastructure. This hub is shared by logistics service providers such as DHL, DPD, UPS, and local Post as a place to store, organize and deliver parcels conjointly in order to save costs. Therefore, in this work, we consider an urban hub for distributing parcels to up to 150 customers in the city center of Vienna disseminated within the 2^{nd}, 3^{rd}, 10^{th}, 11^{th}, and 23^{rd} districts, as shown in the Figure 3.

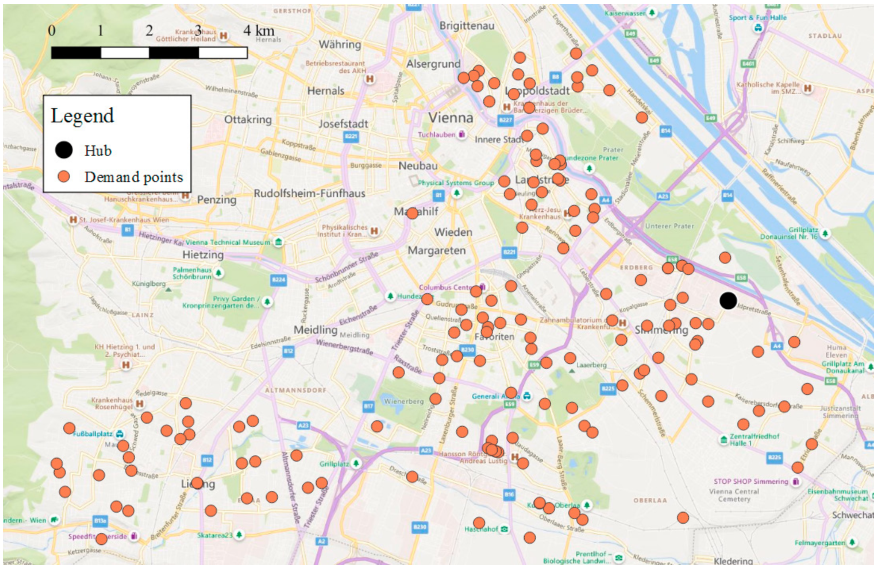

Fig. 3. Map of Vienna with the clients (red dots) and hub (black dot)

However, given the space limitation, this work focuses on the delivery process from the hub to the final customers for a range of scenarios. Therefore, real orders to the companies and the routes from their depots to the hub are out of the scope of this article.

4.2. Parameter setting and results

Experiments are run for a simulation period of one week based on a number of scenarios that will determine the ruling simulation model parameters. Firstly, two different types of vehicles are tested, *i.e.* internal combustion traditional vans and electric-powered cargo bikes. With respective capacities of 50 and 30 parcels per vehicle. Secondly, two demand periods are considered: a regular valley demand and a peak demand characterized by different ordering probabilities. In our experiments, we fixed these probabilities to 30% and 70%, respectively. These values are considered realistic, as shown in works like [12, 5]. Thirdly, two delivery systems are studied, an ultra-fast delivery system in which orders are delivered the following day they were requested; and an end-of-week strategy in which orders are aggregated and consolidated to be delivered at the end of the experimental week. Finally, ordering demands are based on a geometric random variable starting at 1 with a probability of 65%.

With respect to the modeling environment, both the simulation model and the heuristic algorithm are coded in the Java-based Anylogic software. With respect to the VRP heuristic, we fixed the number of iterations to 300 and the skewed biased savings distribution parameter to 0.35.

Figure 4 describes the simulation scenarios that are further detailed in Table 1.

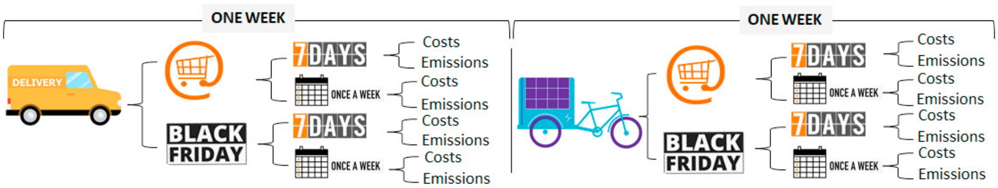

Fig. 4. Description of simulation scenarios

The average distance for traditional van with ultra-fast delivery system in a standard day is about 1,200 km, whereas these distances are slightly higher for the same scenario when using cargo bikes, 1,290 km. On the other hand, when focusing on a peak demand season, with a cargo bike delivering ultra-fast, the distance increases up to 1,500 km.

Table 1. Scenario description and parameter setting

Vehicle	Demand	Delivery	Scenario	Ordering Prob.	Capacity
Traditional Van	Valley	Ultra-fast	S1	30%	50
		End-of-week	S2	30%	50
	Peak	Ultra-fast	S3	70%	50
		End-of-week	S4	70%	50
Cargo bike	Valley	Ultra-fast	S5	30%	30
		End-of-week	S6	30%	30
	Peak	Ultra-fast	S7	70%	30
		End-of-week	S8	70%	30

Table 2. Results of the 8 scenarios studied in this work and their comparison.

Scenario	Distances		Emissions		Distance comparison		
	Average (km)	Sd	Average (kg)	Sd	Setting selected	Comparison	Difference (%)
S1	1203.02	10.15	364.98	4.69	Ultra-fast vs End-of-week	S1 - S2	537,4
S2	223.86	3.71	65.74	1.24		S3 - S4	384.80
S3	1,284.22	11.27	391.93	4.62		S5 - S6	466.30
S4	333.78	4.66	99.31	1.45		S7- S8	316.10
S5	1,288.84	18.62	0.00	0.00	Peak vs Valley	S1-S3	6.80
S6	276.40	7.21	0.00	0.00		S2-S4	49.10
S7	1,482.18	16.38	0.00	0.00		S5-S7	15.00
S8	468.90	7.54	0.00	0.00		S6-S8	69.60

While the end-of-week delivery system, varies from 220 up to 470 km for the different vehicles and periods. Far away from the results of ultra-fast delivery. Similar results can be found when focusing on CO_2 emissions. In this sense, cargo bikes avoid pipe-tail emissions in any situation. However, it is interesting the differences in emissions for traditional vans in peak demand and valley periods as well as in the two delivery strategies studied so far. In particular, 65.74-99.31 kg emissions for the end-of week strategy, respectively; and 364.98-391.93 for the ultra-fast deliveries. Detailed results can be found in the Table 2. Additionally, Table 2 shows the difference between cargo bikes and traditional vans that is more evident on the peak days when the demand is relatively higher, and the distance driven results in up to 15% higher in cargo bikes. Another interesting fact is the difference between the end-of-week delivery on peak days for the two types of vehicles. In this case, the difference is 40.5% in favor of the fuel-based engine vehicles.

5. Conclusions

In this work, an urban hub has been studied as a partial solution to problems generated by last-mile urban distribution. In this way, the routes were consolidated between companies instead of doing each company their own one. For that purpose, the possibility of using traditional vans or cargo bikes has been studied. Furthermore, the way of delivery has been compared between ultra-fast delivery and end-of-week delivery strategies. Finally, two different demand scenarios are considered: peak days with high demand and valley days with lower demand.

After the analysis of the results described in Table 2, a number of conclusions can be drawn:

1. End-of-week delivery system is quite more efficient in terms of costs and emissions. Nonetheless, the ultra-fast one is more popular because of the high delivery companies competition. The cost of such a competition is estimated in 300 – 537% in comparison to the end-of-week delivery.
2. In valley demand periods, it can be observed that the costs from a cargo bike and the ones of the van are not so different, up to 6.65% for ultra-fast delivery. That is because in daily deliveries the capacity of the vehicles is not so important as the quantities are not enough to exceed the maximum capacity.

3. That can be seen as an option to work on a daily basis with cargo bikes. On the other hand, in the peak days the costs of working with cargo bikes clearly rise, making it less useful than the traditional vehicles. Although, the emissions from traditional vans fleet clearly overtake those from cargo bikes.
4. From 65 up to 392 kg CO_2 emissions can be saved when moving to the electric delivery. Additionally, these emissions can be reduced by using the end-of-week delivery. Particularly, emissions savings up to 82.15% can be achieved compared to the ultra-fast deliveries when using the traditional vans.
5. None of these eight scenarios defines an optimal solution. It will require further studies and a trade-off between several possibilities. This leads us to future research based on new scenarios and investigating horizontal cooperation strategies [14].

Acknowledgements

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