Exploring the Use of Urban Consolidation Centers for Efficient Last-Mile Delivery Using Agent Based Modelling and Simulation

Aitor Ballano, Anas Al-Rahamneh*, Adrian Serrano-Hernandez, Javier Faulin

Group GILT-OR, Institute of Smart Cities. Public University of Navarre, 31006, Pamplona, Spain;
*anas.alrahamneh@unavarra.es

SNE 34(3), 2024, 181-184, DOI: 10.11128/sne.34.sn.10703
Selected EUROSIM 2023 Proceedings Publication: 2024-06-18
Received Rev. Improved: 2024-08-06; Accepted: 2024-08-12
SNE - Simulation Notes Europe, ARGESIM Publisher Vienna
ISSN Print 2305-9974, Online 2306-0271, www.sne-journal.org

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. 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 rooted in an agent-based simulation model. Results quantify the effect of having an urban consolidation center and highlight the use of electric cargo bikes for the last-mile distribution.

Introduction

Last-mile deliveries are a challenge all around the world because of the increment in the number of parcels delivered daily that 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 congest city centers and produce such an amount of noise and air pollution. Therefore, urban consolidation centers or city freight hubs arise as an appropriate mitigator of those problems.

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. The use of urban hubs is, therefore, seen as a way of mitigating some of the aforementioned problems as described by Bukoye et al. [1].

Hence, this article explores the use of urban hubs in the city center of Vienna (Austria) [2] 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.

1 Problem Description

As stated before, large cities such as Vienna have a special interest in solving the problems generated by last-mile logistics. For that purpose, the idea of using urban hubs is quite attractive. That way, several companies such as DHL, DPD, UPS, and local Post can share 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 2nd, 3rd, 10th, 11th, and 23rd districts, as shown in Figure 1.

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. Subsequent paragraphs, however, are indented.

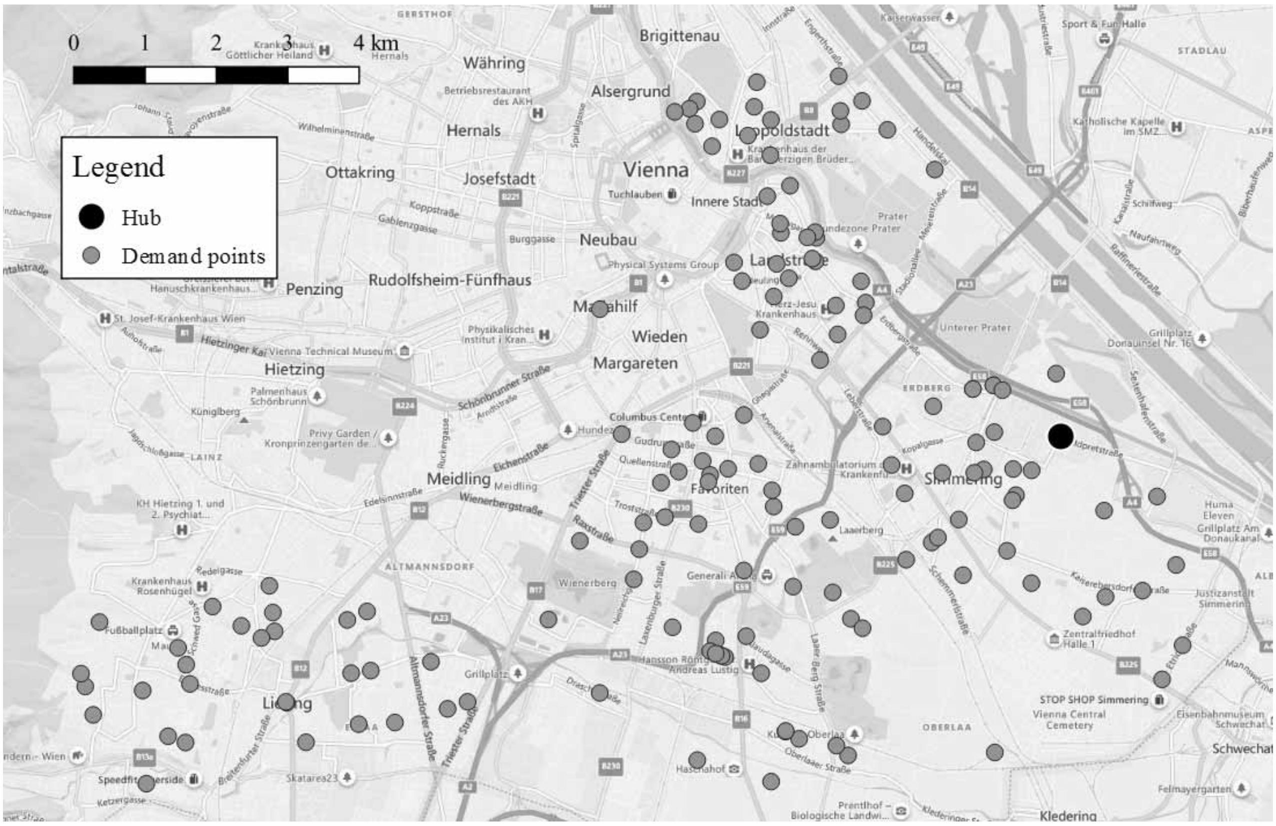

Figure 1: Map of Vienna with the clients (red dots) and hub (black dot).

2 Methods

The agent-based simulation model is based on customer, hub, and vehicle agents. Additionally, an order agent is considered, as well as the heuristic agent. Thus, customer agents are characterized by a demand and an 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 the same capacity.

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 0.30 and 0.70, respectively.

In order to solve our Vehicle Routing Problem (VRP), calculate delivery costs, and measure CO_2 emissions; a biased-randomized solution procedure [3] was implemented on the basis of the concepts presented by Juan et al. [4]. Our approach depends in its work on the implementation of a set of steps in order to reach an optimal 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.

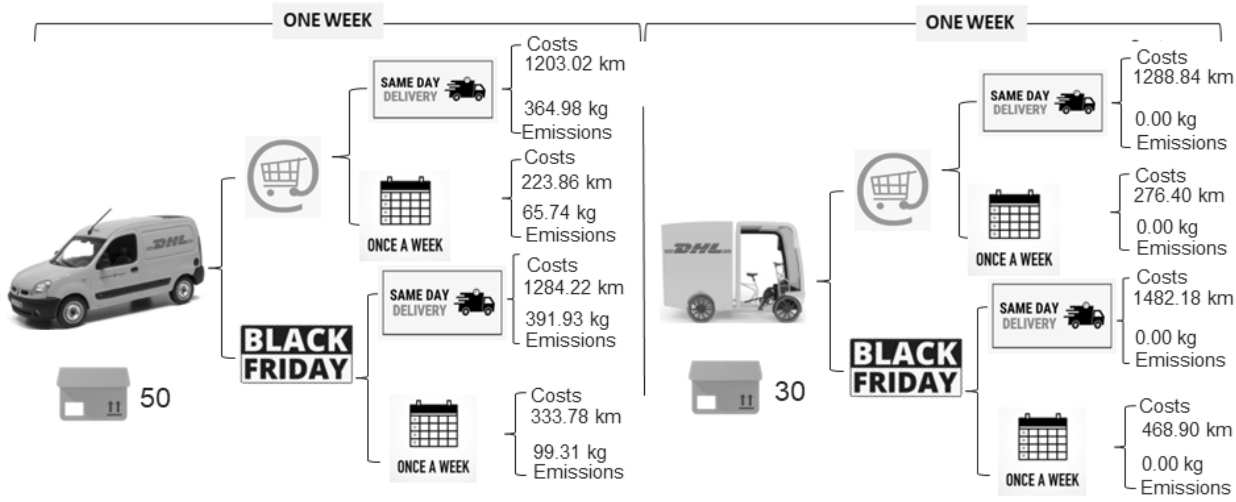

Figure 2: Description of simulation scenarios.

Scenario				Distances	Emissions
Vehicle	Demand	Setting selected		Average (km)	Average (km)
VAN	Valley	Ultra-fast	S1	1203.02	364.98
		End-of-week	S2	223.86	65.74
	Peak	Ultra-fast	S3	1284.22	391.93
		End-of-week	S4	333.78	99.31
Cargo bike	Valley	Ultra-fast	S5	1288.84	0.00
		End-of-week	S6	276.40	0.00
	Peak	Ultra-fast	S7	1482.18	0.00
		End-of-week	S8	468.90	0.00

Table 1: Description of simulation scenarios and results.

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.

3 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, the study examines two distinct vehicle types: traditional internal combustion vans and electric-powered cargo bikes, with parcel capacities of 50 and 30 per vehicle, respectively.

Secondly, two demand periods are analyzed: a regular valley demand and a peak demand, each defined by different ordering probabilities. In our experiments, these probabilities were set at 0.30 for the valley demand and 0.70 for the peak demand.

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 0.65. With respect to the VRP heuristic, we fixed the number of iterations to 300 and the skewed biased savings distribution parameter to 0.35.

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, which in this case is 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. While the end-of-week delivery system, varies from 220 up to 470 km for the different vehicles and periods. Detailed results can be found in Figure 2 and Table 1.

4 Conclusions

This work focused on exploring an urban hub as a potential solution for last-mile urban distribution challenges. Here we considered the use of traditional vans and cargo bikes as well as two delivery strategies (ultra-fast and end-of-week) for comparison purposes. Additionally, two different demand scenarios, peak days and valley days, were examined.

After the analysis of the results described in Table 1, a number of conclusions can be drawn.

Firstly, 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.

Secondly, 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. Finally, 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.

Further studies are necessary to explore various possibilities and determine the trade-offs between them. Additionally, real data collection is required for validation purposes. These efforts will inform future research, which should focus on investigating horizontal cooperation strategies and examining new scenarios.

Acknowledgement

This work has been partially supported by the Spanish Ministry of Science, Innovation, and Universities (RED2022-134703-T; PID2022-140278NB-I00) and the SEPIE Erasmus+ Program (2019-IES01- KA103-062602). Additionally we acknowledge the support from the Public University of Navarra for Young Researchers Projects Program (PJUPNA26- 2022).

References

[1] Bukoye OT, Gadiraju S. Optimal consolidation center to improve urban freight transport: a case of student accommodation in a higher education institution. *Multimodal Transportation*. 2022;1(3):100032.

[2] Anderluh A, Hemmelmayr VC, Rüdiger D. Analytic hierarchy process for city hub location selection - The Viennese case. *Transportation Research Procedia*. 2020; 46:77–84.

[3] Grasas A, Juan AA, Faulin J, de Armas J, Ramalhinho H. Biased randomization of heuristics using skewed probability distributions: A survey and some applications. *Computers and Industrial Engineering*. 2017;110:216–228.

[4] Juan AA, Pascual I, Guimarans D, Barrios B. Combining biased randomization with iterated local search for solving the multidepot vehicle routing problem. *International Transactions in Operational Research*. 2015;22(4):647–667.