Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 58-2 (2024) 186–191

Towards Sustainable Last-Mile Delivery: Introducing an Off-Peak Urban Policy to Mitigate Environmental and Social Impacts

Renata Mansini * **Filippo Ranza** * **Roberto Zanotti** **

* *Department of Information Engineering, University of Brescia, via Branze, 38, 25123, Brescia, Italy (e-mail: renata.mansini@unibs.it, filippo.ranza@unibs.it).*

** *Department of Clinical and Experimental Sciences, University of Brescia, Viale Europa, 11, 25123, Brescia, Italy (e-mail: roberto.zanotti@unibs.it)*

Abstract:
In recent years, last-mile delivery research has shifted from focusing solely on cost minimization to a broader consideration of sustainability and environmental impact. This paper explores the novel trend of evaluating the social impact of last-mile delivery, emphasizing factors such as road safety, congestion, and noise pollution. A key strategy that has garnered attention in addressing these multifaceted concerns is Off-Peak Hours Delivery (OPHD), which involves scheduling deliveries during non-peak hours, often in the evenings or at night. This study investigates implementing a city-wide policy inspired by OPHD, strategically encouraging or discouraging deliveries in specific urban areas and time slots. The objectives of such a policy span from environmental considerations to nuanced social factors, potentially leading to dynamic shifts in time slot preferences. Adopting such a policy aligns with the growing citizen concern for environmental and social issues, leveraging changing attitudes toward sustainable practices. To evaluate this policy, we formalize it as a bi-objective mixed-integer programming model, aiming to strike a balance between the economic interests of retailers and the municipality's overarching goals. Through realistic instances, the paper offers managerial insights, providing valuable perspectives on the practical effects of the proposed policy on delivery operations. This facilitates a deeper understanding of the ramifications of integrating social considerations into the optimization framework.

Keywords: Last-Mile Delivery, Off-Peak Delivery Strategies, Vehicle Routing Problem, Time Windows, Multi-objective optimization, Urban environmental policy

1. INTRODUCTION

The evolution of last-mile delivery within the scientific community has witnessed a continual shift in focus, transitioning from initial considerations centered around cost minimization and profit maximization (Mansini and Zanotti, 2022; Ouyang et al., 2023; Côté et al., 2024) towards sustainability goals. The surge in e-commerce, accentuated by the COVID-19 pandemic, has underscored the relevant impact of last-mile delivery companies not only on their direct customers but on the broader community. Notably, sustainability and environmental evaluation of last-mile delivery impact have garnered significant attention, prompting a thorough examination of various components and the proposal of different solutions. These include analyses of different-sized time windows (Manerba et al., 2018), the integration of parcel lockers (Bonomi et al., 2022b), and the use of drones and autonomous robots (Lemardelé et al., 2021), among other aspects. An emerging trend involves assessing the social impact of last-mile delivery, encompassing considerations such as road safety, congestion, and noise pollution (Viu-Roig and Alvarez-Palau, 2020). Addressing the environmental, social, and cost challenges induced by last-mile delivery, the Off-Peak Hours Delivery (OPHD) strategy has gained attention (Iván Sánchez-Díaz and Brolinson, 2017). OPHD entails scheduling deliveries during evening or overnight hours to bypass traffic congestion, reduce overall delivery time, and achieve concurrent benefits such as cost reduction (Fu and Jenelius, 2018), pollution mitigation (Mousavi et al., 2021; Saleh et al., 2022), and enhanced customer satisfaction (Holguín-Veras et al., 2011). Primarily adopted in freight transportation for the last mile, OPHD faces challenges such as recipient resistance and community rejection due to overnight noise pollution (Holguín-Veras et al., 2006a,b). An additional concern arises from the health and annoyance costs associated with road noise exposure, as reported by the European Environment Agency. These costs escalate from 17€ (noise between 50 and 54dB) to 72€ (over 75dB) per dB (European Environment Agency, 2019).

A municipality can employ several strategies to alleviate the impact of last-mile logistics in urban areas, including the promotion of sustainable mobility through bike rental programs, the establishment of safe paths for foot or bicy-

2405-8963
Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2024.07.112

cle couriers, the identification of restricted traffic zones in densely populated or historical areas, and encouragement of electric or low-emission vehicle use in designated zones. Advanced traffic monitoring systems and the introduction of logistic consolidation hubs further contribute to efficient traffic flow and the use of electric vehicles.

This paper explores the potential impact of a city-wide policy for home deliveries that closely aligns with OPHD, investigating its effects on delivery companies (or retailers) and their operational costs. Instead of imposing night deliveries, which might face limited customer acceptance, we consider a scenario where a city administration seeks to encourage or discourage deliveries in specific time slots according to the urban areas. These time slots could align with the conventional OPHD definition or be chosen for different reasons. For instance, a focus on the social impact of last-mile operations might lead to discouraging deliveries in a mid-afternoon time slot in a district with several schools, coinciding with children going home. Moreover, the flexibility of these time slots allows for dynamic adjustments, such as discouraging deliveries during specific public events that attract crowds. Adopting such a policy holds the potential for favorable reception by citizens, leveraging the increasing importance placed on environmental and social issues. Additionally, coupling this policy with promoting unattended delivery paradigms, like parcel lockers, can mitigate the slight loss in flexibility regarding delivery options. In freight transportation, delivery companies naturally lean towards an OPHD approach due to its inherent benefits (Iván Sánchez-Díaz and Brolinson, 2017). However, customer reluctance often hinders its adoption, even with financial incentives (Holguín-Veras et al., 2006a). Navigating the complex landscape of multi-stakeholder optimization, where each stakeholder may have multiple conflicting goals, presents a significant challenge. Identifying which objectives to optimize and how to achieve a satisfactory balance becomes intricate, especially when dealing with a problem of this magnitude (Bonomi et al., 2024). When the companies' goals align with those of the city administration, particularly in the joint pursuit of environmental goals through time window penalties, there is room to control traffic congestion during peak hours, leading to lower emissions and reduced average time-to-delivery. However, the distribution company's primary goal is to minimize transport costs while ensuring customer satisfaction. This objective may still conflict with the municipality's objectives. It is not uncommon for a delivery company, especially when customers pay a premium for its services, to incur additional costs to meet customers' expectations. These added costs may include expenses related to congestion control implemented by city administrations, typically involving variable urban tolls based on the time of day to discourage unnecessary vehicle access. Conversely, when social considerations dictate penalties for specific time windows, striking the right balance between citizens' benefits and the economic viability of last-mile operations becomes crucial for promoting a more sustainable last-mile logistics system.

To model such a potential trade-off, we propose a bi-objective vehicle routing problem optimizing the goals associated with the main decision-makers: the retailer, primarily interested in minimizing total travel time, and the municipality, which seeks to reduce social and environmental impact by mandating the retailer's minimization of penalties for accessing specific zones within defined time windows. We call this problem the Off-Peak Vehicle Routing Problem (OP-VRP).

The paper is organized as follows. In Section 2, we provide the problem definition, followed by its mathematical formulation in Section 3. Section 4 presents the key findings concerning the application of the proposed policy in a realistic setting. Finally, in Section 5, we present our conclusions and assess potential avenues for future research.

2. PROBLEM DESCRIPTION

Let D be the set of districts (areas, zones) into which a city can be partitioned. The OP-VRP can be formulated on a directed graph $G = (V, A)$ where the node set $V = \{0\} \cup N$ consists of the depot (node 0) and the set N of delivery points (customers) within the urban area, whereas arc set A represents the connections between nodes. Set N can be partitioned into $|D|$ disjoint subsets, i.e., $N = \cup_{d \in D} N_d$ with $N_d \cap N_f = \emptyset \; \forall d, f \in D,\, d \neq f$. Subset N_d represents the subset of delivery points located in district $d \in D$. The travel cost and time associated with each arc $(i, j) \in A$ are denoted as c_{ij} and t_{ij}, respectively. Both travel costs and times satisfy the triangular inequality and are proportional to the distances traveled. The service time required to serve the delivery point $i \in N$ is represented by s_i. We refer to W as the set of disjoint time slots into which the day (or specific periods like morning/afternoon) is partitioned. Penalty coefficient $p_w^d > 0$, used to incentivize or penalize a specific time window of a defined district, serves as a multiplicative factor of the transportation cost incurred by the delivery company when serving delivery points belonging to district $d \in D$ during the time interval $[a_w, b_w]$, where a_w and b_w denote the start and end times of time slot $w \in W$. The fleet of vehicles involved in the service is denoted as K. Each vehicle must return to the depot within a working time limit t_{max}. The retailer's objective is to visit all delivery points, minimizing the total time required for the service and, as a secondary objective, minimizing the total penalties paid for visiting customers within the districts during the selected time slots.

3. MATHEMATICAL FORMULATION

To provide a mathematical formulation of the OP-VRP we introduce the following sets of variables.

For each district $d \in D$ and each time slot $w \in W$, we introduce the binary variable y_w^d, defined as follows:

- $y_w^d = \begin{cases} 1, & \text{if district } d \text{ is visited in time slot } w \\ 0, & \text{otherwise.} \end{cases}$

The second set of binary variables is defined for each arc $(i, j) \in A$ as follows:

- $x_{ij} = \begin{cases} 1, & \text{if arc } (i, j) \text{ is traversed} \\ 0, & \text{otherwise.} \end{cases}$

The final set consists of continuous non-negative variables z_{ij} for all $(i, j) \in A$, defining the arrival time at node j when coming from node i. From now on, for any subset

$S \subset V$, let $\delta^+(S) = \{(i,j) \in A : i \in S, j \notin S\}$ and $\delta^-(S) = \{(i,j) \in A : i \notin S, j \in S\}$ be the sets of arcs leaving from and entering set S, respectively.

The mathematical formulation of OP-VRP as a bi-objective problem is as follows:

$$\min f_1 = \sum_{(j,0)\in\delta^-(0)} z_{j0} \quad (1)$$

$$\min f_2 = \sum_{d\in D}\sum_{w\in W} p_w^d y_w^d \sum_{i\in N_d}\sum_{j\in\delta^-(i)} c_{ji}x_{ji} + \sum_{(j,0)\in\delta^-(0)} c_{j0}x_{j0} \quad (2)$$

$$\sum_{(0,i)\in\delta^+(0)} x_{0i} = \sum_{(j,0)\in\delta^-(0)} x_{j0} \leq |K| \quad (3)$$

$$\sum_{(j,i)\in\delta^-(i)} x_{ji} = \sum_{(i,j)\in\delta^+(i)} x_{ij} = 1 \quad i \in N \quad (4)$$

$$\sum_{(i,j)\in\delta^+(i)} z_{ij} - \sum_{(j,i)\in\delta^-(i)} z_{ji} \geq \sum_{(i,j)\in\delta^+(i)} (t_{ij}+s_i)x_{ij} \quad i \in N \quad (5)$$

$$z_{0i} = t_{0i}x_{0i} \quad i \in \delta^+(0) \quad (6)$$

$$z_{ij} \geq (t_{0i}+t_{ij}+s_i)x_{ij} \quad i,j \in V, i \neq j \quad (7)$$

$$z_{ij} \leq (t_{max}-s_j-t_{j0})x_{ij} \quad i,j \in V, i \neq j \quad (8)$$

$$\sum_{w\in W} a_w y_w^d \leq \sum_{(j,i)\in\delta^-(i)} z_{ji} \leq \sum_{w\in W} b_w y_w^d \quad d \in D, i \in N_d \quad (9)$$

$$\sum_{w\in W} y_w^d \leq 1 \quad d \in D \quad (10)$$

$$x_{ij} \in \{0,1\} \quad (i,j) \in A \quad (11)$$

$$z_{ij} \geq 0 \quad (i,j) \in A \quad (12)$$

$$y_w^d \in \{0,1\} \quad d \in D, w \in W \quad (13)$$

Objective function f_1 in (1) minimizes the sum of the arrival times at node 0 (the depot) of all vehicles after visiting all the customers. In contrast, Objective function f_2 in (2) minimizes the total penalty. For each district $d \in D$, the latter is computed as an approximation of the total traveling costs associated with selected arcs entering nodes of the district ($\sum_{i\in N_d}\sum_{j\in\delta^-(i)} c_{ji}x_{ji}$) multiplied by the penalty term $\sum_{w\in W} p_w^d y_w^d$ that depends on the time slot, among all the available ones, that will be selected for the district (corresponding variable y_w^d set to 1). To account for the cost of returning to the depot, we also add a term ($\sum_{(j,0)\in\delta^-(0)} c_{j0}x_{j0}$). Notice that objective function f_2 directly multiplies variables x and y and thus is non-linear. However, it can be easily linearized as follows:

$$\min \sum_{d\in D}\sum_{w\in W} \gamma_w^d + \sum_{(j,0)\in\delta^-(0)} c_{j0}x_{j0} \quad (14)$$

$$\gamma_w^d \geq p_w^d \sum_{i\in N_d}\sum_{j\in\delta^-(i)} c_{ji}x_{ji} - M_d(1-y_w^d) \quad w \in W, d \in D \quad (15)$$

$$\gamma_w^d \geq 0 \quad w \in W, d \in D \quad (16)$$

where M_d is a large enough value that can be set to $\sum_{i\in N_d} max_{j\in\delta^-(i)} c_{ji}$. Notice that, due to constraints (10), at most one variable y_w^d will take value 1 for each district $d \in D$, eliminating M_d and forcing the corresponding variable γ_w^d to take the value $p_w^d \sum_{i\in N_d}\sum_{j\in\delta^-(i)} c_{ji}x_{ji}$. Constraints (3) indicate that no more than $|K|$ vehicles can be used and that the number of vehicles that leave the depot must also re-enter it. Constraints (4) guarantee that exactly one arc enters and leaves each node $i \in N$. Constraints (5) manage subtour elimination by establishing that if a vehicle visits node j right after node i (i.e., $x_{ij} = 1$), the time elapsed between the arrival times in the two nodes is at least equal to the service time s_i required to serve node i plus the travel time t_{ij} required to go from i to j (Gobbi et al., 2019, 2023). Constraints (6) set the minimum time required to reach the first node i after the depot, whereas Constraints (7)-(8) define lower and upper bounds on the values of each variable $z_{ij}, i,j \in N, i \neq j$. Constraints (9) force the activation of variable y_w^d when the arrival time at node $i \in N_d$ is included in the time slot $[a_w, b_w]$. Constraints (10) impose that, for each district $d \in D$, at most one time slot $w \in W$ can be activated. Finally, the remaining constraints are variable definitions and domain restrictions.

4. EXPERIMENTAL ANALYSIS

In this section, we present the results obtained by solving the OP-VRP mathematical model on realistic instances and evaluate the interplay between the *company oriented* objective function (1) and the *municipality oriented* one (2). All tests have been conducted on a Windows machine equipped with a Ryzen 9 3950X 16-core processor and 32 GB of RAM, using Gurobi 11.0.1 as a Mixed Integer Programming Solver, with all instances solved to optimality.

4.1 Benchmark Instances

We generated instances based on the road graph of San Francisco, CA, USA, using OpenStreetMap data. For each instance, 14 nodes (customers) were randomly selected on the map, with at least one node for each city district ($|D| = 11$) and an additional node outside the city serving as the depot. Hence, $|V| = 15$ in all instances. For each ordered node pair, the arc cost corresponds to the shortest path, and the related travel time is obtained assuming a constant vehicle speed of 30 Km/h. Two values of $|W|$, corresponding to 1-hour and 30-minute time slots, are considered over an operational time window t_{max} of 4 hours. Results should be scalable based on an increase of t_{max} and the number of customers. For each district $d \in D$, we set p_w^d values such that the best time slot has $p_w^d = 1$ (no penalty), and the worst has $p_w^d = 2$ (twice the arc costs). Time slots in between have evenly spaced penalties between 1 and 2. Computed penalties are randomly assigned to each time slot. The number of vehicles $|K|$ is always set to 3. We generated 20 base graphs with different customer locations. Given $|W| \in \{4, 8\}$, the total number of instances is 40. Figure 1 provides the visual representation of an instance with dotted lines indicating district borders, different colors representing each district, and symbols denoting the depot and the customers.

4.2 Managerial Insights and Sensitivity Analysis

The initial analysis revolves around the impact of constraints (9)-(10) that impose entering each district within a single time slot (one-slot policy). Figure 3 illustrates the value deterioration of f_1 when such constraints are incorporated, contrasting the optimization outcomes with and without them. As expected, the use of shorter time

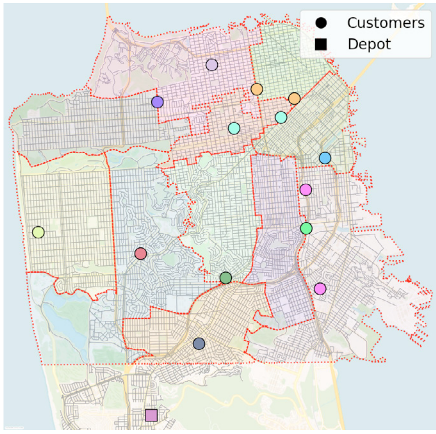

Fig. 1. Example of an instance.

slots ($|W| = 8$) exhibits a more noticeable effect, resulting in a median increase of about 3% in the total time required for delivery operations. Instances with negligible impact (approximately 0%) are observed, while there is one notable case with an increase exceeding 9%. When $|W| = 4$, the median impact stays below 1%, with the maximum hovering around 4.5%. A 1-hour time window appears reasonable for most practical scenarios, such as discouraging visits to commercial areas during rush hours or school districts during the start or end of the school day. This initial assessment shows how the one-slot policy can influence delivery operations. In this scenario, the delivery company can select its preferred time slot without considering how the city decision-makers value it. The more fine-grained the control over the access to a district is, the higher the increase in costs will be. Figure 2 provides a visual representation of how solutions evolve when optimizing f_1 without constraints (9)-(10), with them, and when optimizing f_2, respectively. In this specific instance with $|W| = 4$, the amount of traveled kilometers varies significantly: from 47.9 in the first case to 56.8 in the second, reaching 64.3 in the third one. Notably, the first solution achieves all deliveries with a single vehicle, while the other two require the activation of two vehicles. Interestingly, the one-slot policy forces the company to use a second vehicle to service a single customer. Comparing the solutions in Figures 2(b) and 2(c) with the one in Figure 2(a), we can notice that the path followed to visit nodes located northeast of the city changes. Moreover, in both solutions, the driver exits and re-enters a district after visiting an adjacent one. This is possible when opting for the same time slot in both districts. A trade-off emerges: choosing the optimal slot for neighboring districts or finding a compromise with a *middle ground* slot. A preliminary insight, applicable to all instances, is evident: the introduction of a single-slot policy and the penalization of unwanted slots can result in a noticeable increase in total traveled distance and, consequently, environmental emissions. However, it is important to recognize that this model is more tactical than operational. For instance, if a city discourages a specific time slot due to heavy traffic, yet a company uses it based on lower predicted distance, this may not translate to lower emissions in practice. The company driver may get stuck in traffic in that rush hour slot with the engine of its vehicle still producing emissions. Nevertheless, in certain cases, a trade-off between distance traveled and added social value will emerge. Balancing social (e.g., avoiding a school-day ending) against environmental costs becomes a crucial consideration.

To comprehensively assess the interplay between the two objectives, we employ the ϵ-constraint method considering a specific lexicographic order (Mansini et al., 2023). In this method, we prioritize and optimize objectives sequentially, ensuring that while enhancing lower-priority objectives, higher-priority ones remain within defined boundaries. For example, consider objectives f_1 and f_2, where f_1 takes precedence over f_2. We initially optimize f_1, constraining its value to remain within a certain epsilon of its optimal value in subsequent optimizations. This approach is valuable when the objectives represent incomparable quantities (Bonomi et al., 2022a). Alternatively, a weighted sum approach can be considered if comparability among objectives exists. Additionally, Goal Programming facilitates the setting of specific target values for each objective based on prior knowledge or expert judgment and identifies those solutions that minimize the deviations from these targets. Finally, providing the exact or approximate Pareto-efficient frontier as output is another option if computationally feasible. A comprehensive discussion about different ways of handling a multi-objective problem is available in Ehrgott (2005). For each instance, we conduct 12 optimizations. Initially, we optimize f_1, yielding an optimal value denoted as f_1^{opt}. Subsequently, we solve five additional problems where f_2 is minimized, while bounding f_1 to stay below predefined thresholds: f_1^{opt} (no worsening allowed), $1.05f_1^{opt}$, $1.1f_1^{opt}$, $1.15f_1^{opt}$, and $1.2f_1^{opt}$. The reverse process starts by optimizing f_2. This sequence of optimizations provides a rough idea of how the Pareto-efficient frontier is shaped. Figure 4 illustrates the exact Pareto-efficient frontier for one of the solved instances. The figure suggests that a slight initial deterioration of one objective enables significant enhancement of the other while achieving the optimal value of the second objective requires a significant compromise on the first. This intuitive observation is confirmed by subsequent analyses presented in this section.

Across the 40 instances, a total of 480 optimizations are performed. On average, each optimization required 164 seconds. Solving f_2 first (without constraints on f_1) is much harder than solving f_1 first (without constraints on f_2): 136s vs 3s on average. The optimization of f_1 allowing a degradation of the optimal value of f_2 of 0% required by far the highest amount of time, reaching 755s on average. Figure 5 illustrates the degradation in f_1 when optimizing f_2 first and allowing a certain percentage deterioration in f_2. It is evident that f_2 significantly influences the value of f_1. When no worsening of f_2 is permitted, the median deterioration of f_1 compared to its optimal value exceeds 50%, indicating an impractical scenario. However, this value rapidly diminishes to less than 10% when a 5% worsening of f_2 is allowed, reaching almost 0% when at least a 10% worsening is acceptable. In Figure 6, the outcomes of optimizing f_2 while permitting a certain degradation of the optimal value of f_1 are presented. In this context, the impact of optimizing f_1 first is noticeable but not as pronounced as in the previous scenario. Even when maintaining the degradation of f_1 at 0%, the median deterioration of f_2 is approximately 12%. This approach provides a practical

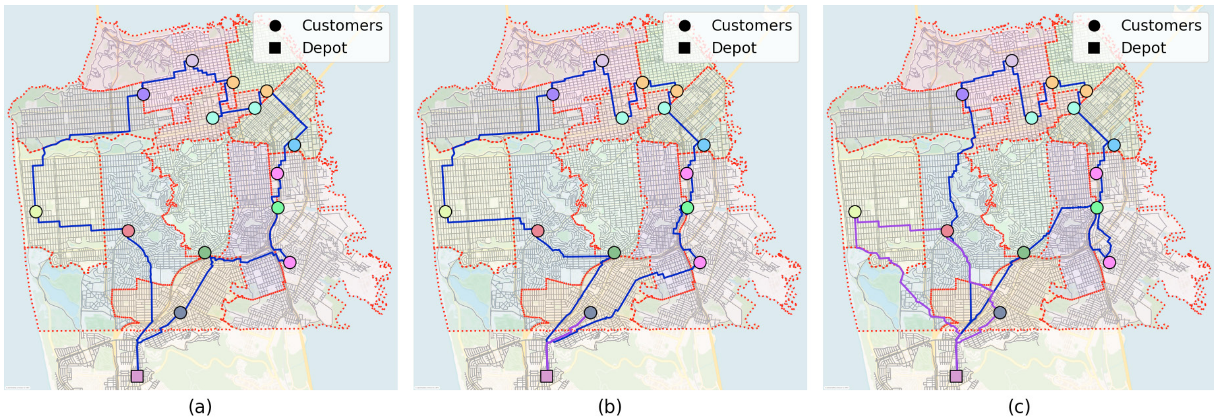

Fig. 2. Example of a solution when optimizing (a) f_1 without constraints (9)-(10), (b) f_1, and (c) f_2.

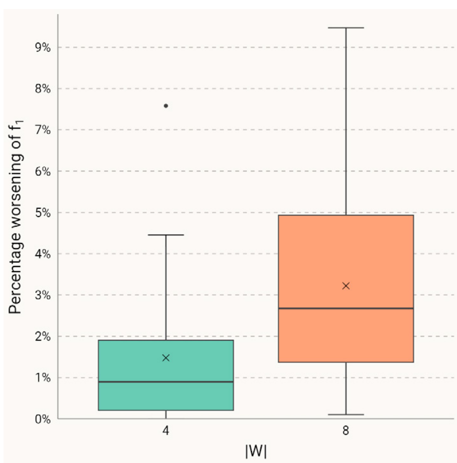

Fig. 3. Worsening of f_1 with constraints (9)-(10).

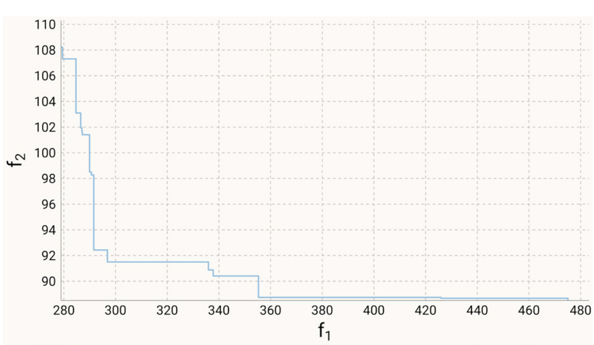

Fig. 4. Example of Pareto frontier for one instance.

way to address the municipality's concerns, allowing the company to understand that by accepting a 5% increase in the total time required for deliveries, solutions within 5% of the municipality's objective can be achieved. Figure 7 highlights the trade-off between an objective function that considers social and environmental costs and one that prioritizes shortest paths, overlooking potential traffic congestion and social concerns. The median increase in traveled distance when optimizing f_2 is about 10%, but there are instances where this increase exceeds 26%.

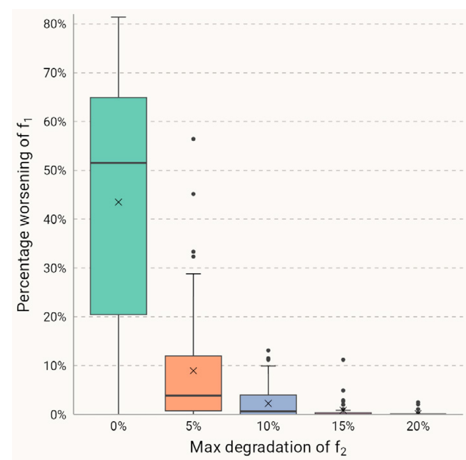

Fig. 5. Worsening of f_1 for different degradations of f_2.

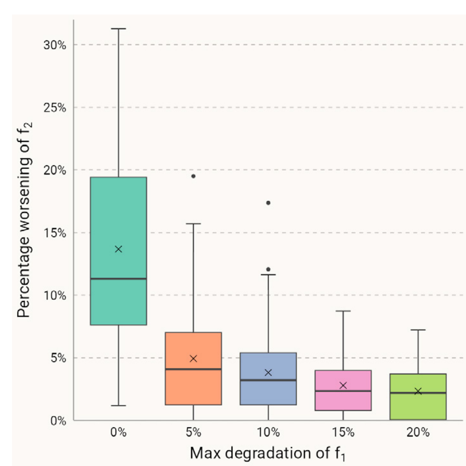

Fig. 6. Worsening of f_2 for different degradations of f_1.

5. CONCLUSIONS

Municipalities can implement different policies to reduce congestion during peak hours, including dynamic toll systems based on traffic density, which dissuade vehicles from entering the city unnecessarily during high-demand periods. In this study, we address a complex optimization problem for last-mile delivery that incorporates both environmental and social considerations to discourage retail companies from delivering in specific time slots. We name

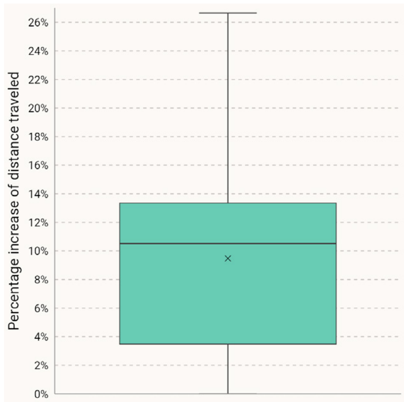

Fig. 7. Increase of distance traveled when optimizing f_2 with respect to the optimization of f_1.

it the Off-Peak Vehicle Routing Problem (OP-VRP) and develop a bi-objective mixed-integer programming formulation optimizing both the traveling time and the total penalty costs incurred by a delivery company. We solve the problem on realistic instances, encompassing 40 delivery scenarios with over 480 optimizations. Results reveal that restricting to one time slot per area leads to a modest median cost increase of approximately 3%, even in the challenging setting of 30-minute time slots. A noteworthy observation is that allowing a 5% cost increase could help delivery companies align their objectives more closely with the city administration's goals. This finding suggests a potential avenue for collaboration, fostering a compromise that benefits both stakeholders. As a future development, we aim to refine the model by incorporating time-dependent travel times and costs, reflecting real-world traffic patterns. This evolution will enhance the model's applicability to urban logistics scenarios, providing a more accurate representation of the challenges and opportunities in the last-mile delivery optimization landscape.

REFERENCES

Bonomi, V., Mansini, R., and Zanotti, R. (2022a). Fairness in home healthcare: can patient-centered and nurse-centered measures concur to the same goals? *IFAC-PapersOnLine*, 55(10), 3136–3141.

Bonomi, V., Mansini, R., and Zanotti, R. (2022b). Last mile delivery with parcel lockers: evaluating the environmental impact of eco-conscious consumer behavior. *IFAC-PapersOnLine*, 55(5), 72–77.

Bonomi, V., Mansini, R., and Zanotti, R. (2024). Mediating governance goals with patients and nurses satisfaction: a multi-actor multi-objective problem including fairness. *International Journal of Production Research*, 62(10), 3753–3780.

Côté, J.F., Mansini, R., and Raffaele, A. (2024). Multi-period time window assignment for attended home delivery. *European Journal of Operational Research*, 316(1), 295–309.

Ehrgott, M. (2005). *Multicriteria optimization*, volume 491. Springer Science & Business Media.

European Environment Agency (2019). The first and last mile — the key to sustainable urban transport.

Fu, J. and Jenelius, E. (2018). Transport efficiency of off-peak urban goods deliveries: A Stockholm pilot study. *Case Studies on Transport Policy*, 6(1), 156–166.

Gobbi, A., Manerba, D., Mansini, R., and Zanotti, R. (2019). A kernel search for a patient satisfaction-oriented nurse routing problem with time-windows. *IFAC-PapersOnLine*, 52(13), 1669–1674.

Gobbi, A., Manerba, D., Mansini, R., and Zanotti, R. (2023). Hybridizing adaptive large neighborhood search with kernel search: a new solution approach for the nurse routing problem with incompatible services and minimum demand. *International Transactions in Operational Research*, 30(1), 8–38.

Holguín-Veras, J., Ozbay, K., Kornhauser, A., Brom, M.A., Iyer, S., Yushimito, W.F., Ukkusuri, S., Allen, B., and Silas, M.A. (2011). Overall impacts of off-hour delivery programs in New York City Metropolitan Area. *Transportation Research Record*, 2238(1), 68–76.

Holguín-Veras, J., Pérez, N., Cruz, B., and Polimeni, J. (2006a). Effectiveness of financial incentives for off-peak deliveries to restaurants in Manhattan, New York. *Transportation Research Record*, 1966(1), 51–59.

Holguín-Veras, J., Wang, Q., Xu, N., Ozbay, K., Cetin, M., and Polimeni, J. (2006b). The impacts of time of day pricing on the behavior of freight carriers in a congested urban area: Implications to road pricing. *Transportation Research Part A: Policy and Practice*, 40(9), 744–766.

Iván Sánchez-Díaz, P.G. and Brolinson, M. (2017). Shifting urban freight deliveries to the off-peak hours: a review of theory and practice. *Transport Reviews*, 37(4), 521–543.

Lemardelé, C., Estrada, M., Pagès, L., and Bachofner, M. (2021). Potentialities of drones and ground autonomous delivery devices for last-mile logistics. *Transportation Research Part E: Logistics and Transportation Review*, 149, 102325.

Manerba, D., Mansini, R., and Zanotti, R. (2018). Attended home delivery: reducing last-mile environmental impact by changing customer habits. *IFAC-PapersOnLine*, 51(5), 55–60.

Mansini, R., Zanella, M., and Zanotti, R. (2023). Optimizing a complex multi-objective personnel scheduling problem jointly complying with requests from customers and staff. *Omega*, 114, 102722.

Mansini, R. and Zanotti, R. (2022). Two-phase kernel search: An application to facility location problems with incompatibilities. In *Proceedings of the 11th International Conference on Operations Research and Enterprise Systems - Volume 1: ICORES*, 105–111.

Mousavi, K., Khan, S., Saiyed, S., Amirjamshidi, G., and Roorda, M.J. (2021). Pilot off-peak delivery program in the region of Peel. *Sustainability*, 13(1), 246.

Ouyang, Z., Leung, E.K., and Huang, G.Q. (2023). Community logistics and dynamic community partitioning: A new approach for solving e-commerce last mile delivery. *European Journal of Operational Research*, 307(1), 140–156.

Saleh, M., Chowdhury, T., Vaughan, J., Wang, A., Mousavi, K., Roorda, M.J., and Hatzopoulou, M. (2022). Climate and air quality impacts of off-peak commercial deliveries. *Transportation Research Part D: Transport and Environment*, 109, 103360.

Viu-Roig, M. and Alvarez-Palau, E.J. (2020). The impact of e-commerce-related last-mile logistics on cities: A systematic literature review. *Sustainability*, 12(16), 6492.