



Sustainable e-grocery home delivery: An optimization model considering on-demand vehicles

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ABSTRACT

The e-grocery sector has experienced a significant boost since the COVID-19 pandemic, dramatically changing consumer buying behaviours. As demand for faster and more efficient delivery options grows, e-grocery retailers face increasing pressure to optimize home delivery operations. Collaborations with third-party logistics providers (3PLs), although still overlooked, have emerged as promising, offering operational flexibility and environmental benefits. This work introduces an optimization model that supports the design of an on-demand delivery fleet conjunctly with delivery routings and schedules, while considering both cost and environmental impact. To this aim, a vehicle routing problem with time windows (VRPTW) is extended to incorporate on-demand fleet design and three different objective functions embodying a cost-efficient, an environmentally-effective and a cost-environmental balanced perspective respectively. Numerical experiments based on an Italian case study show that prioritizing environmental objectives reduces emissions by over 90%, with marginal increases in annual costs. Besides, on-demand vehicles enable flexibility that facilitates the adoption of sustainable delivery options without requiring challenging investments such as delivery fleet. Several contributions are provided: insights into using on-demand vehicles are proposed; a mathematical model jointly optimizing fleet design and delivery routing and scheduling, while considering both costs and environmental objectives, is developed and its practical application is demonstrated using real-world data. The findings highlight the significant impact of environmental considerations on fleet composition and operational efficiency, offering actionable strategies for e-retailers to reduce emissions while maintaining service quality.

1. Introduction

The retail industry's digital transformation has been one of the most significant shifts in the global economy over the past two decades (Heydari and Bakhshi, 2022). It has reshaped the retail landscape, driving a transition from traditional, physical shopping experiences to online platforms leading to the significant growth of e-commerce. Following this trajectory, the grocery sector, traditionally reliant on physical stores, has embraced digitalization, giving rise to the e-grocery model (Shetty et al., 2022). The rise of e-grocery platforms, offering consumers unparalleled convenience, variety, and personalized shopping experiences, has also introduced complex logistical challenges, especially in the domain of last-mile delivery – a critical component in fulfilling the promise of e-grocery by ensuring timely and efficient delivery of perishable goods to consumers' doorsteps (Lan and Suzuki, 2024).

The last-mile delivery in e-grocery encapsulates the most challenging phase of the supply chain, directly impacting customer satisfaction and loyalty. The perishable nature of groceries demands a robust cold chain and timely deliveries, while consumer expectations for speed and convenience pressure the existing supply chain models to innovate continuously (Rasini et al., 2020; Siragusa & Tumino, 2022). For instance, companies like Instacart, DoorDash, and Kroger experiment with innovative delivery models, including drone delivery programs and virtual convenience stores, to enhance the speed and convenience of grocery deliveries (Tahawi, 2022). However, these advancements come with challenges, such as sustainability concerns and the need for streamlined technology to manage online orders effectively (Rasini et al., 2020). Also, when these challenges are compounded by urban congestion, the need for cost efficiency creates a pressing demand for adaptable and scalable logistics solutions (Ray et al., 2020; Seghezzi et al., 2023; Siragusa et al., 2022). Consequently, the increasing consumer expectations

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for delivery speed and visibility necessitate grocers to adopt flexible delivery options and leverage technology platforms for efficient order management. Logistics costs rise due to the complexity of e-commerce logistics, coupled with the need for faster fulfilment and the challenge of expanding capacity to meet growing consumer demand (Bartman et al., 2022). The analysis suggests that logistics costs currently represent a significant portion of e-commerce revenues and are expected to continue rising.

Third-Party Logistics (3PL) providers emerge as strategic partners, offering specialized expertise, technological innovation, and extensive logistics networks to address the multifaceted challenges of last-mile delivery in e-grocery (Pahwa and Jaller, 2023). By leveraging 3PL solutions, e-grocery businesses can access advanced logistics platforms, optimized route planning, and sustainable delivery practices, enabling them to meet the high standards of service quality and efficiency demanded by today's consumers (Wei et al., 2024; Zhao et al., 2024). Delivery outsourcing thus represents a critical axis for transforming the last-mile delivery landscape, promising enhanced operational agility, cost-effectiveness, and environmental sustainability (Heydari & Bakhshi, 2022; Pahwa & Jaller, 2023; von Viebahn et al., 2020; Wei et al., 2024). Given the critical challenges and opportunities within e-grocery logistics, this study aims to scrutinize the efficacy of 3PL solutions in revolutionizing last-mile delivery processes. Specifically, it seeks to unravel the research question (RQ):

“How can 3PL providers drive innovation in e-grocery home delivery by proposing on-demand vehicles as a solution?”

To address the RQ, this study focuses on three primary objectives, which also constitute the main contributions of the research:

- To develop a new mathematical optimisation formulation incorporating on-demand vehicle hired to fulfil last-mile deliveries into a delivery routing and scheduling optimization problem.
- To conduct a sensitivity analysis of fleet composition to environmental objectives and vehicle pool diversity.
- To quantify the impact of on-demand vehicle rental period on fleet efficiency and operating costs.

The new mathematical optimisation model enables different objectives of cost minimisation and environmental impact reduction. Fleet composition quantifies how vehicle diversity parameters influence environmental emissions, the costs of operation, and the capability to satisfy the demand for grocery deliveries. Rental period analysis shows the effect of rental period on fixed and variable costs.

This study highlights the benefits of on-demand vehicle services from 3PL providers in terms of operational effectiveness, environmental sustainability, and customer contentment in e-grocery last-mile delivery. Its outcomes encourage e-grocery retailers to strategically integrate 3PL solutions, optimizing their delivery fleets for reduced costs and emissions while maintaining high service levels. Furthermore, the study is poised to inform 3PL providers on potential service innovations that align with the shifting demands of the e-commerce landscape, highlighting opportunities for differentiation and value creation in a competitive market.

This study significantly contributes to the academic field by addressing the integration of 3PL partnerships and environmental sustainability within the e-grocery sector. In this domain, these aspects are notably underexplored. Furthermore, it uniquely combines these considerations with the challenges of fleet sizing and the optimization of home delivery routing, employing an analytical model to navigate these complexities. From a practical standpoint, this research underscores the viability of on-demand vehicles to enhance economic and environmental sustainability in the last-mile delivery process. It introduces a comprehensive model designed to facilitate the planning and execution of such delivery systems, emphasizing the importance of environmental considerations in shaping delivery outcomes.

The remainder of the paper is organized as follows. Section 2 investigates the academic state-of-the-art on the topic. Section 3 presents the proposed mathematical model formulation after detailing the relative setting and assumptions, while Section 4 illustrates the adopted solution approach. In Section 5 numerical results are discussed through the application of the model to a case study and a sensitivity analysis of relevant parameters. Finally, Section 6 concludes and discusses limitations and implications of the research.

2. Literature review

2.1. E-grocery logistics structure

The structure of e-grocery logistics can be divided into two primary components. At the strategic tier, there is the design of the distribution network, encompassing the selection of the geographic scope of service (von Viebahn et al., 2020; Seghezzi et al., 2023) and of an appropriate fulfilment model (von Viebahn et al., 2020; Calzavara et al., 2023). The order fulfilment process lies at the operational tier (Seghezzi et al., 2023).

Order fulfilment processes in e-grocery logistics are bifurcated into back-end fulfilment operations – picking, storage and consolidation – and last-mile distribution. Last-mile delivery has emerged as a prominently studied area, due to its direct impact on customer satisfaction, marking the sole point of physical interaction between customers and the retailer (Hübner et al., 2016). Key strategic decisions in last-mile delivery include the mode of delivery, the reception type, the delivery timing (both speed and specific time slots), the fleet composition, the selection of delivery providers, and the routing software.

The primary modes of e-grocery delivery are home delivery and Click & Collect. (Hübner et al., 2016; von Viebahn et al., 2020). Home delivery, bringing orders directly to the customer's residence, enhances satisfaction but also adds complexity (Xia et al., 2010). Deliveries can be attended or unattended (Hübner et al., 2016). Customers tend to favour attended delivery for convenience, though it is the more costly option and demands the customer's presence during delivery. Implementing delivery time windows can mitigate missed deliveries and boost satisfaction, albeit it increases operational costs and complexity (Agatz et al., 2008). Delivery velocity, ranging from same-day to longer timeframes, significantly impacts customer satisfaction, though faster delivery increases fulfilment costs and complexity (Hübner et al., 2016; von Viebahn et al., 2020).

Among the decisions concerning last-mile delivery, retailers need to select a delivery fleet (Hübner et al., 2016; von Viebahn et al., 2020) and provider. Since offering home delivery with proprietary requires huge investments in personnel, acquisition, and maintenance costs, many e-grocers prefer to cooperate with 3PLs (Saskia et al., 2016). Although last-mile delivery is widely studied, literature about delivery service providers is still scarce (von Viebahn et al., 2020; Seghezzi et al., 2023). Few examples can be found, such as Heydari and Bakhshi (2022), investigating contract options between e-retailers and 3PLs, and Rodríguez García et al. (2022), presenting an exploratory study of a real company that relies on 3PLs for e-grocery last-mile delivery. Nevertheless, research on last-mile delivery outsourcing is emerging for other online retail sectors. Pahwa and Jaller (2023) developed a framework to assess last-mile resilience, showing opportunities and challenges of different outsourcing channels, while Wei et al. (2024) proposed a data-driven vehicle rental and routing optimization model. Zhao et al. (2024) introduced a model integrating warehouse location and inventory planning with last-mile delivery outsourcing.

2.2. Environmental impact in e-grocery logistics

The environmental impact of last-mile delivery in e-grocery logistics is crucial, as this phase is notably energy-intensive across the distribution spectrum. The increased delivery volumes and consequent traffic

initially raise concerns about potential negative environmental impacts. However, the actual effect on the environment is contingent upon how efficiently these deliveries are executed and the net impact generated by the shift in transportation modes from traditional consumer shopping trips to courier-managed deliveries. This shift and its net impact suggest that optimized delivery systems could offset some of the adverse effects of increased delivery traffic (Trott et al., 2020; Aziz et al., 2022).

Research has investigated the comparative emissions of distribution channels and delivery methods within the e-grocery sector. Several investigations, including those by Siikavirta et al. (2002), Trott et al. (2021, 2020), Siragusa and Tumino (2022), have consistently found that e-grocery shopping can reduce emissions compared to conventional in-store shopping. However, exceptions exist, such as increased emissions due to food cooling during delivery (Heldt et al., 2021).

When examining specific delivery methods, namely home delivery and Click & Collect (C&C), findings present a mixed picture. Home delivery is identified as carrying significant economic and environmental costs related to transportation in the e-grocery sector. In contrast, solutions like pickup points, despite potentially increasing private car trips by customers as indicated by Bjørge et al. (2021), have been shown to reduce CO₂ emissions, particularly when the optimization of locker locations is considered (Leyerer et al., 2020). However, home delivery maintains a lasting advantage over C&C regarding efficiency and emissions (Schnieder et al., 2023).

Further exploration into specific home delivery solutions reveals a growing interest in collaborative delivery efforts among e-grocery entities to decrease total travel distances and emissions (Zissis et al. (2018, 2017); Aktas et al. (2021)). Besides, innovative delivery strategies like electric bikes (Pahwa & Jaller, 2022), autonomous delivery robots (ADRs) (Liu et al., 2021), and drones (Lan and Suzuki, 2024) offer promising solutions to reduce emissions. These studies highlight the need for continued innovation in e-grocery logistics to balance environmental sustainability with operational efficiency.

2.3. Analytical models for home delivery

Analytical models are widely adopted in existing literature to explore various dimensions of home delivery logistics, focusing on strategies such as order pooling, retailers' collaboration, delivery time windows, fleet design, and planning for distribution and routing with an eye on environmental impacts. Order pooling, recognized for enhancing last-mile delivery efficiency, along with retailer collaborations, are thoroughly examined in works by Zissis et al. (2018, 2017) and Aktas et al. (2021), complemented by recent results from Shetty et al. (2022).

Delivery time windows affect customer satisfaction and logistics efficiency. Narrow time windows reduce the likelihood of missed deliveries, but restrict the potential for order pooling and efficient routing, leading to higher delivery costs (Shetty et al., 2022). To mitigate these issues, the literature suggests employing customer demand management techniques, such as incentivizing customers to choose service time slots that align with logistical efficiency. This can be achieved through time-slot pricing (Asdemir et al., 2009; Yang et al., 2016; Klein et al., 2019; Mackert et al., 2019; Koch & Klein, 2020) or allocation policies (Campbell & Savelsbergh, 2006; Mackert, 2019; Vinsensius et al., 2020). These studies collectively highlight the complex interplay between customer convenience and operational efficiency in e-grocery logistics, offering valuable insights into balancing these often-competing priorities through strategic planning and innovative logistics solutions.

Fleet design in e-grocery logistics, as explored by Utomo et al. (2022), is an emerging area that warrants further investigation. In contrast, routing and distribution planning are more thoroughly examined in the literature, predominantly through the Vehicle Routing Problem (VRP) lens. The VRP focuses on optimizing routes for distributing goods from depots to destinations, minimising logistics costs, including per-route transportation costs (Azadiamin and Masel, 2021). Various adaptations of the classical VRP have been developed to address

specific logistics challenges. For instance, the VRPTW incorporate delivery time constraints, essential for scheduling attended home deliveries (Aktas et al., 2021; Pahwa and Jaller, 2022, and others). Lin et al. (2021) also introduced the Electric Vehicle Routing Problem with Time Windows (EVRPTW), considering variable electricity pricing. The VRP with Pick-ups and Deliveries (VRPPD) and the E-grocery Delivery Routing Problem (EDRP) manage goods from multiple pickup points to delivery locations (Emeç et al., 2016). Advanced models like two-echelon VRP (2E-VRP) and its multi-depot (Liu et al., 2022, 2021b, 2020) and multi-modal variants Liu et al. (2021a) explore more complex logistics networks. Innovations in VRP application include data-driven strategies to enhance e-grocery delivery efficiency, as proposed by Pan et al. (2017), and approaches for optimizing last-mile deliveries in urban food supply chains for smart cities, as developed by Leyerer et al. (2020). Azadiamin and Masel (2021) examined the balance between cost efficiency and customer satisfaction within these logistics models.

Moreover, other VRP variants like the Inventory Routing Problem (IRP) integrate inventory management with routing decisions, and the Stochastic Vehicle Routing Problem (SVRP) introduces variability into factors such as customer presence and demand, offering a more dynamic approach to addressing logistical uncertainties (Savelsbergh et al., 2007).

2.4. Summary of literature review and research gaps

The literature review indicates that employing 3PL in the e-grocery sector is a prevalent strategy (Saskia et al., 2016), yet the academic discussion on this subject remains insufficiently explored. For instance, Heydari and Bakhshi (2022) address optimising contractual conditions. To the best of the authors' understanding, no research has focused on partnerships with 3PLs, either concerning optimizing e-grocery home delivery or considering environmental impacts. Furthermore, it is identified that the environmental effects of e-grocery logistics, particularly concerning last-mile delivery, are of significant concern (Siragusa and Tumino, 2022). While there are theoretical and analytical studies on this matter, their quantity is limited.

Research on last-mile delivery and home delivery has been extensive, yet certain areas remain underexplored. Notably, literature addressing fleet sizing is sparse, and studies on routing design often presuppose a fixed number of vehicles, lacking integration with fleet sizing considerations. Furthermore, the simultaneous examination of fleet sizing alongside environmental impacts is rare, and even more scarce are studies that combine these factors with optimization techniques.

The works by Liu et al., spanning from 2020 to 2022, and the study by Utomo et al. (2022), represent efforts to tackle these complex scenarios. Liu et al. (2020) initiates the discussion by addressing optimization in delivery operations without considering environmental impacts or the intricacies of fleet composition. Their subsequent studies in 2021 and 2022 progressively explore optimization but continue to sidestep the integration of environmental considerations and the potential for partnerships with 3PLs. Similarly, Utomo et al. (2022) contribute to this discourse by exploring heuristic solutions for delivery optimization, yet they too overlook the incorporation of time windows, environmental impacts, and collaborative opportunities with 3PLs.

Addressing the identified shortcomings, this research enhances the existing body of knowledge by conducting a quantitative analysis that integrates routing optimization with fleet optimization. It uniquely incorporates the aspect of collaboration with 3PL providers and places a significant emphasis on environmental sustainability. A model is designed to optimize delivery fleets and routes, focusing on economic efficiency and environmental objectives. The model distinguishes itself by utilizing on-demand vehicles from 3PL, offering a novel approach to achieve sustainable and efficient delivery operations. A selection of the most relevant works in home delivery analytical models are reported in Table 1 and compared with the model proposed in this work, reported in the last row of the table.

Table 1

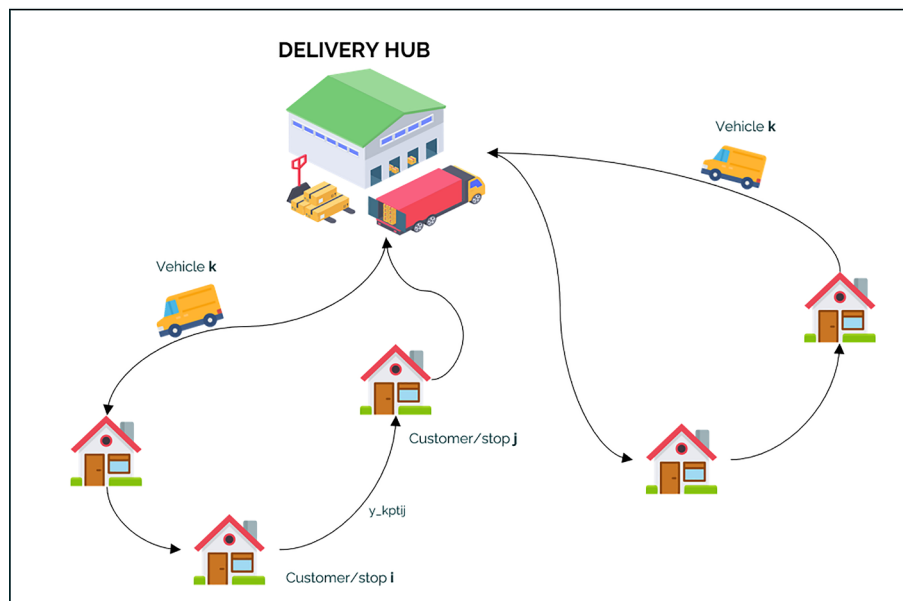
Literature review summary for home delivery analytical models.

References	Main focuses	Simulation/ Optimization	Time windows	Fleet sizing	Environmental impact assessment
Trott et al. (2020)	Online and offline grocery environmental impact	Agent based simulation	N	N	Y
Trott et al. (2021)	E-grocery home delivery environmental impact	Agent based simulation	Y	N	Y
Siragusa and Tumino (2022)	Online and offline grocery environmental impact	Simulation	N	N	Y
Heldt et al. (2021)	Environmental impact of home delivery with refrigerated vans	Simulation	N	N	Y
Schnieder et al. (2023)	Click and collect vs. home delivery environmental impact	Simulation	N	N	Y
Pahwa and Jaller (2022)	E-grocery last-mile delivery analysis	Heuristic Optimization	Y	N	Y
Shetty et al. (2022)	Order pooling in e-grocery last-mile delivery	Simulation	N	N	N
Aktas et al. (2021)	Collaborations in e-grocery home delivery	Simulation + Optimization	Y	N	N
Zissis et al. (2018)	Collaborations in e-grocery home delivery	Optimization	N	N	N
Campbell and Savelsbergh (2006)	Time slot allocation	Optimization	Y	N	N
Asdemir et al. (2009)	Dynamic pricing	Simulation	Y	N	N
Yang et al. (2016)	Dynamic pricing	Simulation	Y	N	N
Koch and Klein (2020)	Dynamic pricing	Simulation	Y	N	N
Klein et al. (2019)	Dynamic pricing	Optimization	Y	N	N
Mackert et al. (2019)	Time slot allocation	Simulation	Y	N	N
Mackert (2019)	Time slot allocation	Optimization	Y	N	N
Vinsensius et al. (2020)	Time slot allocation	Simulation	Y	N	N
Utomo et al. (2022)	Electric and autonomous vehicles mixed fleet for home delivery	Agent based simulation	Y	Y	N
Armbrust et al. (2022)	VRPTW	Heuristic optimization	Y	N	N
Fikar and Braekers (2022)	VRPTW with food quality losses	Optimization	Y	N	N
Lin et al. (2021)	Charging schedule for electric delivery vehicles	Optimization	Y	N	Y
Azadiamin and Masel (2021)	Route planning with customer waiting time	Optimization	N	N	N
Cepolina et al. (2021)	Exact vs heuristic algorithms for e-grocery	Optimization	Y	N	N
Emeç et al. (2016)	E-grocery Delivery Routing Problem (EDRP)	Heuristic optimization	Y	N	N
Liu et al. (2020)	Two-echelon VRP (2E-VRP) with multi-depots	Heuristic optimization	N	Y	Y
Liu et al. (2021b)	Two-echelon VRP (2E-VRP) with multi-depots	Heuristic optimization	Y	Y	Y
Liu et al. (2022)	Two-echelon VRP (2E-VRP) with multi-depots	Heuristic optimization	N	Y	Y
Liu et al. (2021a)	Multi-modal two-echelon VRP (2E-VRP)	Heuristic optimization	N	Y	Y
Pan et al. (2017)	Data-driven strategies to enhance VRP	Optimization	Y	N	N
Leyerer et al. (2020)	VRP in smart cities	Optimization	Y	N	Y
This paper	VRPTW with on-demand fleet composition	Exact optimization	Y	Y	Y

3. Model description and assumptions

This paper studies the optimization of home delivery operations with a focus on the integration of 3PL providers. One research goal is to delineate the components that can be integrated into the e-grocery home

delivery logistics framework to bolster economic and environmental sustainability while enhancing operational flexibility and efficiency. To this end, a delivery model predicated on partnering with 3PL is introduced. This model underscores the strategic advantage of tapping into the expertise of 3PL to elevate service efficiency. Moreover, outsourcing

**Fig. 1.** Structure of the network at the basis of the model.

logistics to 3PL is presented as a strategy to augment operational flexibility. The proposed system is structured around a centralized hub model, where a singular hub orchestrates order fulfilment in collaboration with 3PL. These 3PL partners supply a variety of delivery vehicles and drivers on-demand over a selectable multi-day timeframe, thus granting retailers the flexibility to tailor their delivery fleet to match their needs most cost-effectively and efficiently. Fig. 1 illustrates the structure of the network considered.

The model assumptions are as follows:

- One single fulfilment hub, i.e., a physical store, covers the considered delivery area.
- All consumers receive their orders within the planned time window.
- Customer orders are spread daily along the delivery time horizon.
- Each delivery vehicle starts and finishes its delivery routing at the delivery hub every day.
- Delivery vehicles are supplied by a 3PL, which offers a variety of delivery vehicles on-demand.
- Each vehicle is characterized by renting costs (for the selected renting period of one or more days), consumption cost (per distance travelled), environmental costs (per distance travelled), and capacity.

By applying this model to a case study in Italy, the research enriches the academic dialogue concerning the synergy between 3PL collaboration and environmental sustainability within e-grocery logistics. A mathematical model has been formulated to define the operational system. It generates the optimal delivery routes for each vehicle daily and determines the best fleet composition for each on-demand period. The effectiveness of this model is evaluated based on economic and environmental sustainability, crucial metrics in the e-grocery sector, particularly for last-mile delivery. The model introduces two primary objective functions:

- **Cost Efficiency:** This objective function calculates the system's costs, incorporating the variable costs related to fuel consumption associated with the travel distance and a fixed cost for using on-demand vehicles. This approach models the flexibility gained by utilizing on-demand vehicle rental services, including drivers, to adapt fleet size as needed.
- **Environmental Impact:** This function estimates the environmental impact in terms of emissions, calculated using a methodology that is well-established in the literature (Trott et al., 2021; Siragusa & Tumino, 2022; Pahwa & Jaller, 2022). Emissions are directly correlated with the distance travelled, adjusted by a vehicle-specific conversion factor that translates distance into CO₂ emissions. This work measures the environmental impact in terms of carbon dioxide equivalent (CO₂eq) emissions. This metric encompasses CO₂ emissions and those of other pollutants, converted to CO₂ emissions, facilitating comparisons across different scenarios. National reports, such as the ones released by the Italian Institute for Environmental Protection and Research (ISPRA), provide the conversion factors for greenhouse gas emissions, updated annually.

A combined objective function seeks to optimize costs and emissions through a weighted sum, converting emissions into their monetary equivalent using a conversion coefficient (Colicchia et al., 2016).

The proposed model extends the classical VRPTW formulation. This extension is justified by the VRP's common application in home delivery studies and the similarities between the proposed system and VRPTW settings, including a single hub delivery area, delivery time windows, and a set list of orders for each day. However, unlike traditional single-day VRPTW scenarios, this model accounts for fleet design and optimization over a multi-day period, allowing for a diverse vehicle pool selection. The model employs two binary decision variables to represent the scenario:

- The variable x_{kp} indicates whether vehicle k is activated during period p (1 if activated, 0 otherwise).
- The variable y_{kptij} , adapted for this model to include day and period indicators, represents whether vehicle k travels from node i to node j on day t of period p .

Additionally, the variable w_{kpti} , derived from VRPTW and modified to indicate when a vehicle serves a customer on a specific day and period, is used. The model's objective function and constraints have been adjusted to reflect the research goals, detailed in Section 3.1. Section 4 presents a numerical analysis exploring how changes in vehicle rental service factors or variations in the emphasis on environmental impact influence fleet composition and delivery system performance.

3.1. Mathematical formulation

This article proposes a mathematical model optimizing the fleet composition and delivery routing within the e-grocery sector, particularly focusing on including on-demand vehicles. The foundation of our approach builds upon the VRPTW, a method initially introduced by Cordeau et al. (2007) and later adapted by Aktas et al. (2021). This adaptation was specifically designed to align with our research goals and to effectively handle the inputs and outputs pertinent to the study.

Central to our model is a single fulfilment hub, typically a physical store, from which distribution to a designated area occurs. This area is mathematically represented by a set of nodes $N = \{1, \dots, n\}$, with N being a subset of E , the ensemble of all nodes involved, including the hub itself ($E = \{0, 1, \dots, n, n+1\}$), where '0' and $n+1$ denote the hub's position, serving as both the commencement and conclusion points of any delivery route.

A distinctive feature of our model is the introduction of a set of on-demand vehicles, denoted as V , each with its own specifications regarding capacity (q_k), fuel consumption cost (variable cost) (c_k), and fixed cost (f_k). The temporal dimension is captured through P , the set of periods covering the entire study timeline, and T , representing the days within each period. During any given period, there exists the option to activate the on-demand service for any vehicle at a predetermined rate, enabling its use throughout the period for daily deliveries.

The model employs two binary decision variables for operational control. The variable x_{kp} is set to 1 when a vehicle is activated for the period p , and 0 otherwise. Similarly, y_{kptij} is 1 when a vehicle is active for period p on day t and is assigned a route from node i to node j , with 0 indicating inactivity. This mechanism ensures that a vehicle's usage is tightly linked to its activation status for the specific period.

The demand from each customer i on day t of period p , denoted as r_{ipt} , is fully met, ensuring complete service coverage. Time windows for delivery ($[a_{ipt}, b_{ipt}]$) are respected, where a_{ipt} and b_{ipt} represent the start and end of the customer's preferred delivery window. The model also accounts for the distance (d_{ijpt}) and travel time (t_{ijpt}) between nodes, which vary daily and by period, reflecting the dynamic nature of the demand and delivery landscape.

Table 2 provides a comprehensive overview of the sets, parameters, and variables involved, facilitating a clear understanding of the model's structure and application to optimizing e-grocery delivery systems. This model aims to advance the academic and practical discourse on fleet sizing, routing optimization, and the integration of environmental sustainability in the rapidly evolving domain of e-grocery logistics.

The mathematical formulation for the capacitated VRPTW, which incorporates using on-demand vehicles with predetermined rental periods, is outlined below.

$$\min f_1 = \sum_p \sum_k f_k x_{kp} + \sum_p \sum_T \sum_V \sum_{i=0}^{n+1} \sum_{j=0}^{n+1} c_k d_{ijpt} y_{kptij} \quad (1)$$

Table 2

Sets, parameters and variables involved in the model.

Set	
$N = \{1, 2, \dots, l, \dots, n\}$	Set of customer nodes
$E = \{0, 1, \dots, n + 1\}$	Set of total nodes including the hub
$V = \{1, 2, \dots, k, \dots, v\}$	Set of available on-demand vehicles
$T = \{1, 2, \dots, t, \dots, g\}$	Set of daytimes in a period P
$P = \{1, \dots, p, \dots, \varphi\}$	Set of periods in which the vehicle can be activated
Parameters	
c_k	transportation cost of vehicle k per unit of distance
e_k	emission conversion factor of vehicle k per unit of distance
α, β	weighting coefficients for the objective functions
d_{ijpt}	distance between the nodes i and j
f_k	fixed cost for the activation of vehicle k
q_k	capacity of each vehicle k
t_{ijpt}	travel time between the nodes i and j
s_i	time to unload at i
r_{ipt}	demand of customer i on day t of period p
a_{ipt}	opening of the TW of i
b_{ipt}	closing of TW of i
CC	Conversion coefficient from emissions to monetary value
M_{ijpt}	$\max\{0; b_{ipt} + s_i + t_{ijpt} - a_{ipt}\}$
Variables	
y_{kptij}	1 if the vehicle k moves from i to j during day t , 0 otherwise
x_{kp}	1 if the vehicle k is rented in period p , 0 otherwise
w_{kpti}	time at which k visits customer i

$$\min f_2 = \sum_p \sum_T \sum_V \sum_{i=0}^{n+1} \sum_{j=0}^{n+1} e_k d_{ijpt} y_{kptij} \quad (2)$$

$$\min f_3 = \alpha f_1 + \beta CC f_2 \quad (3)$$

Subject to:

$$\sum_V \sum_{j=1}^n y_{kptij} = 1 \quad \forall i \in N, \forall t \in T, \forall p \in P \quad (4)$$

$$\sum_{j=1}^n y_{kpt0j} \leq 1 \quad \forall k \in V, \forall t \in T, \forall p \in P \quad (5)$$

$$\sum_{i=1}^n y_{kpt0i} = \sum_{j=1}^n y_{kptj(n+1)} \quad \forall k \in V, \forall t \in T, \forall p \in P \quad (6)$$

$$\sum_{i=0}^{n+1} \sum_{j=0}^{n+1} y_{kptij} \leq \text{BigM} \sum_{j=1}^n y_{kpt0j} \quad \forall k \in V, \forall t \in T, \forall p \in P \quad (7)$$

$$\sum_{i=0}^{n+1} y_{kptil} = \sum_{j=0}^{n+1} y_{kptij} \quad \forall l \in N, \forall k \in V, \forall t \in T, \forall p \in P \quad (8)$$

$$\sum_{i=1}^n \sum_{j=1}^n r_{ipt} y_{kptij} \leq q_k \quad \forall k \in V, \forall t \in T, \forall p \in P \quad (9)$$

$$w_{kptj} \geq w_{kpti} + s_i + t_{ijpt} - M_{ijpt} (1 - y_{kptij}) \quad \forall i, j \in E, \forall k \in V, \forall t \in T, \forall p \in P \quad (10)$$

$$w_{kpti} \geq a_{pti} \quad \forall i \in E, \forall k \in V, \forall t \in T, \forall p \in P \quad (11)$$

$$w_{kpti} \leq b_{pti} - s_i \quad \forall i \in E, \forall k \in V, \forall t \in T, \forall p \in P \quad (12)$$

$$\sum_T \sum_{j=1}^n y_{kpt0j} < \text{BigM} x_{kp} \quad \forall k \in V, \forall p \in P \quad (13)$$

The presented formulation applies to three independent optimization models with three different objective functions, i.e., Eq. (1), Eq. (2), and Eq. (3), which share constraints (4) – (13).

Eq. (1) defines the objective function f_1 , aimed at minimizing the total operational cost. This cost is comprised of two main elements: the fixed cost associated with activating the on-demand vehicle and the variable transportation cost, which accounts for fuel consumption based on the distance covered. The transportation cost is calculated by multiplying the cost per unit distance for the specified vehicle (c_k) by the total distance travelled.

Eq. (2) sets forth the objective function f_2 , which seeks to minimize the total CO₂ emissions. These emissions are determined by applying the

CO₂ emission conversion factor for the vehicle (e_k) to the distance travelled.

Eq. (3) introduces the combined objective function f_3 , which integrates the objectives of minimizing both cost (f_1) and emissions (f_2) using the weights α and β , respectively. They enable the model to optimize results for various policies, by assigning different relative weights to the cost (f_1) and emissions (f_2) objectives. A conversion coefficient (CC) is employed to translate emissions into their monetary equivalent, facilitating a balanced weighted sum.

The model is constrained by several conditions to ensure feasibility and optimality:

Constraint (4) mandates that every customer is visited exactly once.

Constraint (5) stipulates that each vehicle k can be deployed no more than once per daytime t , with a sum value of 1 indicating usage and 0 denoting non-use.

Constraint (6) ensures that a vehicle returning to the hub concludes its route.

Constraint (7) prohibits any vehicle k from traversing a route without being activated for the day's operations.

Constraint (8) maintains route continuity or flow conservation for each vehicle.

Constraint (9) enforces that the vehicle's capacity limit is not exceeded.

Constraint (10) maintains consistency in time variables, marking the visitation time for each node. The linearization factor M_{ijpt} is defined as $M_{ijpt} = \max\{0; b_{ipt} + s_i + t_{ijpt} - a_{ipt}\}$, following Cordeau et al. (2007).

Constraints (11) and (12) require adherence to predefined time windows, effectively preventing subtours, as adapted from Aktas et al. (2021).

Constraint (13) asserts that a vehicle must be activated for period p to be utilized on any day within that period.

The following section highlights the novel aspects of our model compared to the conventional VRPTW approach, as outlined in Aktas et al. (2021). The introduction of the sets P (periods) and T (daytimes within those periods) marks a significant departure from traditional models. Incorporating distinct periods and daytimes into the modelling process is a pioneering feature, enriching the model's ability to accurately reflect real-world operational complexities.

A pivotal innovation in our model is the integration of a fixed cost for vehicle rental over a specified period. This aspect is realized through the new parameter f_k and variable x_{kp} , modifying the traditional objective function to include these costs. Unlike classical VRPTW models that primarily focus on minimizing the distance travelled or variable costs with a predefined number of vehicles, our model expands the objective to consider strategic fleet size and composition decisions. Adding the second and third objective functions further enrich this broader scope.

Furthermore, a critical modification is observed in constraint (5), limiting the use of each vehicle k to once per daytime t , introducing the flexibility to select which vehicles from the set are deployed. This adjustment diverges from traditional formulations that mandate the deployment of all available vehicles, thereby making the number of vehicles used a decision variable in our model. Constraint (6) has been adapted to reflect that only vehicles that have been deployed need to return to the hub.

To prevent vehicles from traversing arcs without being activated for departure from the hub on a given day, constraint (7) is introduced. This equation is absent in traditional models where vehicle activation is assumed. Moreover, constraint (13) is introduced to establish a cross-dependency between variables x and y , ensuring that a vehicle is only utilized within period p if it has been activated for that period. A slight modification is also made to the capacity constraint (9), where the vehicle capacity is variable and dependent on the specific vehicle, contrasting with traditional models that treat capacity as a constant. The rest of the constraints remain largely unchanged, except for the application of subscripts p and t to accommodate the new period and daytime

dimensions.

4. Solution approach

The VRPTW, enhanced in this study to include on-demand vehicles and fleet sizing considerations, is formulated as a Mixed Integer Linear Programming (MILP) problem. This type of problem is well-recognized in operational research for incorporating linear objective functions and constraints, with certain decision variables required to be integers. Drawing from the foundational VRPTW model, known for its NP-hard complexity, our approach extends this traditional framework to better align with our research objectives, including the nuanced dynamics of fleet composition and the strategic deployment of vehicles.

Given the NP-hard nature of the VRPTW, heuristic optimization methods have been predominantly utilized in the literature (Ombuki et al., 2006; Pureza et al., 2012; Corstjens et al., 2020). However, in instances where time windows are sufficiently constrained, allowing for a realistic size of the problem, mathematical programming techniques can optimally solve the problem (Savelsbergh et al., 2007). Unlike heuristics, exact optimization methods provide an exact solution to minimize distance, aligning with our model's emphasis on fleet optimization and the strategic selection of vehicles for activation. The complexity of integrating on-demand vehicle options and determining the optimal fleet size necessitates using exact optimization methods to potentially solve the model to optimality, albeit with the limitation of applicability to smaller case studies. This does not alter the inherent NP-completeness of the VRPTW problem when considering a fixed fleet size, as our model maintains a fixed pool of vehicles from which an optimal selection is made.

The mathematical model is implemented through a Python program, whose pseudocode is presented in Fig. 2. The program requires various inputs such as customer demand, location coordinates, time windows, available vehicle pool, and associated costs. The program calculates distances using the GeoPy library's Geodesic function, adjusting for real-world accuracy with a multiplication factor. Travel times are derived from these distances, considering an average travel speed.

For the optimization phase, the model is applied to single on-demand periods, with annual costs calculated from the aggregation of individual period optimizations. This approach leverages the problem's linearity to simplify the model for computational efficiency. Implemented using the PuLP linear programming modeler and solved with the Gurobi solver, known for its optimal performance across various instances, the model also includes an additional constraint to determine the minimum necessary vehicles per day based on capacity. This expedites computation and aids in narrowing optimality gaps, showcasing the model's comprehensive approach to addressing the dual challenges of operational efficiency and environmental impact in e-grocery logistics.

During the implementation phase of the mathematical model, an

ALGORITHM

```

Set vehicles characteristics ( $f, c, e, q$ )
Set customer demand distribution
Set boundaries of the delivery area covered by the hub
Set conversion coefficient from emissions to monetary value ( $CC$ )
Set length ( $g$ ) of period  $P$ 
Set weighting coefficients for the objective functions ( $\alpha, \beta$ )


---


for  $p$  in  $(1: P)$ :
    for  $t$  in  $(1: g)$ :
        Generate customer demand based on demand distributions
        Generate random customer locations within the defined served area
        Compute distances ( $d_{ijpt}$ ), travel times ( $t_{ijpt}$ ) and linearization
        factors ( $M_{ijpt}$ ) for each arc between nodes  $i$  and  $j$ 
    end
    Solve optimization problem
    Save results
end

```

Fig. 2. Pseudocode of the developed algorithm.

essential parameter known as M is established for each potential route, thereby creating the matrix M . This parameter serves as a linearization factor, crucial for transforming (10) within the optimization model. This equation plays a vital role in ensuring the consistency of time-related variables across the model. The process for calculating M involves setting the parameter $\text{big}M$ to a substantial value, chosen here as 1,000, and determining the service time required for each customer visit. Service time is estimated to be 12 min, with 10 min allocated for parking and an additional 2 min for the actual delivery of the order. This breakdown aligns with the assumptions and findings of Aktas et al. (2021), ensuring that the model reflects realistic operational constraints and time considerations.

Also, during the implementation phase of the mathematical model, an extra constraint, referred to as (14), is introduced. This constraint ensures the minimum number of vehicles required each day to meet customer demand, considering the capacity of each vehicle. Although the capacity of individual vehicles is already addressed through (9), adding (14) is not strictly necessary for the model's mathematical integrity. However, its inclusion is crucial to enhancing the model's computational efficiency. Specifically, it significantly reduces the time needed to solve the model and contributes to narrowing the optimality gaps—the disparity between the model's primal and dual cost functions. This adjustment, therefore, not only streamlines the computational process but also improves the accuracy and reliability of the optimization outcomes.

$$\sum_v \sum_{j=1}^n q_k y_{kpt0j} \geq \sum_{i=1}^n r_{ipt} \forall t \in T, \forall p \in P \quad (14)$$

5. Results and discussion

The model devised in this study is applied to a real-world scenario, exploring how environmental impact influences fleet sizing decisions for attended home delivery in the e-grocery sector, particularly in the context of on-demand vehicle rentals. Through a detailed analysis of the results and a sensitivity analysis, this application sheds light on the complex interplay between environmental considerations and logistical strategies, offering insights into how e-grocery businesses can optimize their delivery fleets to balance efficiency, cost-effectiveness, and environmental sustainability.

5.1. Business case

The case study focuses on an Italian retailer making its debut in the online grocery market through an omnichannel approach. Data have been anonymised and modified to maintain confidentiality while presenting a realistic scenario for the Italian context. The case exemplifies a retailer with limited physical stores and low order volume, aiming to provide next-day scheduled deliveries amidst growing and uncertain demand. This scenario highlights the potential advantages of partnering with 3PL providers.

The operational model is centred around a single hub located within a specific distribution area in the Monza district (Italy), utilizing on-demand vehicles for delivery. This area covers 44.2 square kilometres and encompasses 350 customer locations, a scale that reasonably approximates delivery points within each location (Fig. 3). Positioned centrally within the delivery zone, the hub is strategically placed to optimize distribution efficiency.

Given the retailer's entry status in the e-grocery market, it faces limited initial demand (Table 3), distributed differently during different weeks, days, and days. Notably, demand surges are observed in the weeks leading up to Easter and Christmas (weeks 13 and 51), while post-Christmas weeks (52 and 1) and August (weeks 31 to 35) typically see reduced activity. Additionally, a trend of increased orders towards the end of each week, peaking on Saturdays, is identified, combined with increased orders at the end of each day. The study spans 52 weeks (364

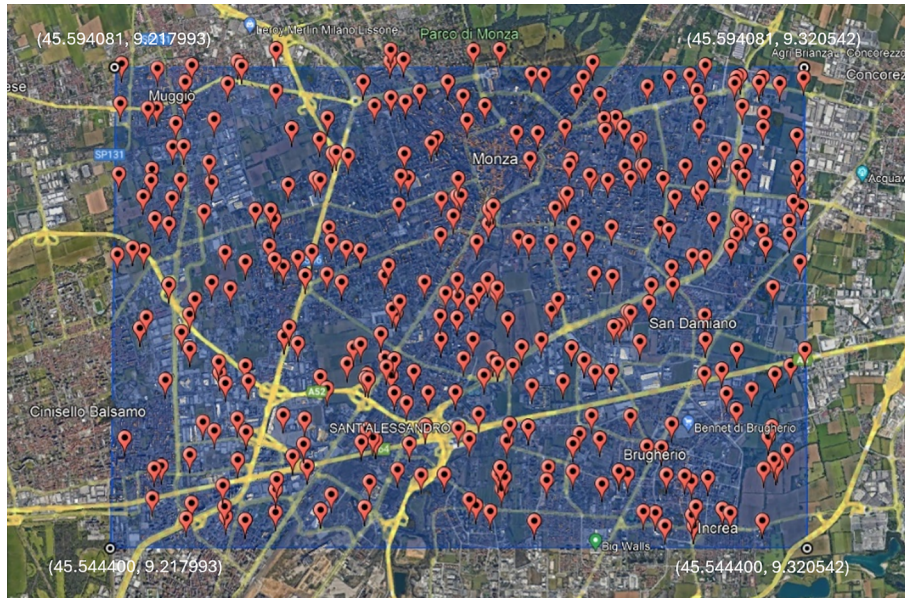


Fig. 3. Delivery area served by the hub (blue area, geographical coordinates of the corners in white) and random generated customer locations within the area (red pins).

Table 3

Business case input and assumptions.

Business case input	Assumptions
Number of delivery locations	350
Average order frequency per location	1 order every 2 weeks
Expected total annual orders for mean daily demand computation	9100 orders/year
Daily standard deviation (σ), for demand computation	0.4
Time horizon considered	52 weeks (364 days)
Delivery time slots	8 possible delivery time slots, ranging from 7 a.m. to 11 p.m., divided into 2-hour intervals
Delivery fleet	Fully on-demand
On-demand period length (g)	1 day

days), considering weekly and daily demand pattern variations. The annual order forecast and demand distribution across the year and week are utilized to calculate the average daily demand (μ) for each day of the year. Daily demand figures are then generated using a Gaussian distribution. The vehicle capacity is set to exceed the 5 sigma level of the Gaussian that generates the daily demand. In the rare instance of demand exceeding the vehicle capacity, the software warns the user and a new demand value is generated. The number of orders for each day is randomly allocated among the available time slots based on the pre-defined demand distribution, providing a detailed framework for analysing the retailer's delivery logistics and the impact of environmental considerations on fleet sizing and scheduling decisions in a nascent market context. Other assumptions and settings of the case are in Table 3.

In this study, three types of vehicles are available for the on-demand service to form the delivery fleet: diesel vans, bio-diesel vans, and electric vans. These vehicles are categorized as Light Commercial Vehicles (LCVs), which are prevalently used in Lombardy for home deliveries. The vehicle data set is constructed based on real vehicles to accurately represent the characteristics of each type (detailed in Table 4). Notably, the model does not incorporate a constraint for the electric vans' range. This decision stems from the observation that the range of the electric vans selected for this case study exceeds the requirements for daily deliveries. Even after completing the longest delivery route, a significant portion of the battery capacity remains,

Table 4

Vehicle characteristics.

Vehicles characteristics	Symbol	Values		
		Diesel Van	Bio-diesel Van	Electric Van
On-demand service cost [€/day]	f_k	348	348	383
Consumption [€/km]	c_k	0.62	0.65	0.45
Capacity [kg]	—	970	970	765
Capacity [orders]	q_k	26	26	21
Environmental impact [g CO ₂ eq/km]	e_k	241.78 ¹	15.08 ²	98.99 ³

¹ Mean Emission Factors, Data by Italian Institute for Environmental Protection and Research (ISPRA) (<https://fetransp.isprambiente.it/#/>, last accessed on October 15, 2023).

² Greenhouse Reporting: Conversion Factors, UK Department for Energy Security and Net Zero (<https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2022>, last accessed on October 15, 2023).

³ Indicators of efficiency and decarbonisation of the national energy system, Report by ISPRA (<https://www.isprambiente.gov.it/files2022/publicazioni/rapporti/r363-2022.pdf>, last accessed on October 15, 2023).

validating the assumption commonly held in literature that electric vehicle ranges are typically adequate for last-mile delivery routes (Iwan et al., 2021).

The environmental impact assessment adheres to the ISO 14083 standard, implemented following the Global Logistics Emissions Council (GLEC) framework guidelines. Emissions are quantified in CO₂eq units, enabling the standardization and comparison of various greenhouse gases (GHGs) climatic effects based on their Global Warming Potential (GWP), measured in grams of CO₂ per gram of GHG. The analysis includes emissions of carbon monoxide (CO), CO₂, methane (CH₄), and nitrous oxide (N₂O), which are the primary GHGs produced by transportation contributing to global warming. The emission factors for each delivery mode are derived from country-specific data provided by the ISPRA dataset, with GWP values supplied by the IPCC. These factors are used to calculate each delivery option's total emissions (Table 4).

In the scenario under review, the duration of the on-demand vehicle rental period is determined to be one day, resulting in the evaluation of 364 separate instances. For each of these instances, three distinct ap-

plications of the model are assessed, illustrating various approaches to addressing the logistical challenges presented. These cases demonstrate the model's flexibility and adaptability in optimizing fleet composition and delivery strategies under differing operational conditions and objectives:

- i. **Cost-Efficient Approach (Case 1):** This base case focuses solely on the first objective function (f_1), which considers the costs associated with the delivery service. These costs include fixed costs, stemming from the use of on-demand services, and variable costs, related to consumption. This case offers potential cost savings and efficiency gains without considering environmental impact.
- ii. **Environmental-Effective Approach (Case 2):** In this scenario, the model is adjusted to evaluate only the second objective function (f_2), which is centred on the environmental impact, specifically the CO₂ equivalent (CO₂eq) emissions generated by the delivery fleet. The intention here is to assess the effectiveness of strategies to minimise environmental emissions.
- iii. **Comprehensive Approach (Case 3):** This approach integrates costs and environmental impact considerations within a unified cost function (f_3). It employs a weighted sum of the cost-centric (f_1) and environmental (f_2) objective functions, converting the latter from kilograms of CO₂eq into monetary values using a conversion parameter (CC) set at 199 €/kg CO₂eq, following the methodology of (Colicchia et al., 2016). The weights assigned to economic (α) and environmental (β) performances are equal, at 0.5 each, reflecting an initial attempt to balance cost and environmental considerations equally. This model aims to identify an optimal compromise between minimizing operational costs and reducing the environmental impact of the delivery fleet.

The model presents the trade-offs and synergies between cost efficiency and environmental responsibility in e-grocery logistics through these varied approaches.

For each day of the year analysed, the model yields the optimal fleet composition and the best routing and scheduling for each vehicle within the fleet. By comparing the outcomes across the three distinct cases—cost-efficient, environmental-effective, and comprehensive approach—the study evaluates various performance metrics, including:

- **Size and Composition of the Daily Vehicle Delivery Fleet:** This metric assesses how the number and types of vehicles required for daily operations vary across the cases. It reflects the strategic selection of diesel vans, bio-diesel vans, and electric vans to meet the day's delivery demands while considering cost, environmental impact, or a balance of both.
- **Fixed Cost:** This cost is associated with the on-demand renting price of the vehicles. It presents the financial implications of renting different types of vehicles and how the emphasis on cost minimization or environmental considerations influences the overall expenditure on vehicle rentals.
- **Variable Costs (Fuel consumption cost):** These costs arise from the fuel consumption (or electricity usage in the case of electric vans) generated by the vehicles while completing the delivery routes. This metric highlights the operational costs linked to the chosen fleet composition and routing strategies, shedding light on the efficiency of different vehicle types from a cost perspective.
- **Emissions of CO₂eq:** The total greenhouse gas emissions produced by the delivery routes, expressed in terms of CO₂eq, measure the environmental footprint of the delivery operations. This outcome is crucial for understanding the ecological impact of each case and the effectiveness of strategies aimed at reducing emissions.

5.2. Interpretation of results

The business case presented in Section 5.1 was used to implement the

model (Section 3.1) in a real-world situation. The solution method presented in Section 4, involving Gurobi solver and PuLP linear programming modeler, was used to solve the mathematical model via a computer with an Intel i7 @ 1.7 GHz CPU and 16 GB RAM. Generally, the MILP problem was solved optimally, with an average running time of 20 s for instances with 20 customers or less per daytime and 5 min for instances with customers between 21 and 40. However, due to the significant computational time required for larger instances, the algorithm was run in truncated mode with a maximum running time of 1 h. For these instances, the effective running time spanned from 5 min to 1 h and the optimality gap was registered when the problem was not optimally solved within the time limit, which happened in the 3% of the instances. The average registered gap is 15%.

Table 5 presents the optimisation results of the conducted cases. For each optimization approach, the resulting delivery vehicle type is first reported. Each approach always leads to the same type of vehicle throughout the analysed time horizon. Then, minimum, maximum, and average fleet sizes are reported throughout the analysed time horizon. Lastly, the total annual figures for the obtained performances, i.e. variable costs, fixed costs, total costs (defined as the sum of the previous costs), distance travelled and emissions, are reported. The fixed costs associated with the on-demand rental service, including hiring drivers, represent more than 90 % of the total costs across all cases. This highlights the significant impact of fixed costs on the overall fleet management strategy.

In Case 1, prioritizing cost efficiency leads to a preference for diesel vans, aiming to reduce the fleet size and minimize fixed costs, even at the expense of increased travel distances and fuel consumption costs. This strategy effectively lowers the total costs but increases operational expenses due to extended delivery routes.

Conversely, Case 2 focuses exclusively on reducing CO₂eq emissions, disregarding the impact of fixed costs and the number of activated vehicles on the optimization objective. This scenario opts for a larger fleet of biodiesel vans to decrease the total distance each vehicle covers and the minimal emission factor, prioritizing sustainability over costs.

Case 3 seeks a balance between cost and environmental impacts. This results in a slightly larger fleet than in Case 1, exclusively utilizing biodiesel vans. Despite these vans having similar fixed costs and capacities as diesel vans, their marginally higher fuel costs are offset by significantly lower emissions. This balance results in a modest increase in total annual costs compared to Case 1 (by 0.6%) yet achieves a substantial reduction in emissions (by 93.8%).

The outcomes (Table 5) illustrate the strategic decisions involved in fleet composition, highlighting the trade-offs between minimizing costs and reducing environmental impact.

The graphical representations in Fig. 4 aggregate the monthly results of the analysis, offering a visual comparison of the outcomes across the three cases:

- **Fixed Costs (Fig. 4 (a)):** Case 1 displays the lowest fixed costs among all cases, a direct result of its focus on minimizing the number of

Table 5
Results of the different cases.

Performance	Metric	Case 1	Case 2	Case 3
Type of van		Diesel	Bio-diesel	Bio-diesel
Min number of vans	[Vans]	1	2	1
Max number of vans	[Vans]	3	5	3
Average number of vans	[Vans]	1.71	4	1.72
Total cost	[€/year]	232,845	526,382	234,311
Fixed cost	[€/year]	217,152	512,604	217,848
Fuel consumption cost (variable cost)	[€/year]	15,693	13,778	16,463
Distance travelled	[km/year]	25,300	21,000	25,300
Emissions	[kg CO ₂ eq/year]	6,125.32	317.96	379.92

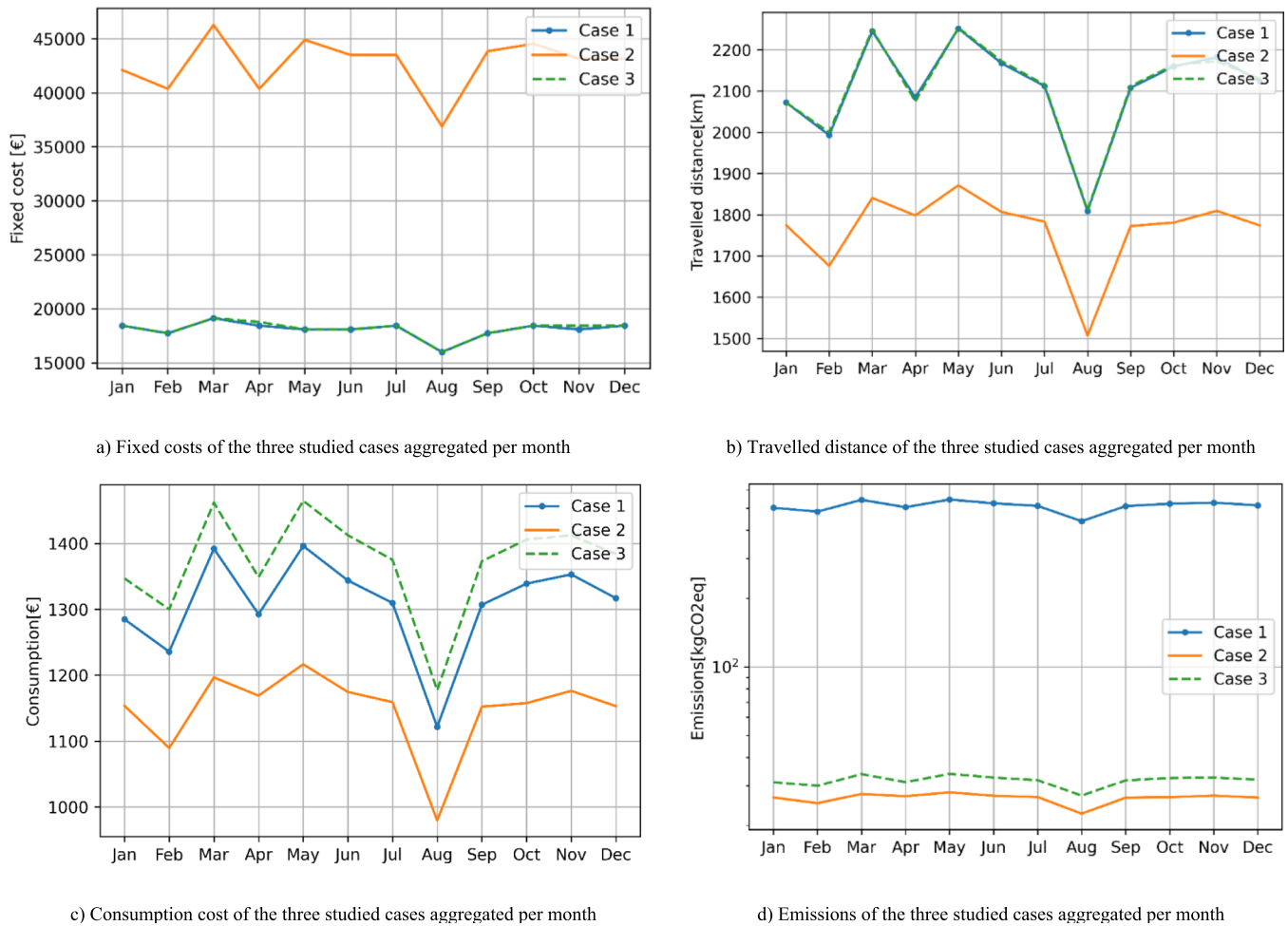


Fig. 4. Performances of the three studied cases aggregated per month.

vehicles to reduce expenses. Case 2, prioritizing environmental impact, incurs the highest fixed costs due to the larger fleet size required to minimize travel distances. Case 3's fixed costs are often comparable to, and occasionally slightly higher than, those of Case 1, reflecting its attempt to balance cost and environmental considerations.

- **Travelled Distance (Fig. 4 (b)):** Aligning with the objectives of each approach, the travelled distance is minimized in Case 2, where the model aims to reduce emissions through efficient routing. In contrast, Cases 1 and 3 report significantly higher distances, with Case 1 optimizing for cost and Case 3 seeking a compromise between cost and emissions.
- **Fuel Consumption Costs (Variable cost) (Fig. 4 (c)):** Due to the optimized routing that minimizes distances, Case 2 achieves the lowest consumption costs, despite the inherently higher operational costs of biodiesel vans. Case 3, while adopting biodiesel vans for their environmental benefits, incurs the highest consumption costs due to the combination of high per-unit costs and considerable travel distances, comparable to Case 1, which leverages diesel vans known for their lower consumption rates.
- **Environmental Impact (Fig. 4 (d)):** The emissions outcomes align with the distinct goals of each case. Case 1, focusing solely on cost-efficiency, results in the highest emissions. Case 2 achieves the lowest emissions by optimizing for environmental effectiveness. Notably, Case 3, which integrates cost and environmental goals, significantly narrows the gap to Case 2, indicating that a balanced approach can yield substantial environmental benefits without sacrificing cost objectives significantly.

These findings underscore the effectiveness of a comprehensive approach (Case 3) in achieving notable environmental improvements while maintaining a close eye on cost management. By comparing these cases, the analysis illuminates the potential for strategic fleet composition and routing decisions to influence both the economic and ecological footprint of e-grocery delivery services.

Fig. 5, which aggregates the annual costs and emissions into a singular, comprehensive view, offers a clearer understanding of the overarching trends and outcomes from the study. The analysis (Fig. 5) demonstrates the advantages of transitioning from a purely cost-efficient

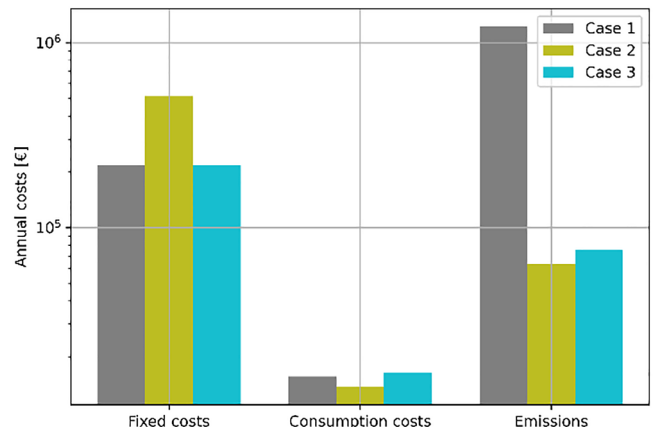


Fig. 5. Annual total costs of each of the three cases per cost component.

strategy (Case 1) to a comprehensive approach (Case 3). This shift can dramatically reduce emissions for a relatively minor increase in total costs. This insight underlines the effectiveness of integrating environmental considerations into fleet management and routing decisions, highlighting the potential for e-grocery delivery services to enhance sustainability without incurring prohibitive expenses.

5.3. Sensitivity analysis

A sensitivity analysis is conducted to explore the impact of varying input parameters on the behaviour and outcomes of the model. This examination focuses on the initial 30 days of the year, considered sufficient for the purposes of this study. The analysis scrutinizes three key variables: the length of the on-demand vehicle rental period (g), the conversion coefficient (CC) for translating CO₂eq emissions into monetary terms, and the composition of the available vehicle pool.

Initially, the analysis evaluates different lengths for the on-demand rental period (g), a critical parameter dictating the duration (in days) for which vehicles can be rented. The model mandates setting g to a specific value, representing the sole option for the duration of the on-demand service. Table 6 details the examined values of g and the corresponding fixed cost (f_k) for each vehicle type. f_k escalates as g increases, displaying sub-additive growth. This pattern suggests that longer rental periods are subject to an increasing discount (s) on the daily cost, reflecting economies of scale in the rental pricing structure.

Fig. 6 (b) and (c) detail the outcomes of adjusting g to 3 and 5 days, respectively, against the baseline scenario of $g = 1$ (Fig. 6 (a)), from the initial experiment. These figures document the daily number of activated on-demand vehicles for the analysed period of 30 days, with blue vertical axes delineating the period transitions. An expansion in g correlates with an augmented availability of vehicles throughout the evaluated timeframe. Despite these adjustments, the preference for biodiesel vans remains constant, affirming their selection under the comprehensive approach due to their environmental and cost benefits. An enhanced vehicle availability, facilitated by longer rental periods, contributes to a decrease in travel distance, as shown in Fig. 7. This reduction leads to corresponding decreases in consumption costs and emissions (Table 7). While an extension of g suggests potential increases in fleet size due to the cost benefits of longer rental periods, such expansions are not observed for the g variations considered. The discount offered for extended rentals does not sufficiently offset the costs of additional vehicles, indicating that the model favours the operational flexibility provided by shorter rental durations over the cost savings of longer terms. Moreover, fixed costs continue to dominate the cost structure, with their reduction from increased vehicle availability not compensating for the higher consumption and emissions costs. This finding underscores the model's inclination towards biodiesel vans, which, despite higher operational costs, offer advantages in fixed and emissions-related expenses.

Secondly, the analysis explores changes in the conversion coefficient (CC), which translates the weight of CO₂eq emissions into their monetary equivalent. This coefficient is pivotal in the optimization process, as its magnitude dictates how emissions are weighed against costs in the minimized objective function. Establishing an accurate value for CC is challenging due to the lack of specific guidance in existing literature and the broad range of potential values. In this study, CC is initially set at 199 €/kg CO₂eq (Colicchia et al., 2016). Nonetheless, the authors advocate for a sensitivity analysis on CC, suggesting a range of plausible

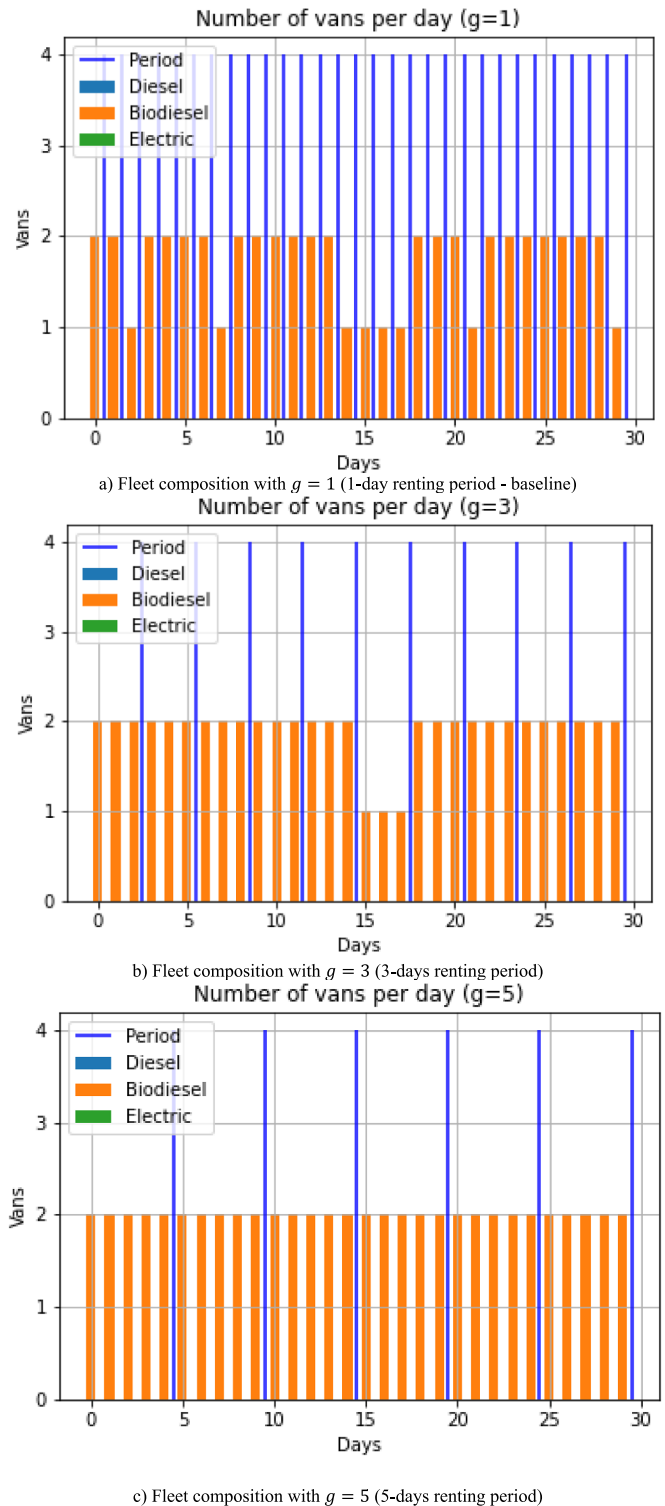


Fig. 6. Sensitivity analysis against g (renting period length in days).

values for examination: 199 €/kgCO₂eq; 131 €/kgCO₂eq; 91 €/kgCO₂eq; 46 €/kgCO₂eq; 26 €/kgCO₂eq; 16 €/kgCO₂eq; 4 €/kgCO₂eq. The analysis reveals that the model's outcomes are consistent across the range of CC values tested, demonstrating robustness against variations in this parameter. For CC values exceeding 4 €/kgCO₂eq, environmental performance does not alter the model's results.

In the final phase of the analysis, the model's response to a different selection of available vehicles is assessed. Initially, with a vehicle pool that includes diesel, biodiesel, and electric options, electric vans are

Table 6

Data of different scenarios evaluated through the sensitivity analysis.

g [days]	$f(\text{dieselvan})$ [€]	$f(\text{biodieselvan})$ [€]	$f(\text{electricvan})$ [€]	s [%]
1	348	348	383	0
3	1028	1028	1132	1.5 %
5	1696	1696	1867	2.5 %

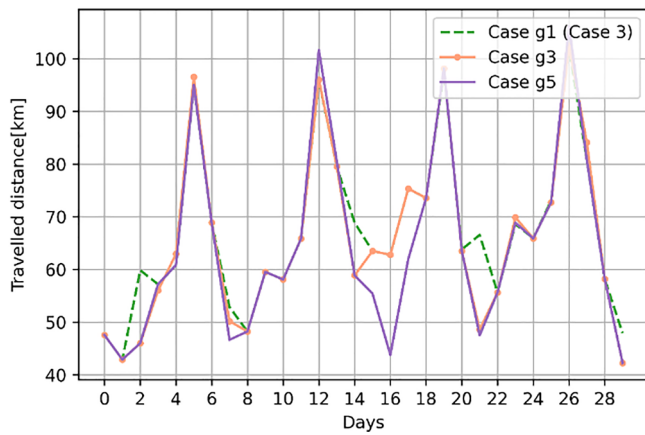


Fig. 7. Daily distance travelled for different values of g ($g = 1; g = 3; g = 5$).

Table 7

Results of sensitivity analysis varying on-demand period (g).

Performance per 30 days	$g = 1$ (baseline)	$g = 3$	$g = 5$
Total cost [€]	25,424.76	26,707.3	27,374.95
Fixed cost [€]	18,096	19,532	20,352
Distance [km]	2,016	1,974	1,932
Consumption [€]	1,311	1,282.91	1,255.93
Emissions [kg CO ₂ eq]	30.24	29.61	28.98
Emissions monetary value [€]	6,017.76	5,892.39	5,767.02

consistently not chosen, being overshadowed by the other types. To examine the model's dynamics deeper and evaluate the viability of electric vehicles, the vehicle pool is intentionally limited to diesel and electric vans. This modified setup aims to shed light on how electric vehicles perform when biodiesel options are removed from consideration.

Applying the comprehensive approach, which evaluates both cost and environmental impacts, the model is tested under varied conversion coefficient (CC) settings to see how changes in the valuation of CO₂eq emissions influence the selection of vehicles. This analysis comprises three distinct scenarios, each with a different CC value, to understand the conditions under which electric vans become a more attractive option compared to diesel vans:

- **Reduced Vehicle Pool with CC Set at 199:** This scenario evaluates the model's behaviour and fleet composition decisions when the vehicle pool is reduced and the monetary value of CO₂eq set equal to the baseline (i.e., 199), reflecting a strong emphasis on environmental impact within the optimization process. Starting from CC set equal to 99, which is the highest value in the suggested list of figures to be considered, lower values are evaluated.
- **Reduced Vehicle Pool with CC Set at 91:** By adjusting CC to a lower value, this case aims to explore the middle ground where environmental considerations are still significant but less dominant, allowing for a nuanced analysis of cost versus environmental performance in vehicle selection.
- **Reduced Vehicle Pool with CC Set at 4:** With a much lower CC value, this scenario examines the model outcomes when emissions have a minimal monetary impact, focusing primarily on the cost aspects of fleet optimization.

These scenarios provide a comprehensive view of how varying the emphasis on environmental impact influences the feasibility and desirability of electric vehicles within the delivery fleet (Table 8).

When compared to the baseline scenario (Fig. 8 (a)), where the comprehensive optimization approach involving the full spectrum of vehicle options and a CC of 199 is applied, distinct variations are

Table 8

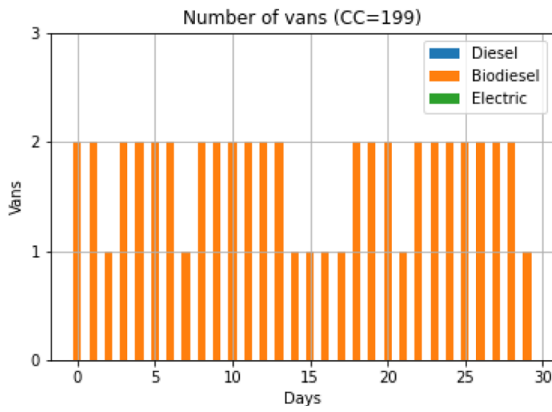
Performances for diesel/electric fleet.

Performance per 30 days	Baseline case (Full pool and CC = 199)	Case (a) (CC = 199)	Case (b) (CC = 91)	Case (c) (CC = 4)
Total cost [€]	25,424.76	60,792.82	39,506.40	21,222.57
Fixed cost [€]	18,096	21,065	20,682	18,621
Distance [km]	2,016	1,971	1,990	2,054
Consumption [€]	1,311	887	895.58	1,122.33
Emissions [kg CO ₂ eq]	30.24	195.18	197.02	369.81
Emissions monetary value [€]	6,017.76	38,840.82	17,928.82	1,479.24
Capacity [deliveries]	1,352	1,155	1,134	1,277
Saturation [%]	53 %	64 %	66 %	56 %

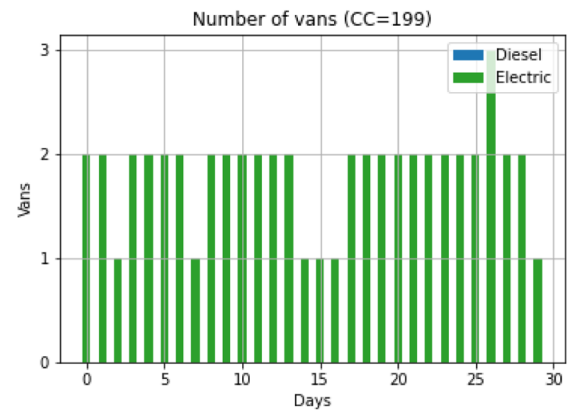
observed across the modified scenarios with different vehicle pools and CC values:

- **Case (a) – Reduced Vehicle Pool with CC = 199:** This scenario sees an exclusive selection of electric vans (Fig. 8 (b)), occasionally leading to a larger fleet size than in the baseline. Despite their higher fixed costs, the environmental advantages of electric vans justify their selection over diesel vans to meet environmental goals (Table 8). The need for an expanded fleet is driven by two factors: electric vehicles' lower operating costs and higher emission factor, concerning biodiesel vans, encourage a reduction in travel distance to lower emissions and total costs, and their smaller capacity compared to diesel and biodiesel vans necessitates more vehicles to fulfil demand (Table 8).
- **Case (b) – Reduced Vehicle Pool with CC = 91:** With a lower CC, indicating a diminished emphasis on emissions, the fleet size decreases slightly from Case (a) but remains larger than in the baseline case, i.e., the result of the comprehensive optimization approach with the full spectrum of vehicle options and a CC equal to 199 (Fig. 8 (c)). This adjustment reflects a shift towards prioritizing cost efficiency, tolerating increased travel distances and emissions to minimize the number of required vehicles (Table 8). Despite this, the fleet size cannot be reduced further due to capacity constraints, maintaining a larger size than observed in the baseline.
- **Case (c) – Reduced Vehicle Pool with CC = 4:** A significant reduction in the value of CC diminishes the weight of environmental performance, resulting in a mixed fleet of diesel and electric vans (Fig. 8 (d)). Diesel vans, with their lower fixed costs and larger capacity, offer cost benefits, especially when their capacity can prevent the need for additional vehicles (Table 8). Electric vans, favoured for their lower operating costs and emissions, are optimal for longer routes where their capacity is not limiting. This mixed fleet strategy achieves a balance between cost and environmental considerations.

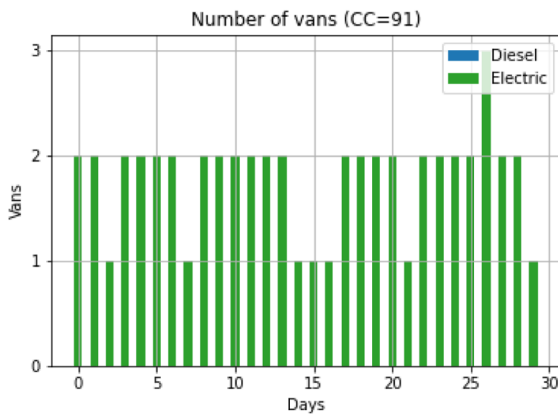
The exclusion of biodiesel vans leads to increased fixed costs, which decrease as CC is lowered, given the relatively higher cost of electric vehicles (Table 8). In scenarios (a) and (b), enlarged and entirely electric fleets facilitate a reduction in travel distances, thereby lowering consumption costs due to both decreased distances and the vehicles' efficient operation (Table 8). However, these benefits do not offset the increased emissions from a higher emission factor (Table 8). As CC is adjusted to 4 in scenario (c), the model produces a fleet where travel distances and consumption compare to the baseline case. Yet, emissions significantly exceed those of the comprehensive approach with a full vehicle pool, that leads to the selection of a biodiesel fleet. Furthermore, analysis of fleet capacity and utilization reveals that, despite a larger number of vehicles, electric fleets offer lower overall capacity and higher utilization rates than the biodiesel fleet in the baseline case. The scenario with a mixed fleet (c) approaches the total capacity observed in the baseline case, with an average utilization rate of 56 % (Table 8). Separately, diesel vans exhibit lower utilization rates, while electric



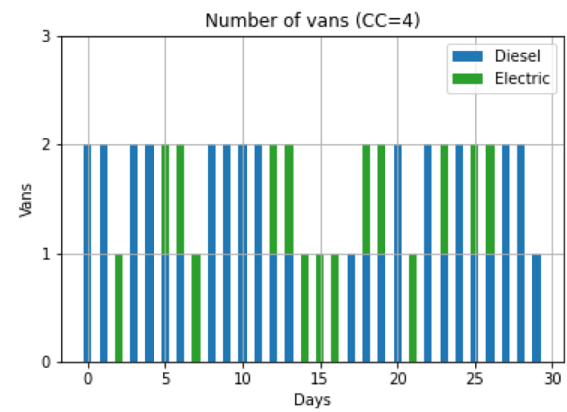
a) Fleet composition in the baseline case (full pool and CC=199)



b) Fleet composition for case (a) (reduced pool and CC=199)



c) Fleet composition for case (b) (reduced pool and CC=91)



d) Fleet composition for case (c) (reduced pool and CC=4)

Fig. 8. Results of the sensitivity analysis testing a reduced vehicle pool with different values for CC.

vehicles consistently show high utilization above 80 %, the highest observed in this study. This underscores the effective use of electric vehicles under conditions that maximize their operational advantages.

6. Conclusions and future recommendations

This research focuses on the last-mile distribution of home deliveries, a critical aspect of e-grocery order fulfilment. The study highlights the cost implications and the environmental impacts of home delivery operation as challenges characterizing the sector and addresses them by investigating the use of 3PL service. This problem is driven by the growing demands for flexible, cost-efficient, and environmentally sustainable delivery solution. Despite the widespread use of 3PL partnerships among e-retailers to enhance distribution flexibility and service levels, academic investigations into such collaborations remain limited.

This paper proposes a system that employs an on-demand vehicle rental service from a 3PL service provider, enabling e-retailers to tailor their delivery fleet to changing demand while emphasizing environmental sustainability. While existing research has examined fleet design (Utomo et al., 2022) and routing optimization (Aktas et al., 2021; Pahwa and Jaller, 2022) in the context of e-grocery delivery, no studies simultaneously optimize both aspects in the context of e-grocery home delivery with time windows. Additionally, unlike the prevalent approach in the literature (Pahwa and Jaller, 2022; Siragusa and Tumino, 2022; Trott et al., 2021), where environmental impact is assessed ex-post, our model incorporates environmental considerations

into the optimization process. Applied to an Italian e-grocery retailer scenario, the study offers insights into fleet size, composition, delivery routes, costs, and environmental impacts under varying conditions.

Results highlight the effectiveness of a comprehensive approach – balancing costs and environmental objectives – in achieving notable environmental improvements while managing costs effectively. The analysis shows the potential for strategic fleet composition and routing decisions where cost-efficient strategies reduce operational expenses. However, a balanced approach that factored in environmental considerations led to a remarkable reduction in carbon emissions by over 90% for a slight cost increase. Furthermore, results offer a thorough understanding of how adjusting the focus on environmental impact can affect delivery fleet design.

This paper contributes to closing the gap between academic research and practical application by integrating 3PL collaboration, on-demand vehicles, and environmental considerations into the VRPTW framework. It presents a tool for grocery sector managers to strategize and manage daily operations regarding fleet composition and delivery scheduling, aligned with cost and environmental goals. Additionally, the study advances towards SDG 11 (“Sustainable City and Communities”) and SDG 13 (“Climate Action”) by supporting environmentally sustainable last-mile delivery in the growing e-grocery sector. However, the work has limitations, including a fixed on-demand period length, independent optimization for each period, and the challenge of solving the optimization problem within a reasonable computational timeframe. The study’s applicability to a specific case scenario and the potential for

different outcomes in other settings also underline the need for caution in generalizing the results. Future research directions include implementing heuristic algorithms for overcoming computational constraints linked to adopting an exact optimization method and applying the model to both small-scale and larger-scale scenarios to compare the results of the two solution methods. Future recommendations include examining on-demand vehicle policies for same-day delivery to enhance customer satisfaction and operational flexibility.

CRedit authorship contribution statement

Vittoria Tudisco: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sara Perotti:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Banu Yetkin Ekren:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Emel Aktas:** Writing – review & editing, Validation, Supervision, Software, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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