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Research paper

Zero-emission vehicle adoption towards sustainable e-grocery last-mile delivery

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ABSTRACT

In recent years, sustainable eco-friendly vehicles have been demonstrated as an adequate solution for urban deliveries and restricted areas facing traffic congestion and traffic zone limitation. Therefore, in this paper, a novel Decision Support System has been proposed for evaluating the efficiency of e-grocery home delivery through eco-friendly vehicle adoption. A mathematical model, formulated as Electric Vehicle Routing Problem with Time Windows and Partial Recharging (EVRPTW-PR), has been applied for selecting the best zero-emission vehicle for e-grocery home delivery. The comparison of the most emerging electric light-duty vehicles (e-cargo bikes, e-mopeds, and e-vans) has been carried out through key performance indicators related to the drivers' salary, the total delivery time, the fuel (energy) costs, the vehicle investment costs, and the average payload capacity utilization. The overall evaluation encourages the adoption of zero-emission strategies and helps e-grocery commerce to adopt the best option that fits with the environmental as well as the economic aspects.

1. Introduction

The growth of environmental awareness in cities has been enforcing different policies implementation by introducing novel technologies for achieving environmental-friendly urban freight transportation. For instance, Hardy & Wagner (2019) analyzed the energy savings and CO_2 emissions of different vehicles in Munich, Germany. The results showed that the usage of Internal Combustion Engine Freight Vehicles would lead to CO_2 savings of around 49.5 kgCO_2 per delivery tour, or 73.3%. Instead, Electric Freight Vehicles would lead to the of approximately 58 kgCO2, or 85.8%. In addition, Ehrler et al. (2021) discussed the challenges and perspective for shifting to electric trucks for e-grocery deliveries by focusing on the German market. The case study of England proposed by Motte-Baumvol et al. (2023) showed that online purchases of working couples combined with a home delivery system can significantly influence CO_2 emissions reduction. Especially in large cities, besides environmental benefits, eco-friendly vehicles introduce many advantages such as lower operating costs, higher flexibility and reduction of time needed for loading/unloading operations, parking flexibility, accessibility to historical and/or zones with traffic limitations (Caggiani et al., 2021). For example, the evidence from the study proposed by Dalla Chiara et al. (2023), indicates the short parking time for cargo cycles of around 4 min, as well as the proximity to the customers' locations (around 30 m on average). Especially in restricted traffic zones and historical areas, where traffic regulations are important factors when choosing the best route, the application of these vehicles is beneficial in terms of delivery time and cost savings e.g., driving distance reduction, service time reduction, energy savings, fuel economy, operational/delivery costs (Vasiutina et al., 2021). However, the lack of policies regarding infrastructure requirements is often seen as a limiting factor considering the scarce cycling network infrastructure and safety-related issues, as well as the low range of recharging stations (Carracedo & Mostofi, 2022). From a logistics perspective, the application of e-cargo bikes and e-mopeds (bicycle logistics) in urban areas is influenced by several parameters such as frequency, size and weight of orders, and spatial factors. Consequently, these vehicles are intended for payload capacity up to 200 kg and for carrying out packages no greater than 25 kg (Gruber et al., 2014). Thus, bicycle logistics is opportunistic for the deliveries of small packages and boxes e.g., food, posts, pharmaceutics, and home deliveries (Vasiutina et al., 2021).

The recent research has been mostly focused on the e-grocery market analysis and strategies for the last mile e-groceries distribution which requires an understanding of the patterns between shopping areas and individual trips, infrastructure accessibility, development of local mobility hubs (Bjørgen et al., 2021). The stated preference and willingness to adopt e-grocery in Rome and Milan showed that the best

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strategies for increasing the e-grocery shares are the expansion of the range of products available online and the differentiation of transportation fees based on delivery criteria or customers' socio-demographic characteristics (Maltese et al., 2021). Moreover, the growth of e-grocery services due to the COVID-19 pandemic has generated home delivery trips increase, mostly by conventional Internal Combustion Engine (ICE) light-duty vehicles. Thus, the environmental and economic aspects might be seen as the most challenging ones for e-grocery growth. Consequently, the motivation for the presented study lies in proposing a sustainable e-grocery service that aims at decreasing private car mode e-grocery trips with home delivery services (provided by freight operators using zero-emission vehicles). Therefore, in this paper, a novel Decision Support System (DSS) has been developed for evaluating eco-friendly vehicles' performance for e-grocery home deliveries. In specific, the comparison among zero-emission vehicles (e-moped, e-cargo bike, and e-van) has been carried out by adopting a modified Electric Vehicle Routing Problem with Time Windows and Partial Recharging (EVRPTW-PR) proposed by Caggiani et al. (2021). The objective function of the EVRPTW-PR aims at minimizing the total costs regarding the energy costs, initial vehicles' investment costs, and drivers' salary costs, while the constraints of the model are related to capacity, time windows, and partial recharging. The scope of this paper is to highlight the usage of eco-friendly vehicles and to evaluate the comparison between them in terms of Key Performance Indicators (KPIs). Moreover, the results of the comparison could be perceived as decision-making support for e-grocery companies to adopt the suitable Light-Duty Vehicle (LDV) technology that will deal with emissions as well as total travel and operation costs minimization.

The paper is summarized as follows. Section 2 provides insight into the papers related to the proposed topic, while Section 3 describes the mathematical formulation of the EVRPTW-PR. Section 4 reports the results of the numerical application in which the model has been tested on the instances proposed by Colovic and Prencipe (2020). Section 5 reports the discussion of the study followed by the policy recommendations. Finally, conclusion and further developments are reported in Section 6.

2. Literature review

Recently, several studies on groceries have been devoted to proposing different strategies and methods for e-grocery delivery (i.e., home delivery, pick-up from store, pick-up from locker, crowdsourcing strategies, etc.) by taking into account customer preferences (Calzavara et al., 2023; Milioti et al., 2021). Mangiaracina et al. (2019) proposed a literature review related to innovative solutions to increase last-mile delivery efficiency in B2C e-commerce considering the overall logistics costs. Following this, Section 2.1 is devoted to the factors that might influence e-grocery shopping behavior. The preference towards e-grocery shopping, especially after the COVID-19 pandemic period, required new strategies for managing e-grocery last-mile deliveries from both economic and environmental perspectives. Some studies dealt with the economic comparison between traditional and zero-emission vehicles for last-mile logistics, as reported in section 2.2. However, there is a lack of studies focusing on developing a DSS eco-friendly vehicle adoption for the home delivery service from the e-grocery company perspective.

2.1. Factors influencing the e-grocery shopping behavior

The current research studies on e-grocery have been mostly focused on the factors affecting customers' decisions, attitudes, and choices regarding online shopping (Lagorio & Pinto, 2021). The evidence from the case study of Brazil indicated order fulfillment and delivery service price as the main factors influencing the customer willingness for e-grocery shopping, (Magalhães, 2021). Another study, proposed by Kvalsvik (2022), individuates the health and mobility issues as well as the store proximity as trigger factors for elderly e-grocery purchases. Gumasing et al. (2022) provided a survey study in the Philippines in which they identified that performance expectancy and perceived severity were the key indicators that influence customers' behavior regarding the usage of online grocery apps. However, COVID-19 has left an impact on e-grocery services and significant changes in supply-chain management travel patterns, in-store shopping, and land use planning. The results of the study in the USA conducted by Shen et al. (2022) stated that females, vehicle ownership, higher income, and health constraints are the ones that would increase the probability of selecting e-grocery service after the pandemic period; furthermore, elderly people and frequent physical grocery store customers are more likely to use e-grocery service in the post-pandemic period. Also, the study of the Dutch online supermarket, proposed by Baarsma and Groenewegen (2021), showed that both local and national COVID-19 conditions have affected demand for online food shopping by increasing app traffic by 7.3% and sales per order by 0.31%. Furthermore, the evidence from a large-scale survey in Finland showed the influence of socio-demographic characteristics, and in particular, the willingness of those with higher household size and earnings, and with less than 45 years to purchase e-grocery, due to COVID-19, Eriksson and Stenius (2021). Due to these, grocery retail is usually focused on ways of keeping a satisfactory level of customer loyalty by offering different pricing strategies such as personalized price promotions (Hallikainen et al., 2022). Besides customers' decisions and attitudes regarding e-grocery adoption, Aziz et al. (2022) provided an extended literature review by focusing on the factors influencing e-grocery from environmental and energy consumption perspectives. As the authors stated, there is a scarcity of papers related to the eco-friendliness of online grocery channels that would stimulate consumers towards sustainable choices when purchasing their groceries. Motivated by the outcome of the above-mentioned systematic review, this work proposes a DSS that considers these premises and encourages zero-emission vehicle adoption.

2.2. DSS for e-grocery delivery and fleet selection

To the best of the authors' knowledge, there are no studies that dealt with developing a DSS or framework that would help decision-makers in creating more sustainable e-grocery services by incorporating both economic and sustainable solutions for last-mile delivery. There are a few studies that dealt only with the economic comparison between traditional and zero-emission vehicles for last-mile logistics. For example, according to a case study in Berlin, the comparison of cargo bikes with commercial vehicles showed a reduction of emissions costs by up to 22% and delivery costs by up to 28%. Compared with diesel vehicles, this technology offers a wide spectrum of possibilities for delivering shipments on smaller distances, especially on distances up to 5 km (Rudolph & Gruber, 2017). Another case study in Berlin carried out the comparison between cargo bikes and car messengers in terms of traversed distance, the volume of shipments, and delivery service (Gruber et al., 2014). Total traversed distance on last mile deliveries considering zone restrictions, narrow streets, and traffic regulations, accounted for 5.1 km for cargo bikes and 11.3 for car messengers. The comparison of these two modes considering the total weight and volume carried by vehicles on last-mile deliveries showed that 42% of shipments could be replaced by cargo bikes. Moreover, the comparison between eco-friendly technologies, in particular e-cargo bikes and e-mopeds, has been scarcely investigated in the literature except by Nocerino et al. (2016). The authors made a comparison between traditional and e-fleet including e-mopeds, e-cargo bikes, vans, and e-bikes alternatives for urban deliveries through a real case study application. Specifically, the authors observed through four pilots the effectiveness of e-fleet in terms of reduction of CO_2 emissions and energy savings in urban logistics. In addition, Comi and Savchenko (2021) proposed a methodology for choosing the most sustainable mode for delivering goods within urban areas. However, the market for LDV e-fleet has not been showing its full potential. The opportunities for LDV adoption are mainly determined by the typology, commercial achievements, and targets of stakeholders (Rudolph & Gruber, 2017), while the main barrier parameters for adopting e-cargo bike technology are social, economic, environmental parameters and regulations (Carracedo & Mostofi, 2022). For example, the study by Caggiani et al. (2020) provided a DSS that can help e-cargo bike drivers choose the optimal route path choice considering two options such as minimum travel time and minimum emission exposure. On the other side, e-mopeds have been barely investigated as last-mile logistics modes.

However, few studies in the literature support the interests of e-grocery decision-makers by incorporating customers' attitudes and preferences when developing a DSS. For instance, Fikar et al. (2021) created a DSS that focuses on redesigning the e-grocery operations and service offers by collecting data on customers' preferences and by applying agent-based simulation for designing e-grocery operations. As a result, the design of the e-grocery service required the interaction between decision-makers in marketing and logistics by focusing on delivery fees, vehicle utilization, and shelf-life requirements. Another paper proposed by Fikar (2018) proposed a DSS for investigating food losses in e-grocery deliveries by incorporating an agent-based simulation and dynamic routing procedures. On the other side, the study proposed by Mkansi and Mugurusi (2023) developed a framework that explored the influence of financial inclusion on e-grocery supply chain innovation. The outcome of their framework provided a platform for e-grocery market business innovation by focusing on subsidized payment infrastructural costs, e-customer transactional trust, and privacy concerns.

2.3. E-grocery home delivery optimization models

Several optimization models, such as Vehicle Routing Problems (VRPs), have been applied for achieving cost-effective e-grocery home delivery by considering aspects related to the hard delivery time-windows, parking restrictions, service time, etc. For instance, Pan et al. (2017) proposed a novel approach that improved the success rate of e-grocery delivery by estimating the absence probability of a customer through mining electricity consumption data. The authors applied Vehicle Routing Problems with time windows (VRPTW) for estimating time windows with a lower probability of inoccupation (absence). Differently, Leyerer et al., (2020) proposed a multi-echelon optimization model for planning e-grocery deliveries that applies location routing problem for finding optimal grocery locker locations, as well as VRPTW with split deliveries for calculating van routes from a depot to opened lockers, and e-cargo bike routes from lockers to customer. Also, Aktas et al. (2021) applied a capacitated VRPTW to solve the grocery last-mile delivery problem in Tottenham Hale, UK, by minimizing total travel distance. Following the future perspective of innovative solutions for e-grocery distribution, Liu et al. (2020) proposed a two-echelon vehicle routing problem with mixed vehicles (2E-VRPMV) that optimizes total transport and emissions costs by using autonomous delivery vehicles. Also, another paper proposed by Liu et al. (2021) applied 2E-VRPMV and mixed satellites to determine the location of grocery facilities and optimize the number of parcels delivered to customers.

2.4. Contributions

To the best of the authors' knowledge, there is a lack of studies that enhanced the application of sustainable urban freight vehicle technology when developing DSS for e-commerce logistics (Heumann et al., 2021; Perboli & Rosano, 2018). Research studies on e-grocery have been mostly focused on customer preferences for e-grocery shopping (Galvez-Cruz & Renaud, 2006; Park, 2023) and factors that influence e-grocery service (section 2.1). However, none of the found papers tackled the e-grocery DSS following the logistics company perspective and the possibilities for decreasing the environmental impact of e-grocery deliveries. Moreover, from modelling perspective, this study differs from the literature by applying a modified version of EVRPTW-PR that considers partial recharging for E-LDVs and comprehensive evaluation of costs in the objective function.

Therefore, in this paper, a further step has been made in proposing a new DSS for e-grocery commerce by following a modelling perspective for the best vehicle type/service selection (i.e., among e-mopeds, e-cargo bikes, and e-van), and evaluating their cost comparison from KPIs point of view. Furthermore, the proposed DSS offers the possibility for e-grocery commerce to investigate the opportunities for shifting from traditional to E-LDVs.

3. Methodology

Order fulfillment in e-grocery is especially challenging due to the necessity for cost optimization (storage, inventory, and vehicle utilization) on one side, and for meeting customers' special requirements on the other side. Moreover, e-grocery is facing high competition due to the increasing willingness of customers to purchase products online, and lower willingness to pay extra home delivery fees (Magalhães, 2021). Consequently, the proposed DSS focuses on providing a novel management strategy for e-grocery by adopting eco-friendly vehicles for last-mile deliveries. Following this purpose, a novel DSS and a dedicated flow chart for e-grocery home delivery through different service delivery vehicle alternatives have been developed. In addition, the support for a novel fleet management strategy is carried on through the comparison among different types of electric LDVs for e-grocery last-mile delivery, assuming that e-grocery is already operating with the Internal Combustion Engine (ICE) fleet.

The proposed DSS for e-grocery provides an overview of main processes such as customer, storage, loading, and routing operations. Firstly, the Order Management System (OMS) collects the relevant information for customers dedicated to the type and number of groceries, time-window preferences as well as their personal information (ID and the address of home delivery) through the customer interface (web platform, smartphone app, telephone for vulnerable people such as persons with disabilities and the elderly). Here, the proposed study focuses on home deliveries which require customers to be present at home on the day and specified time window of delivery. Thus, the unattended home delivery option has not been considered as an alternative in the proposed e-grocery framework. All of this information is stored in the historical database according to which e-grocery companies can have an insight into e-grocery acquisition rate and foster further analysis such as annual demand forecasting. Secondly, the information processed in OMS is transmitted to the Warehouse Management System (WMS) which checks the availability of groceries based on the number of packages and the stock levels. In the case of the unavailability of the requested grocery article, the proposed DSS, as depicted in Fig. 1, offers the following options to customers: i) delete the item from the order; ii) replace the item with similar in type and cost; iii) receive a call by an operator. After obtaining confirmation from the customers and after the accomplishment of warehouse operations, the orders are assigned to the vehicle.

The process of vehicle type selection is depicted in the flow chart in Fig. 2. The vehicle type selection refers to an alternative $a \in A$, where A is the total number of alternatives considered for the e-grocery home delivery service. At the beginning of the process, all data are initialized. For each alternative a within the stop criteria ($a < A$), three vehicles' strategies have been evaluated such as vehicle ownership, vehicle leasing, and vehicle long-term rental options. Also, for all vehicles' strategies, has been evaluated the adoption of eco-friendly vehicles (E-LDVs) or traditional vehicles (ICE-LDVs) by considering their corresponding specifications such as capacity, recharging rate, fuel consumption rate, average speed, battery capacity, electric energy/fuel cost, driver salary cost, and vehicle initial investment cost. According to the vehicle type selection, the considered vehicle routing problems are

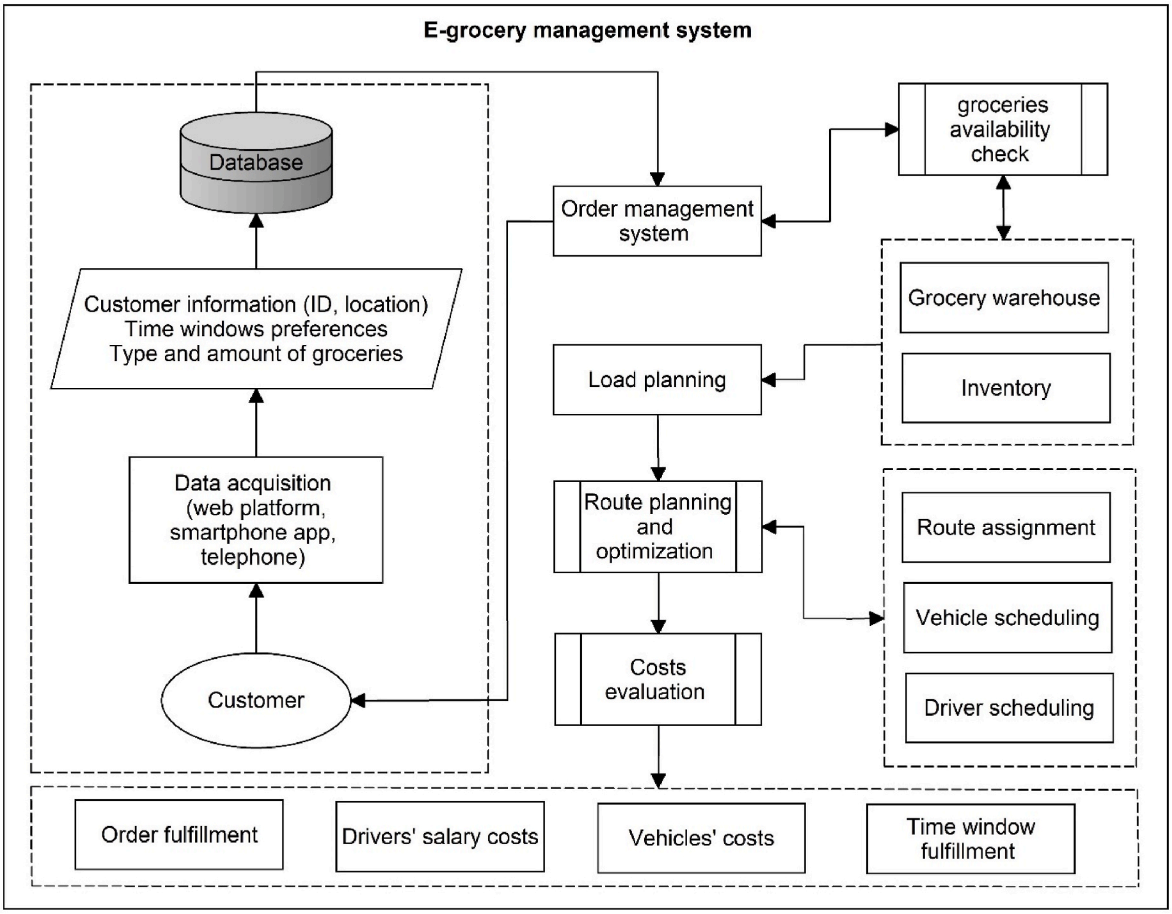


Fig. 1. The proposed e-grocery DSS.

EVRPTW-PR for E-LDV and VRPTW for ICE-LDV. The EVRPTW-PR model deals with practical issues of logistics regarding the constraints of vehicle capacity and partial recharging in the case of eco-friendly vehicles, as well as the customers' specifications related to time windows and service time. Additionally, the vehicle routing optimization model calculates the number of needed vehicles and assigned drivers for accomplishing customer orders. The total costs are evaluated according to the output of the vehicle routing optimization models related to travel costs, initial vehicles' investment costs, and drivers' salary costs. Consequently, the vehicle type selection is evaluated according to the available budget resources and KPIs. However, in the case of vehicle leasing and vehicle long-term rental strategies (no vehicle ownership) the initial investment costs are replaced by leasing and long-term rental costs. Furthermore, if none of the vehicle strategies is selected, the option for e-grocery companies is to choose a third-party delivery service and pay for shipping services according to the contractual agreement. Finally, the proposed flow chart saves the best vehicle type alternative based on the best KPIs evaluation and corresponding vehicle/service type selection.

3.1. EVRPTW-PR description

In this section, the mathematical formulation of the modified EVRPTW-PR proposed by Caggiani et al. (2021) is described. The goal is to evaluate which zero-emission vehicle (in this case e-moped, e-van, or e-cargo bike) would be the best option for the last-mile e-grocery home delivery. The problem is defined on a directed graph $G = (V_{d,N+1}, A)$ where sets of arcs $A = \{(i,j) \mid i, j \in V_{d,N+1},\ i \neq j\}$. The set $V_{d,N+1}$ is composed of the depot V_d, the set of customers V_c, the set of dummy stations $\widetilde{V}_s$, where the set of dummy stations $\widetilde{V}_s$ allows several visits to each recharging station. Also, the set of homogenous vehicles $K = \{1, \ldots, w\}$ is located at the depot V_d so that the total number of vehicles w are starting the trip from $V_d = \{0\}$ and finishing at $V_d = \{N+1\}$, located at the same point. Therefore, sets, parameters, and decision variables of the EVRPTW-PR model are reported in Table 1.

The mathematical formulation of the EVRPTW-PR is then specified as follows:

$$f(x) = \sum_{k \in K} \sum_{i,j \in \widetilde{V}_{d,N+1}} d_{ij} \cdot x_{kij} \cdot c_e^w + c_v^w \cdot w + c_d \cdot \left(w + \left(t_{ij} + s_{ij}\right) \cdot x_{kij}\right), i \neq j \quad (1)$$

s.t.

$$\sum_{j \in \widetilde{V}_{N+1}} x_{kij} = 1, \forall k \in K, i \in V_d = \{0\}, i \neq j \quad (2)$$

$$\sum_{j \in \widetilde{V}_{N+1}} x_{kji} = 1, \forall k \in K, i \in V_d = \{N+1\}, i \neq j \quad (3)$$

$$\sum_{k \in K} x_{kij} + \sum_{k \in K} x_{kji} \leq 1, \forall i \in \widetilde{V}_d, \forall j \in \widetilde{V}_{N+1}, i \neq j \quad (4)$$

$$\sum_{k \in K} \sum_{i \in \widetilde{V}_d} x_{kij} = 1, \forall j \in V_c, i \neq j \quad (5)$$

$$\sum_{k \in K} \sum_{i \in \widetilde{V}_{N+1}} x_{kji} = 1, \forall j \in V_c, i \neq j \quad (6)$$

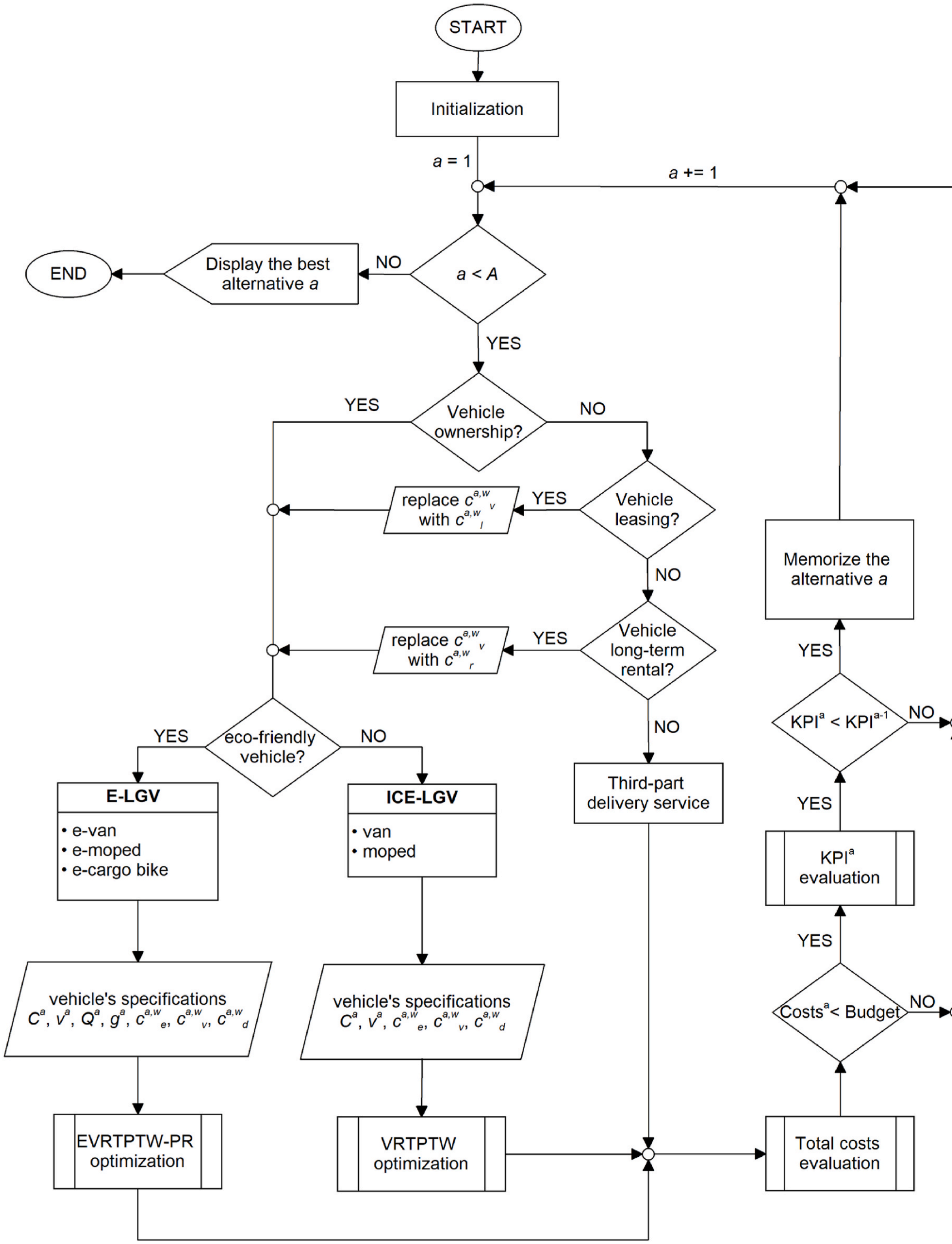


Fig. 2. The proposed e-grocery vehicle/service type selection flow chart.

$$\sum_{i\in\tilde{V}_d} x_{kij} - \sum_{i\in\tilde{V}_{N+1}} x_{kji} = 0, \forall j \in V_c, \forall k \in K, i \neq j \tag{7}$$

$$\sum_{i\in\tilde{V}_{N+1}} x_{kij} \geq 0, \forall j \in \tilde{V}_s, \forall k \in K, i \neq j \tag{8}$$

$$\sum_{i\in\tilde{V}_{N+1}} x_{kji} \geq 0, \forall j \in \tilde{V}_s, \forall k \in K, i \neq j \tag{9}$$

$$\sum_{i\in\tilde{V}_d} x_{kij} - \sum_{i\in\tilde{V}_{N+1}} x_{kji} = 0, \forall j \in \tilde{V}_s, \forall k \in K, i \neq j \tag{10}$$

$$x_{kij} + x_{kji} \leq 1, \forall i \in \tilde{V}_{N+1}, \forall j \in \tilde{V}_s, \forall k \in K, i \neq j \tag{11}$$

$$0 \leq u_{ki} \leq C, \forall k \in K, i \in V_d = \{0\} \tag{12}$$

$$0 \leq u_{kj} \leq u_{ki} - q_{ki} \cdot x_{kij} + C \cdot (1 - x_{kij}), \forall i \in \tilde{V}_d, \forall j \in \tilde{V}_{N+1}, \forall k \in K, i \neq j \tag{13}$$

Table 1
Nomenclature of the EVRPTW-PR.

Sets	
V_d	Depot, $V_d = \{0\}$, $V_d = \{N+1\}$
V_s	Set of stations, $V_s = \{1, \dots, m\}$
$\widetilde{V}_s$	Set of dummy stations
V_c	Set of customers, $V_c = \{1, \dots, n\}$
$\widetilde{V}_{N+1}$	Set of dummy stations and customers, $\widetilde{V}_{N+1} = \widetilde{V}_s \cup V_c \cup \{N+1\}$
K	Set of vehicles, $K = \{1, \dots, w\}$
$V_{d,N+1}$	Set of all nodes, $V_{d,N+1} = V_d \cup \widetilde{V}_{N+1}$
Parameters	
n	Number of customers
m	Number of stations
w	Number of vehicles
d_{ij}	Distance between vertices i and j
t_{ij}	Travel time between vertices i and j
C	Capacity of vehicles in K
g	Recharging rate of vehicles in K
h	Fuel consumption rate of vehicles in K
v	Average speed of vehicles in K
Q	Battery capacity of vehicles in K
$[e_i, l_i]$	Time window of each vertex $i \in \widetilde{V}_{V_d,N+1}$
s_i	Service time of each vertex $i \in \widetilde{V}_{V_d,N+1}$ where $s_{V_d}, s_{\widetilde{V}_s}, s_{N+1} = 0$
q_i	Demand of each vertex $i \in \widetilde{V}_{V_d,N+1}$ $[kg]$
c_e^w	Electric energy cost of vehicles w $[€/km]$
c_v^w	Vehicle's w initial investment cost $[€/h]$
c_d^w	Driver's salary cost of vehicles $w[€/h]$
Decision variables	
τ_{ki}	Arrival time at vertex $i \in \widetilde{V}_{V_d,N+1}$ for all $k \in K$
u_{ki}	Remain cargo on arrival at vertex $i \in \widetilde{V}_{V_d,N+1}$ for all $k \in K$
y_{ki}	Remain charge level on arrival at vertex $i \in \widetilde{V}_{V_d,N+1}$ for all $k \in K$
Y_{ki}	Battery state of charge on departure from vertex $i \in \widetilde{V}_{V_d,N+1}$
x_{kij}	Binary decision variable where $k \in K$ and $i,j \in \widetilde{V}_{V_d,N+1}$

$$0 \le y_{kj} \le y_{kj} - h \cdot d_{kij} \cdot x_{kij} + Q \cdot \left(1 - x_{kij}\right), \forall i \in V_d \cup V_c, \forall j \in \widetilde{V}_{N+1}, \forall k \in K, i \neq j \tag{14}$$

$$y_{kj} \le Y_{ki} - h \cdot d_{kij} \cdot x_{kij} + Q \cdot \left(1 - x_{kij}\right), \forall i \in V_d \cup \widetilde{V}_s, \forall j \in \widetilde{V}_{N+1}, \forall k \in K, i \neq j \tag{15}$$

$$y_{ki} \le Y_{ki} \le Q, \forall i \in V_d \cup \widetilde{V}_s, \forall k \in K \tag{16}$$

$$\tau_{ki} + \left(t_{kij} + s_{ki}\right) \cdot x_{kij} - l_0\left(1 - x_{kij}\right) \le \tau_{kj}, \forall i \in V_d \cup V_c, \forall j \in \widetilde{V}_{N+1}, \forall k \in K, i \neq j \tag{17}$$

$$\tau_{ki} + t_{kij} \cdot x_{kij} + g \cdot (Y_{ki} - y_{ki}) - (l_0 + g \cdot Q) \cdot \left(1 - x_{kij}\right) \le \tau_{kj}, \forall i \in \widetilde{V}_s, \forall j \in \widetilde{V}_{N+1}, \forall k \in K, i \neq j \tag{18}$$

$$x_{kij} \in \{0, 1\}, \forall i, j \in \widetilde{V}_{d,N+1}, \forall k \in K, i \neq j \tag{19}$$

$$u_{ki}, y_{ki}, Y_{ki}, \tau_{ki} \ge 0, \forall i \in \widetilde{V}_{d,N+1}, \forall k \in K \tag{20}$$

The objective function (1) minimizes the total costs, such as travel costs, initial vehicles' investment costs, and drivers' salary costs. Constraints (2)–(3) ensure that each vehicle starts and finishes its route at the depot. Constraint (4) avoids the cycles between nodes. Constraints (5)–(6) ensure that each customer can be visited by one vehicle once. Constraint (7) ensures the number of arcs leaving and entering each customer node. Constraints (8)–(9) ensure that each station can be visited more times by one or more vehicles. Constraints (10)–(11) are related to the number of links entering and leaving each station by avoiding cycles between stations. Constraints (12)–(13) meet the demand request at each node and ensure nonnegative remaining cargo load. Constraints (14)–(16) are related to the battery's partial charging for each vehicle at the station. Constraints (17)–(18) are related to the time window constraints and sub-tour elimination. Constraint (19) is related to the binary variable that is equal to 1 if the vehicle k is travelling on arc (i, j), 0 otherwise. Constraint (20) ensures that the remaining cargo level u, remaining charge level y, battery state of charge Y, and arrival time τ are greater or equal to zero.

4. Application and results

The EVRPTW-PR has been implemented in CPLEX 12.10 which uses the exact method as a solution approach. The proposed model has been validated in the instances with 10 and 15 customers proposed by Colovic and Prencipe (2020). The values of capacity C, average speed v, capacity of battery Q, and recharging rate g for e-moped and e-cargo bikes have been set based on Nocerino et al. (2016), while in the case of e-van, the values were set according to Caggiani et al. (2021). Additionally, the values of fuel consumption rate h, electric energy costs c_e^w have been set. However, the vehicle's initial investment costs c_v^w for e-mopeds and e-cargo bikes were represented as daily costs based on the annual time horizon values (Nocerino et al., 2016), while the daily values for e-vans were set according to Ploos van Amstel et al., (2018). The value c_d^w related to the drivers' hourly salary costs was set according to the 8-h working period shift as 10 €/h for each driver. For e-moped and e-cargo bike has been assumed one driver, while for e-van has been assumed two drivers. All parameters for e-cargo bike, e-van, and e-moped are summarized in Table 2. Since the proposed methodology considers e-grocery vehicle type selection, the focus in the numerical application is only on the alternative sustainable e-grocery E-LDV (i.e., e-moped, e-cargo bike, and e-van), considering that the e-grocery is currently already operating on existing ICE-LDV vehicles. Thus, ICE-LDV vehicles are not a matter of validation in this paper since those KPIs are already familiar to each e-grocery company. In this way, the focus is only on the performance of the aforementioned type of vehicles (e-cargo bikes, e-mopeds, and e-vans) that would encourage the traditional ICE-LDV vehicle shift for e-grocery companies. Consequently, the comparison of these sustainable vehicles can give a general overview of the KPIs that can be seen as a benchmark for their future adoption. The KPIs of E-LDV vehicles are expressed in terms of i) Driver salary costs per hour [€/h]; ii) Total shipment travel time [h]; iii) Fuel (energy) costs [€]; iv) Vehicle investment costs [€/day]; v) Average payload capacity utilization [%].

4.1. The KPI results

The results of the KPI comparison between e-mopeds, e-cargo bikes, and e-vans are reported in Table 3 (the best values are highlighted in bold). For all instances of 10 customers, optimal solutions are obtained in a low computation time, while for some instances with 15 customers are obtained near-optimal solutions. For instances with 15 customers, the time limit was fixed as 3600 s. In general, the number of used e-mopeds for the instances of 10 customers is up to 2, while for e-cargo bikes is up to 3. However, the number of used vehicles for instances of 15 customers increased up to 4 for e-cargo bikes and up to 3 for e-mopeds, which is due to the higher payload capacity of e-mopeds. Instead, the number of used e-vans for all instances is 1 due to their higher capacity. Based on the values of the objective function $f(y)$, it is observed that e-cargo bikes are the more economically convenient solution than e-moped when the number of needed vehicles is equal, as reported for the instances r102C10, rc102C10, and r102C15. Even though all KPIs have a

Table 2
The values of the parameter used in EVRPTW-PR.

C [kg]	175	80	700
v [km/h]	16	17	25
Q [kWh]	4.00	0.54	40.00
g [kWh/h]	0.035	0.010	4.444
c_e^w [€/km]	0.0021	0.0006	0.0318
c_v^w [kWh/km]	8.300	0.274	69.863
c_d^w [€/h]	10	10	20

Table 3
The KPIs comparison results among e-cargo bikes, e-mopeds, and e-vans.

Instance	Type of vehicle	No. vehicles	No. drivers	Driver salary based on delivery time [€/h]	Total travel time [h]	Fuel costs [€]	Vehicle investment costs [€/day]	Obj. fun. $f(y)$ [€/day]	Average payload capacity utilization [%]
c101C10	e-cargo bike	3	3	**14.48**	1.45	**0.0071**	**0.82**	**45.31**	**83.33%**
	e-moped	2	2	14.58	1.46	0.0238	16.60	51.20	57.14%
	e-van	1	2	26.50	**1.33**	0.4571	69.86	116.82	28.57%
c103C15	e-cargo bike	4	4	18.41	1.84	**0.0073**	**1.10**	59.52	**81.25%**
	e-moped	2	2	**18.17**	1.82	0.0232	16.60	**54.79**	74.29%
	e-van	1	2	32.58	**1.63**	0.4005	69.86	122.84	37.14%
c104C10	e-cargo bike	3	3	13.40	1.34	**0.0060**	**0.82**	**44.23**	**75.00%**
	e-moped	2	2	**12.87**	1.29	0.0180	16.60	49.48	51.43%
	e-van	1	2	21.25	**1.06**	0.2483	69.86	111.36	25.71%
c106C15	e-cargo bike	3	3	**16.36**	1.64	**0.0052**	**0.82**	47.19	70.83%
	e-moped	1	1	17.68	1.77	0.0216	8.30	**36.01**	**97.14%**
	e-van	1	1	30.74	**1.54**	0.3274	69.86	120.93	24.29%
r102C10	e-cargo bike	2	2	**5.68**	0.57	**0.0049**	**0.55**	26.23	**96.88%**
	e-moped	1	1	6.15	0.61	0.0210	8.3	**25.30**	88.57%
	e-van	1	2	8.99	**0.45**	0.2912	69.86	99.15	22.14%
r102C15	e-cargo bike	3	3	**7.96**	0.80	**0.0068**	**0.82**	**38.79**	**79.58%**
	e-moped	3	3	7.99	0.80	0.0226	24.90	62.91	36.38%
	e-van	2	4	11.87	**0.59**	0.3723	139.73	191.96	13.64%
r103C10	e-cargo bike	2	2	**3.85**	0.39	**0.0031**	**0.55**	24.40	**86.88%**
	e-moped	1	1	3.92	0.39	0.0104	8.30	**22.23**	79.43%
	e-van	1	2	5.62	**0.28**	0.1571	69.86	95.64	19.86%
r105C15	e-cargo bike	3	3	**7.45**	0.74	**0.0063**	**0.82**	**38.28**	**87.92%**
	e-moped	2	2	8.80	0.88	0.0254	16.60	45.43	60.29%
	e-van	1	2	14.44	**0.72**	0.4747	69.86	104.78	30.14%
rc102C10	e-cargo bike	3	3	**7.87**	0.79	**0.0072**	**0.82**	**38.69**	**75.42%**
	e-moped	2	2	7.98	0.80	0.0240	16.60	44.61	51.71%
	e-van	1	2	11.34	**0.57**	0.3844	69.86	101.58	25.86%
rc103C15	e-cargo bike	3	3	8.13	0.81	**0.0070**	**0.82**	**38.96**	**85.00%**
	e-moped	2	2	**7.97**	0.80	0.0226	16.60	44.60	58.29%
	e-van	1	2	10.90	**0.54**	0.3339	69.86	101.10	29.14%
rc108C10	e-cargo bike	2	2	**7.08**	0.71	**0.0064**	**0.55**	27.63	**91.25%**
	e-moped	1	1	7.20	0.72	0.0214	8.30	**25.52**	83.43%
	e-van	1	2	9.74	**0.49**	0.3208	69.86	99.92	20.86%
rc108C15	e-cargo bike	4	4	9.68	0.97	**0.0086**	**1.10**	50.79	**86.56%**
	e-moped	2	2	**7.80**	0.78	0.0220	16.60	**44.42**	79.14%
	e-van	1	2	10.43	**0.52**	0.3153	69.86	100.61	39.57%

significant impact on the minimization of the total costs, the overall costs of using e-vans are the highest compared to e-mopeds and e-cargo bikes in all instances due to the higher initial investment costs. However, the required travel time for delivering from grocery to customers is the lowest for e-vans due to the higher average speed.

The first KPI related to the driver's salary considering the total time [h] needed for delivering goods is more cost-effective for e-grocery when utilizing e-cargo bikes or e-mopeds with slight differences in the range from 0.03 to 1.88 [€/h], while the costs of e-vans are mostly twice higher. The KPIs related to the energy costs and the vehicle's investment costs are the lowest for e-cargo bikes in all instances. However, the highest KPI related to the average capacity utilization is in the range of 75%–97% considering e-cargo bikes and e-mopeds which is due to the lower capacity requirements for visiting 10 or 15 customers. In all instances with 10 customers, the average capacity utilization of e-cargo bikes is from 6% to up to 43% higher than for e-mopeds; differently, in the case of the instance c106C15, the number of vehicles/drivers and, consequently, the average capacity utilization of vehicle had a significant influence on the minimization of the total costs. However, the lowest capacity utilization resulted to be for e-vans. In addition, the total cost evaluation of e-vans can be more convenient in the case when the number of customers, as well as the distance between the e-grocery shop and customers is higher. Since it has been assumed that e-grocery deliveries are generally small packages for a low number of clients, the advantages of e-cargo bikes or e-mopeds are more user-friendly, especially when in the case of shorter distances between customers, or narrow streets in restricted traffic zones.

4.2. Cost analysis

The graphical comparisons of the e-cargo bikes, e-moped, and e-vans in terms of the investigated KPIs are reported in the following figures: i) The total travel time comparison in Fig. 3; ii) The driver salary comparison in Fig. 4; iii) The average capacity utilization comparison in Fig. 5 iv) The overall costs comparison in Fig. 6.

As represented in Fig. 3, the total delivery travel time comparison is lowest for e-vans due to the assumed higher average speed and the lower number of required vehicles. Specifically, the average travel time of e-cargo bikes, e-mopeds, and e-vans for all instances is around 60.18min, 60.97min, and 48.69min, respectively. Additionally, the average travel time for all instances with 10 customers, i.e., 49.20min, is around 20min lower than the average travel time of the instances with 15 customers due to the lower number of required vehicles. Furthermore, in instances c103C15 and c106C15 is observed that the e-cargo bikes and e-mopeds required higher shipment travel times due to the hard time windows constraints, while for the other instances, the required shipment travel time was almost twice lower. However, the maximum delivery time is less than 2h for both types of instances considering all types of vehicles. This outcome points out a good opportunity for e-groceries growth compared to time-consuming in-store shopping.

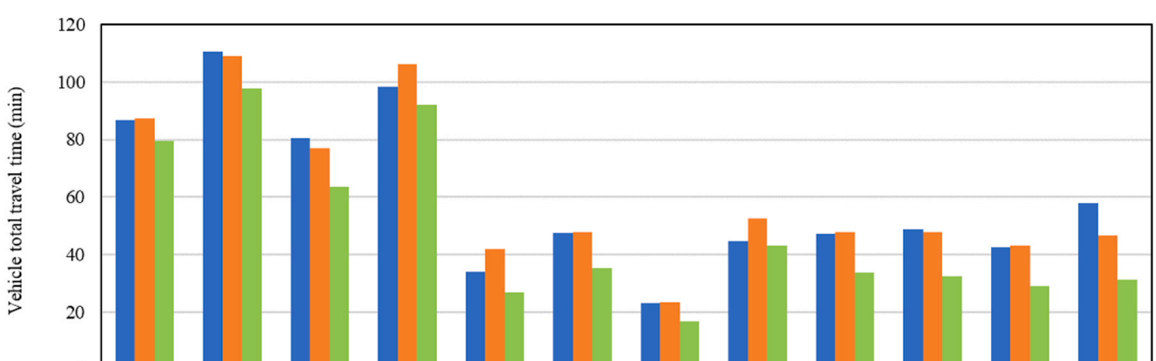
The comparison of drivers' salary costs among e-cargo bikes, e-mopeds, and e-vans is shown in Fig. 4. As reported, driver's salary costs of e-vans are the highest since two drivers (one as a driver and another one as the delivery person) have been assumed due to a common delivery practice within specified time-windows. For example, e-vans drivers' salary is highest for the instances c101C10, c103C15, and c106C15, while for the other instances, the costs of e-vans drivers' salary were only slightly higher compared to e-cargo bikes and e-mopeds. The influence of the number of required vehicles is noted in the overall drivers' salary costs evaluation e.g., instance c103C15 required 4 e-cargo bikes and 2 e-mopeds. Differently, the instance r102C15 resulted in the lowest costs due to the lower number of needed vehicles i.e., 2 e-cargo bikes and one e-moped.

Fig. 5 depicts the vehicle average capacity utilization comparison among e-cargo bikes, e-mopeds, and e-vans. For all instances, e-cargo bike, e-moped, and e-van resulted on average in 83.33%, 68.10%, and 26.41%, respectively. Additionally, the average payload capacity utilization of e-vans is around 57% lower than e-cargo bikes and around 42% than e-mopeds. Therefore, e-cargo bike resulted to be the best option regarding the average capacity utilization (i.e., up to 96.88%), while the average capacity utilization for e-vans was lower than 30%. It is noticed that e-cargo bikes are the most efficient solutions in terms of payload capacity utilization considering a low/medium number of customers for e-grocery home delivery.

The comparison of the overall costs is similar for e-cargo bikes and e-mopeds while for e-vans is more than twice higher, as shown in Fig. 6. In specific, the overall costs for all instances with 10 and 15 customers for e-cargo bikes, e-mopeds, and e-vans are on average 40€, 41.54€, and 113.89€, respectively. It is worth noticing that the initial investment costs have the greatest influence on overall e-van costs. Differently, e-cargo bikes and e-mopeds resulted in similar overall costs, even though e-moped investment costs are higher than e-cargo bikes. This is probably based on the similar values in the required travel delivery time and drivers' salary costs. Furthermore, it can be noticed that overall costs are not influenced by the number of visited customers in all instances. For example, the total overall costs for all types of vehicles in the case of instance c104C10 are higher than for instances r105C15 and rc103C15 with 15 customers due to the higher number of required vehicles and capacity utilization.

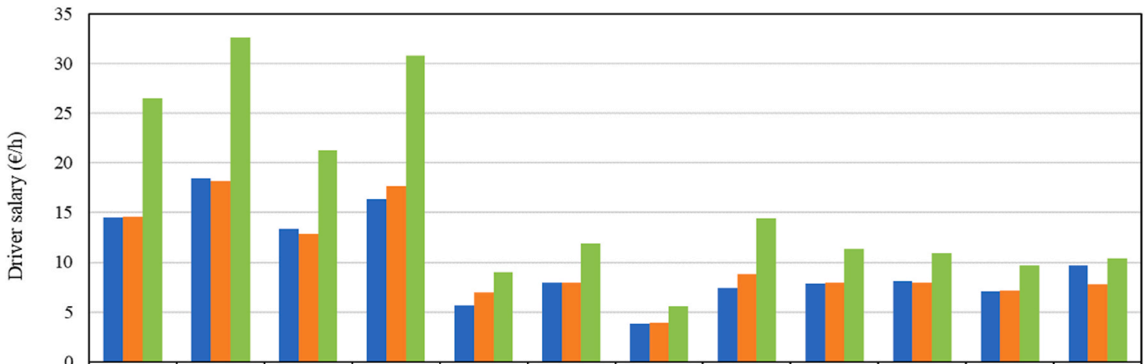
Based on the above-mentioned, the comparison among e-mopeds, e-cargo bikes, or e-vans can be resumed as follows. For all instances, e-cargo bikes and e-mopeds resulted in being the best options for e-grocery home delivery considering average overall costs. Furthermore, from Table 3 is observed that the driver's salary costs are the ones that have the greatest influence on the overall costs of e-cargo bikes and e-mopeds. However, for all instances, e-vans resulted in the highest costs due to the high vehicles' investment costs, and the best option regarding total delivery time. Thus, in most cases, one e-van can be substituted with two/three e-cargo-bikes/e-mopeds since the gap between e-cargo bikes/e-mopeds and e-van is around 12 min. For all instances, the KPI related to drivers 'salary costs of e-cargo bike, e-moped, and e-van resulted in 10.02€/day, 10.09€/day, and 16.20€/day on average, respectively.

Finally, after the overall cost evaluation, the e-grocery needs a price strategy in order to obtain profits for the home delivery service. According to Figliozzi and Keeling (2019), there are several pricing strategies such as per-trip fees, membership fee requirements, minimum delivery fees, and extra fees in item prices. For all pricing strategies, the minimum delivery fee is required and if combined with other pricing strategies may generate profits for e-grocery. For example, two per-trip fee strategies, i.e., such as 5€ (scenario A) and 10€ (scenario B), have been assumed for evaluating e-grocery home delivery profits. As shown in Fig. 7, the profits for all instances for both scenarios can be obtained by adopting e-cargo bikes and/or e-mopeds while the adoption of e-vans requires a higher per-trip fee, i.e., more than 10€ per trip per customer. For example, the adoption of e-cargo bikes and/or e-mopeds on the instance r103C10 with 10 customers, can return profits of around 27€ with scenario A and around 77€ with scenario B. However, the adoption of e-vans returns a profit only in scenario B.



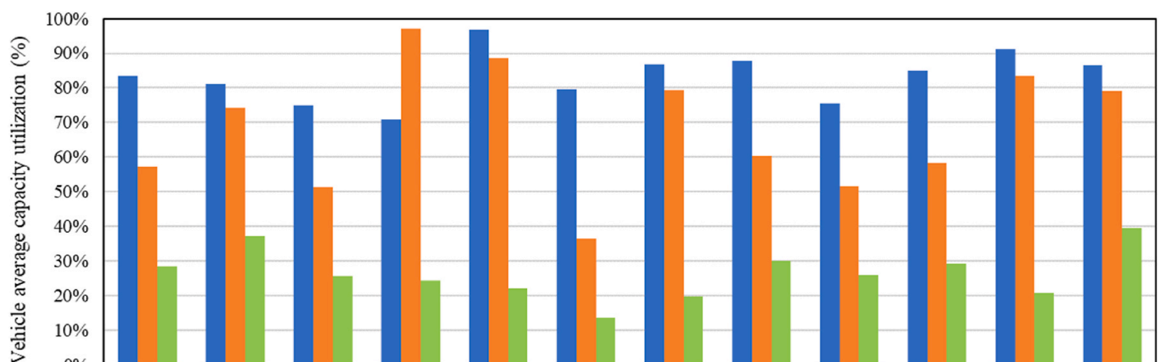
	c101C10	c103C15	c104C10	c106C15	r102C10	r102C15	r103C10	r105C15	rc102C10	rc103C15	rc108C10	rc108C15
e-cargo bike	86.87	110.47	80.38	98.19	34.05	47.77	23.12	44.70	47.19	48.81	42.48	58.09
e-moped	87.47	109.02	77.20	106.11	41.89	47.93	23.53	52.80	47.91	47.84	43.17	46.80
e-van	79.50	97.73	63.74	92.21	26.98	35.60	16.86	43.33	34.01	32.70	29.21	31.29

Fig. 3. The total travel time comparison among e-cargo bikes, e-mopeds, and e-vans.



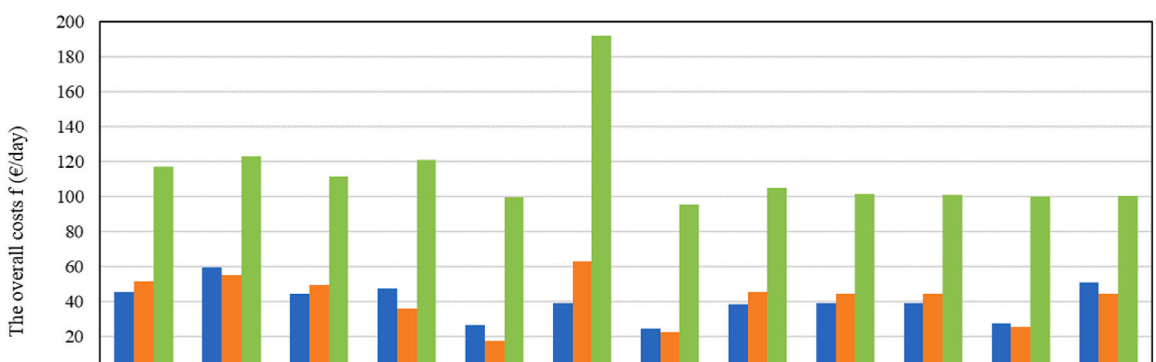
	c101C10	c103C15	c104C10	c106C15	r102C10	r102C15	r103C10	r105C15	rc102C10	rc103C15	rc108C10	rc108C15
e-cargo bike	14.48	18.41	13.40	16.36	5.68	7.96	3.85	7.45	7.87	8.13	7.08	9.68
e-moped	14.58	18.17	12.87	17.68	6.98	7.99	3.92	8.80	7.98	7.97	7.20	7.80
e-van	26.50	32.58	21.25	30.74	8.99	11.87	5.62	14.44	11.34	10.90	9.74	10.43

Fig. 4. The driver salary comparison among e-cargo bikes, e-mopeds, and e-vans.



	c101C10	c103C15	c104C10	c106C15	r102C10	r102C15	r103C10	r105C15	rc102C10	rc103C15	rc108C10	rc108C15
e-cargo bike	83.33%	81.25%	75.00%	70.83%	96.88%	79.58%	86.88%	87.92%	75.42%	85.00%	91.25%	86.56%
e-moped	57.14%	74.29%	51.43%	97.14%	88.57%	36.38%	79.43%	60.29%	51.71%	58.29%	83.43%	79.14%
e-van	28.57%	37.14%	25.71%	24.29%	22.14%	13.64%	19.86%	30.14%	25.86%	29.14%	20.86%	39.57%

Fig. 5. The vehicle average capacity utilization comparison among e-cargo bikes, e-mopeds, and e-vans.



	c101C10	c103C15	c104C10	c106C15	r102C10	r102C15	r103C10	r105C15	rc102C10	rc103C15	rc108C10	rc108C15
e-cargo bike	45.31	59.52	44.23	47.19	26.23	38.79	24.40	38.28	38.69	38.96	27.63	50.79
e-moped	51.20	54.79	49.48	36.01	17.26	62.91	22.23	45.43	44.61	44.60	25.52	44.42
e-van	116.82	122.84	111.36	120.93	99.15	191.96	95.64	104.78	101.58	101.10	99.92	100.61

Fig. 6. The overall cost comparison among e-cargo bikes, e-mopeds, and e-vans.

5. Discussion

With respect to the existing literature, this work presents a novel e-grocery DSS that investigated the opportunities for switching from traditional diesel to E-LDVs through KPI analysis. The literature review section showed that most of the recent works on e-grocery have been focused on the behavior, attitude, and willingness of users to make online purchases, as well as on the factors that influence customer decisions, such as order fulfilment and customer loyalty. In addition, the COVID-19 pandemic has generated the growth of e-grocery requests,

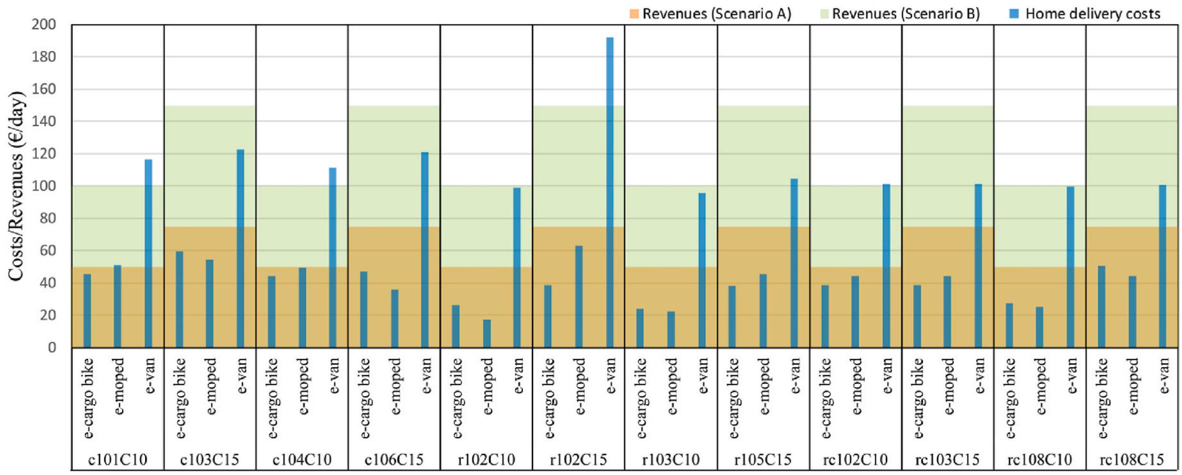


Fig. 7. The pricing strategies (scenario A and scenario B) for e-groceries.

which has left an impact on e-grocery services. Thus, the challenges of e-grocery delivery are related to meeting a high number of requests by optimizing KPIs, such as travel time and vehicle utilization, and maintaining an efficient level of customer order satisfaction. Those aspects have been implemented in the proposed EVPTW-PR through time-windows delivery constraints that manage customers' requests based on their service time preferences. However, the proposed model considers not only delivery fulfillment, but also the interest of e-grocery logistics company perspective related to minimization of travel costs, initial vehicles' investment costs, and drivers' salary costs when determining the best delivery vehicle type selection.

Even though several DSS on the supply chain can be found in the literature (e.g., Heumann et al., 2021; Mkansi & Mugurusi, 2023; Perboli & Rosano, 2018), only a few of them focused on e-grocery following customer preferences/e-commerce strategies (Fikar, 2018; Fikar et al., 2021). Instead, this work is the first that evaluates the economic aspects of adopting E-LDVs as a suitable solution for e-grocery home delivery moving towards CO_2 targets. In addition, the carried-out evaluation of the E-LDVs comparison highlights the future economic benefits for e-grocery companies such as better average capacity utilization and lower total delivery travel time, as shown in Table 3. Moreover, E-LDVs are demonstrated as efficient and more suitable for urban deliveries, especially for e-grocery commerce, which often handles customers' requests for small packages up to a total of 25 kg. This resulted in better vehicle average capacity utilization as well as the reduction of "empty" rides. Also, the dimensions of e-cargo bikes and e-mopeds can contribute to reducing the total service time required for home delivery service to e-grocery customers located in historical zones, city centers with parking regulations (restricted traffic zones), or congested narrow streets. Therefore, the outcome of this analysis reflects the importance of adopting E-LDVs as an alternative e-grocery last-mile home delivery solution, especially in high-density urban areas and for people with limited mobility.

6. Conclusions

The paper proposes a novel DSS that supports a novel management strategy related to the best vehicle/service type selection for e-grocery home deliveries. In particular, a modified mathematical formulation of the Electric Vehicle Routing Problem with Time Windows and Partial Recharging (EVRPTW-PR) has been applied to selecting the best zero-emission vehicle (i.e., e-cargo bike, e-moped, or e-van) for e-grocery home delivery. The comparison was tested on a set of instances with 10 and 15 customers provided by Colovic and Prencipe (2020), considering the parameters in the literature which might vary based on different socio-economical aspects and vehicle type specifications. Based on the comparison, the obtained results showed the benefits of adopting E-LDVs (see Table 3). This result supports the objective of e-grocery companies to accomplish a higher number of deliveries within hard time windows fixed by customers. Furthermore, this could increase customers' satisfaction and incentivize a higher adoption of e-grocery home delivery services (Calzavara et al., 2023; Milioti et al., 2021).

The novel DSS for e-grocery E-LDVs selection encourages implementing the public authority's initiative related to environmental impact reduction in the urban areas devoted to the city logistics freight deliveries. The growth of e-grocery would have an impact on the transportation system, resulting in higher traffic congestion and travel time, especially during peak hours. According to a recent study proposed by Lezcano et al. (2023), if e-grocery deliveries are shifted to off-peak hours is possible to obtain a congestion reduction of about 3.4%. Thus, government initiatives and incentives to shift from diesel to electric vehicle technologies could benefit transportation planners by reducing travel costs and creating less pollution in cities. The public authorities should financially support the development of sustainable logistics systems, and thus, the transition to sustainable last-mile transportation solutions. At the same time, the advantages of E-LDVs should allow e-grocery companies to achieve not only environmental aspects but also economic and competitive logistics markets. However, the recommendation of future transport policy implications should be also focused on investing in charging infrastructure installation. As a consequence, the existence of charging infrastructure could also play a key role in promoting E-LDV adoption, and mobility habits and enhance the utilization of sustainable vehicle technologies. In addition, e-grocery companies could encourage customers to choose eco-friendly delivery methods through incentives or discounts on purchases/home deliveries (Sarkar, 2023).

The proposed work could be perceived as a first-step analysis for evaluating eco-friendly vehicle adoption for e-grocery companies. However, the evaluation of the initial investment costs of the vehicles did not take into account the maintenance and depreciation costs of the vehicles, which will be included in the forthcoming benefit-cost analysis. Additionally, it would be worthwhile to investigate the resolution of real case studies involving a larger number of customers by utilizing agent-based or metaheuristic/heuristic approaches as potential solutions. Another development will be introduced in the comparison of Environmental Life Cycle Costing (ELCC) to better understand the convenience of the systems from a wider perspective.

CRediT authorship contribution statement

Luigi Pio Prencipe: Conceptualization, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review &

editing. **Aleksandra Colovic:** Conceptualization, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Mario Binetti:** Writing – review & editing. **Michele Ottomanelli:** Funding acquisition, Supervision, Writing – review & editing.

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.

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