Wiley
Journal of Advanced Transportation
Volume 2025, Article ID 8859606, 30 pages
https://doi.org/10.1155/atr/8859606

WILEY

Review Article

Trends and Advances in Urban Logistics Research: A Systematic Literature Review

Angie Ramírez-Villamil,[1,2] **Jairo R. Montoya-Torres**,[3] **and Anicia Jaegler**[2]

[1]*School of Engineering, Universidad de La Sabana, Km 7 Autopista Norte de Bogotá, D.C., Chía, Colombia*
[2]*Sustainability Center of Excellence, Kedge Business School, 40 Avenue des Terroirs de France, Paris 75012, France*
[3]*Département de Génie des Systèmes, École de Technologie Supérieure, 1100 Rue Notre-Dame Ouest, Montréal H3C 1K3, Quebec, Canada*

Correspondence should be addressed to Anicia Jaegler; anicia.jaegler@kedgebs.com

Received 30 November 2024; Accepted 2 May 2025

Academic Editor: Socrates Basbas

It is important to establish appropriate performance indicators so that decision-makers can better determine the best alternatives for sustainable urban freight distribution systems. This literature about urban logistics and routing problems is structured and analyzed through a systematic literature review of a total of 201 papers from 2002 to 2023. Three main axes were considered: problem modeling and solution approaches, multimodal transportation, and indicators to assess the performance and sustainability of the distribution networks. There is a growing trend of research on this topic. Indeed, the paper highlighted the academic interest in the analysis of case studies to test the scenarios and network configurations and proposed solution approaches, as well as the adoption of greener transportation modes. To the best of our knowledge, no previous studies have analyzed the literature from the thematic lines proposed in this review, especially those that refer to performance indicators to assess both the freight distribution networks and the transportation modes considered. Advancing stochastic modeling, expanding case studies to underrepresented regions, integrating AI-driven multimodal logistics, and developing social impact indicators are key research directions to enhance the sustainability and efficiency of urban logistics. This review provides a structured foundation for future research by identifying gaps in the literature and offering a thematic roadmap to advance the study and implement sustainable urban logistics solutions. In addition, its findings can assist decision-makers and logistics planners in evaluating current practices, identifying opportunities for improvement, and supporting the development of more sustainable and efficient distribution strategies.

Keywords: last-mile delivery; performance indicators; routing problems; sustainability; transportation modes; urban logistics

1. Introduction

Over the past few years, the retail sector has experienced notable growth, largely attributed to the circumstances of the pandemic. These conditions prompted an expansion in the sector and led many businesses to transition to e-commerce to sustain their operations [1]. According to Janjevic et al. [2], e-commerce represents 10% of the global retail market and has been the biggest driver of retail growth. In addition, the increase in population worldwide generates greater demand for goods and commodities. E-commerce activities have a very close relationship with last-mile delivery services, especially for parcel and food delivery. This has triggered an increase in deliveries in urban areas, where the transportation and mobility sector has become essential to cover these demands. This has made delivery operations more complex and expensive.

The use of many vehicles in urban delivery systems has important implications in terms of air pollution, since transportation activities are the source of approximately 25% of carbon dioxide equivalent (CO_2e) emissions, 30% of nitrogen oxide (NOx) emissions, 40% of energy consumption, and 50% of particle matter [3, 4]. The world's population is exposed to poor air quality that exceeds the World's Health Organization guideline limits, causing cardiovascular and pulmonary diseases [5]. Furthermore, these vehicles generate an increase in traffic congestion, and they saturate parking spaces, making driving difficult when carrying out irregular parking practices that invade public spaces [6]. Limited space in inner-city areas does not allow an expansion of logistics infrastructure. Therefore, in many cities, as a strategy to improve living conditions and make them more sustainable, the access of delivery vehicles to urban areas is restricted [7].

These two trends have led to innovative models of urban distribution [8] and to the promotion and introduction of initiatives to use more environmentally friendly transportation modes with the aim to reduce the negative externalities and to achieve sustainable logistics operations. For instance, governments are promoting regulations to increase the use of electric vehicles (EVs) for urban delivery. In addition, several logistics service providers are incorporating different types of transportation modes (e.g., drones, delivery robots, cargo bikes, and public transport) in their networks [9]. Promising results are found in the literature and in practice regarding the adoption of cleaner energies and alternative transportation modes.

To the best of our knowledge, there are no previous studies that analyze the literature from the thematic lines proposed in this review, especially the one that refers to the indicators that have been used to measure the performance of both the distribution networks and the solution methods applied. As background, there are mainly three reviews that address issues related to the need of making urban distribution networks more sustainable. The work of Patella et al. [10] studied challenges and issues regarding the adoption of green vehicles in urban freight transportation and e-commerce activities and classified the documents into three categories: optimization and scheduling, policy, and sustainability dimensions. Silva et al. [11] classified research works on sustainable urban logistics published between 2016 and 2022 in clusters: supply chain and channels, delivery methods, innovative transportation modes, logistic infrastructures, and emerging business models. The authors organized the solutions that were identified for the last-mile drawbacks into three groups: vehicular, operational, and organizational solutions. Some of the advantages and disadvantages of these solutions were discussed. Golinska-Dawson and Sethanan [12] focused on the emerging solutions in terms of hardware and software applied by logistics service providers that can support the adoption of environmentally friendly (in terms of energy) smart cities. The study classified the solutions in urban freight consolidation or transshipment, customers as service providers (i.e., the use of crowdshipping), and modes of transportation. In contrast to those previous works, the proposed literature about urban logistics and routing problems is structured and analyzed through a systematic literature review. The findings are classified into three main axes: problem modeling and solution approaches, multimodal transportation, and indicators to assess the performance and sustainability of the delivery networks.

The remainder of the paper is organized as follows. Section 2 presents the methodology of the systematic literature review. A descriptive analysis of the selected papers is presented in Section 3. Section 4 presents the most common modeling and solution approaches used in the papers with a technical outline of adopted methodologies, their reference to practice, and a thorough analysis of their properties. Section 5 presents an analysis of the different transportation modes with some of the benefits, advantages, and disadvantages. A detailed description of the indicators used to measure the performance of the distribution networks is given in Section 6. Finally, Section 7 presents the conclusions and outlines opportunities for future research.

2. Research Methodology

This section describes the research methodology. A systematic review involves a detailed analysis of the scientific literature under a planned and carefully executed process, with the purpose of reducing bias through the identification and synthesis of previously published findings on a particular topic, to answer a specific research question [13]. From the academic side, this approach increases methodological rigor; while, for practitioners and managers, it can help to develop a trustworthy knowledge base by consolidating knowledge from a set of studies [14]. We followed the method and steps proposed by [14], whose process begins by defining one or more research questions to define the scope of the review. Our study has the aim of giving answers to the three following questions:

1. How are urban parcel delivery problems modeled?
2. Which solution methods are employed to deal with urban parcel delivery problems?
3. Which are the transportation modes that have been considered in literature?
4. Which are the performance indicators applied in the literature to assess the sustainability and efficiency of multimodal urban parcel delivery systems?

Based on these questions, the second stage is to define the search criteria. To locate the set of publications relevant to our purposes, three keywords were used: "Urban logistics," "city logistics," and "routing problems." After testing different combinations of such keywords, the final search string was defined as follows: TITLE-ABS-KEY (urban OR city AND logistics AND "routing problems"), because it contained a more complete list of articles. The database used in this search was Scopus since it is one of the major databases that provide access to several peer-reviewed literature including high-quality scientific journals, books, and conference proceedings. The study selection consists of five steps (see Figure 1). First, the initial number of publications available in Scopus is extracted: 658 documents were found between 2002 and December of 2023. At the end of the exclusion process, a final set of 201 papers were thoroughly read and classified in this review.

The subsequent section offers a comprehensive analysis of the reviewed literature. Publications were categorized

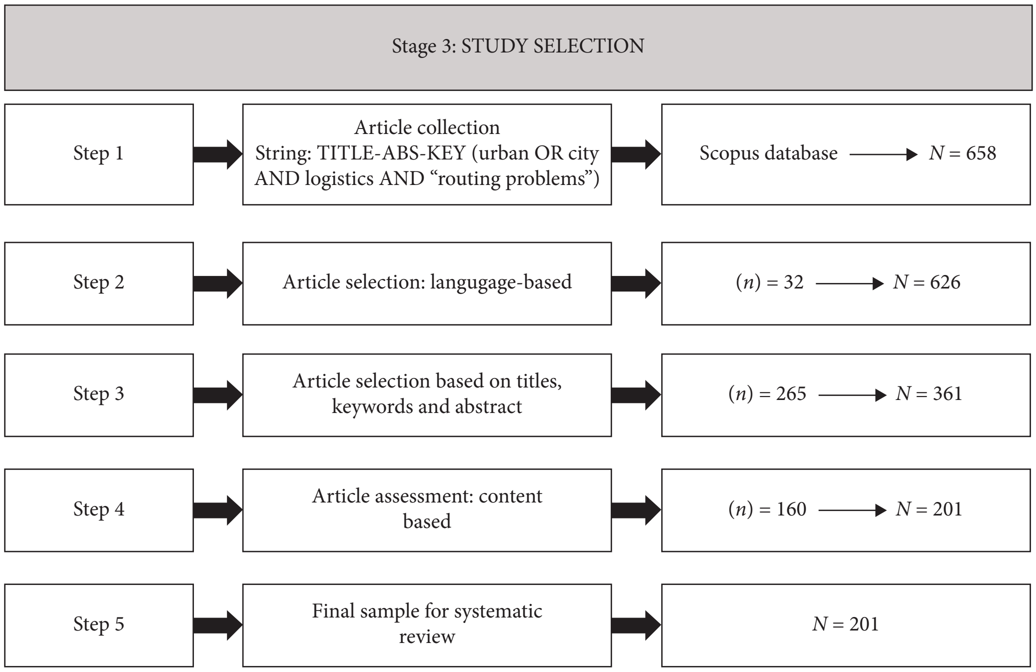

Figure 1: Methodology for literature review, Stage 3: study selection and evaluation.

based on various criteria including year, document type, authors, and countries featuring case studies. Furthermore, the documents were sorted according to their modeling approach, solution methods, transportation modes, and performance assessment indicators for delivery networks. Building upon these classifications, the subsequent phase involves detailing the findings of this systematic review and outlining potential research avenues.

3. Descriptive Analysis

Over the last 6 years, research interest in urban logistics operations has grown significantly. The timeframe for this review is 2002–2023, but it is important to note that the search on Scopus using the string defined in the previous section, without any time limit, shows that the first work was published in 2002. Since 2017, the number of documents has increased, reaching its highest point in 2022. The increase in demand for e-commerce and the crisis caused by the pandemic in 2020 could have influenced this growth. About 65% of the papers analyzed in the present study were published between 2020 and 2023 (see Figure 2).

According to the document type, 73% of short-listed documents are journal articles, 24% are conference papers, and 3% are book chapters. The set of journals that published the most about this topic are given as follows (Table 1) The concentration of publications in these specific journals further suggests that urban logistics is primarily being approached from the operational research and transportation perspectives, with a growing shift toward incorporating sustainability aspects. This trend points to the increasing importance of considering both the efficiency and environmental impact of urban logistics systems as urbanization and congestion continue to pose challenges [15].

The authors that published the highest number of papers on this topic are Jairo R. Montoya-Torres (10 papers), followed by Y. Wang (9 papers), H. Wang (8 papers), and finally, X. Wang, Y. Huang, D. Rezgui, H. Bouziri, and W. Aggoune-Mtalaa, who are authors of 6 publications each one within the defined timeframe.

In addition, to identify the most influential works in the field, the top 10 most cited papers were analyzed (see Table 2). These studies, with citation counts ranging from 180 to 110, show a notable increase in publications after 2018, highlighting the growing interest in sustainable and technology-driven logistics solutions. Overall, the findings reveal a shift toward automation, sustainability, and multiechelon distribution strategies, reflecting both academic and industry priorities in technological advancements and environmentally conscious logistics solutions.

Several studies have considered case studies to simulate real-life logistics networks and evaluate the effects of applying the proposed methodologies, the scenarios described and/or employed transportation modes. Among the 201 papers reviewed, there are 101 documents that have used case studies in different countries (50%). Figure 3 shows a world map colored according to the number of case studies per country and their relative frequency. There are 27 different countries in which case studies have been considered: China (28%), the United States (9%), Germany (7%), France (7%), and Italy (6%).

4. Modeling and Solution Approaches

In this section, a description of the modeling approaches and solution methods to deal with routing problems using multiple modes of transportation is presented to answer the two first research questions (Table 3). The former attends to

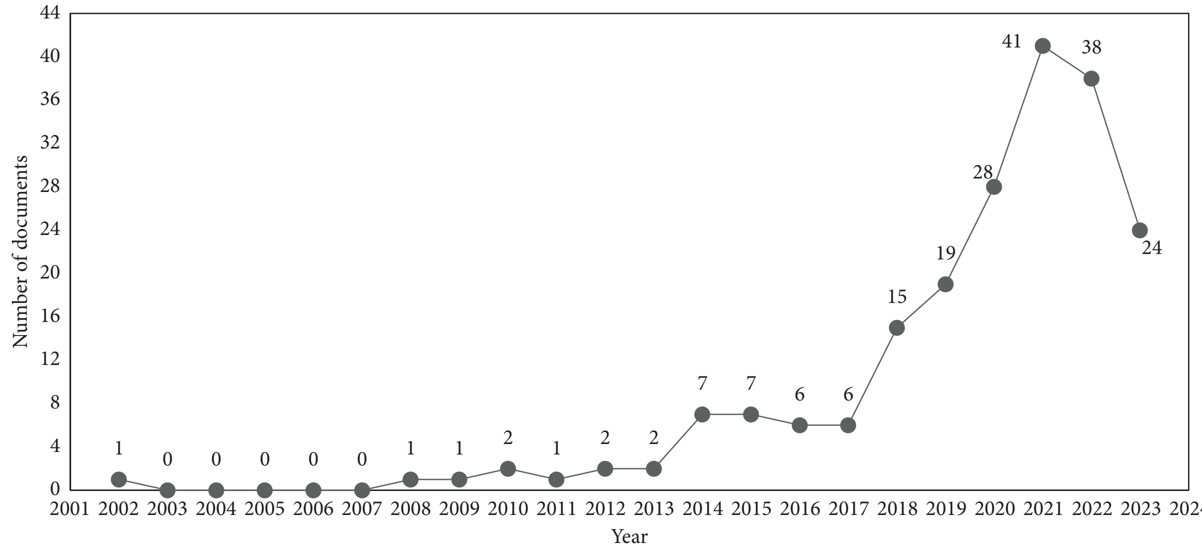

Figure 2: Number of papers across the years (2002–2023).

Table 1: Number of publications per journal.

Journal	Number of papers
European Journal of Operational Research	14
Transportation Research Part E: Logistics and Transportation Review	11
Sustainability	8
Computers and Operations Research	5
Computers and Industrial Engineering	5
Expert Systems with Applications	5

Table 2: Top 10 most cited papers.

Rank	Reference	Citations
1	[16]	180
2	[17]	179
3	[18]	157
4	[19]	142
5	[20]	142
6	[21]	141
7	[22]	136
8	[23]	127
9	[24]	121
10	[25]	110

the characteristics of the problem regarding the type of routing problem under consideration. Furthermore, the variants of the problem will be addressed. The latter aims to identify the most common solution approaches and trends to generate efficient solutions. The type of problems and the solutions approaches are detailed in the Appendix.

As Cuda et al. [26] explain, there are two types of planning decisions in routing problems: tactical and strategic. Tactical decisions refer to the routing through the distribution network, and for the case of two or multiechelon problems, these decisions include the allocation of customers to the intermediate facilities. Strategic decisions are related to the network's infrastructure such as the location and number of facilities. The traveling salesman problem (TSP), vehicle routing problem (VRP), and multiechelon VRP involve tactical decisions, while the location routing problem (LRP) and its multiechelon variants involve the strategic decisions of locating the facilities followed by the routing part. In the reviewed literature, 79% of the papers used the VRP as a basis for modeling the research problems; 14% considered the LRP; 3% modeled their problems as the TSP; and the remaining 4% represent studies that modeled their problems as production routing problem (PRP), drone routing problem (DRP) and mixed truck and robot routing

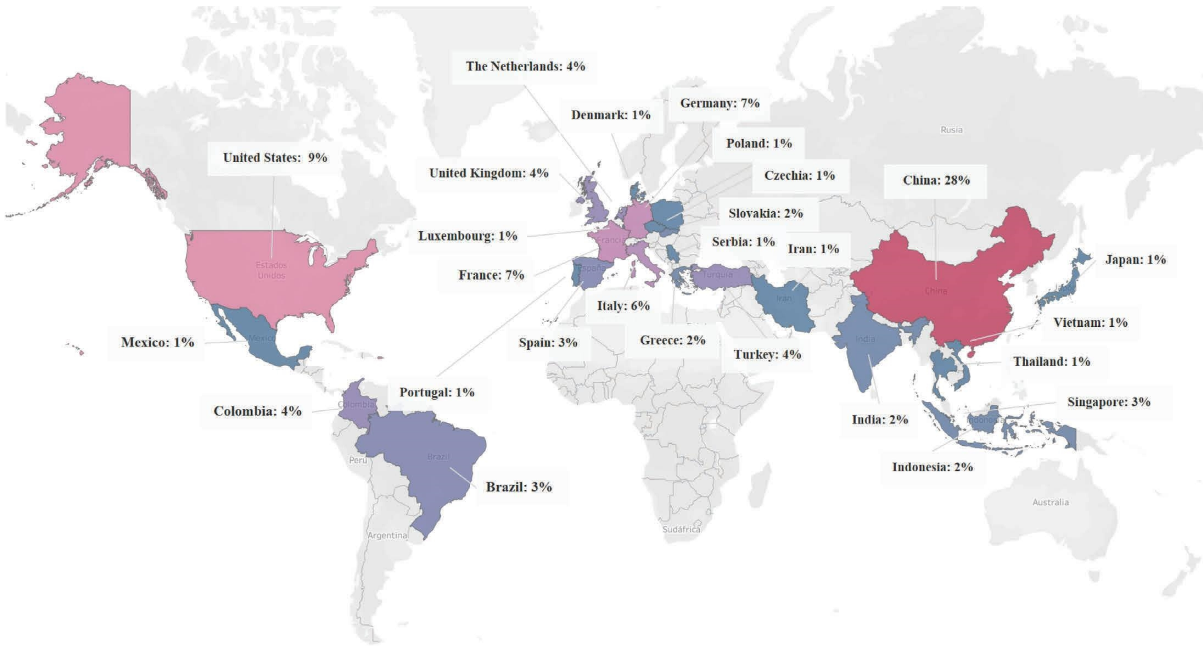

Figure 3: Map of the countries where case studies have been evaluated.

Table 3: Main results.

Aspect	Findings
Routing problem types	79% VRP, 14% LRP, 3% TSP, and 4% other (PRP, DRP, and MTR–RP)
Planning decisions	Tactical: VRP, TSP, and multiechelon VRP; strategic: LRP and multiechelon LRP
Problem modeling	87% deterministic approximations with rich routing features (time windows, delivery options, synchronization constraints, and green routing)
Problem complexity reduction	Common approaches include simplifications to reduce complexity using deterministic scenarios
Uncertainty consideration	13% of studies address stochastic issues (traffic congestion, energy consumption, and demand fluctuations)
Solution methods usage	84% heuristics/metaheuristics, 25% exact methods (small–medium problems), 11% simulation, and 3% dynamic programming

problem (MTR–RP). In addition, 87% of the studies have chosen to make approximations in their problems to reduce the complexity of the scenarios, addressing them in a deterministic way, by considering rich routing problems that include multiple characteristics such as time windows (one of the most studied) [25], delivery options [27], or synchronization constraints [28]. There are also green routing problems, Wang et al. [29] and Yildiz and Altiparmak [30], that incorporate the minimization of emissions using, in some cases, new transportation modes such as drones, delivery robots, EVs, or heterogeneous fleets that combine them and lead to modifications and adjustments to the problem for their integration.

Real-life urban parcel delivery problems deal with uncertainty in different aspects such as vehicle speed, traffic congestion, fuel or energy consumption, demand, travel times, CO_2e emissions, and delivery time: 13% of the documents addressed stochastic issues. This represents a research opportunity since the inclusion of real-life aspects in these problems is becoming more imperative and is of interest to the community.

Solution methods are also an important topic to consider. They allow the development of decision support systems that could help logistics service providers, dispatchers, and schedulers in making good decisions when solving intracity routing problems. For instance, Ioannou et al. [31] proved that a reduction of over 8% in terms of lost sales can be achieved with the implementation of such tools. Moreover, they have obtained interesting improvements in the number of vehicles and routes. In 84% of the studies, approximation algorithms (heuristics and metaheuristics) are the most applied solution approaches, followed by exact methods (25%) which are usually implemented to solve small–medium sized instances due to the complexity of the problem. Also, simulation approaches are used to solve routing problems with stochastic elements in 11% of the cases. Finally, dynamic programming with 3% of the total articles is considered. Several solution methods have been studied, including hybrid decomposition methods [32], combinations of exact methods and heuristics (mataheuristics) [19], or combination of Monte Carlo simulation and optimization to solve problems with stochastic features (simheuristics) [9]. To address large-scale instances, methodologies combining data science and machine learning techniques have been introduced to enable data clustering and optimization using heuristics and metaheuristics to reduce the complexity of the problems [33–35].

5. Multimodal Transportation

This section aims to answer the third research question. Over the years, the use of conventional internal combustion vehicles (ICVs) in last-mile delivery operations has negatively impacted the environment in several ways. The CO_2e generated by these vehicles not only affects the environment but also causes respiratory health problems for city residents [36]. Delivery companies and researchers are paying more attention to reducing emissions to achieve sustainable logistics [37]. Different transportation modes have been evaluated for urban distribution. This section presents an overview of different transportation modes, some of their advantages and disadvantages, and results obtained in the literature.

5.1. EVs. EVs and their charging infrastructure are becoming very popular in major cities around the world. This transportation mode is an environmentally friendly initiative. In urban parcel delivery, the use of EVs is increasing [38] to decrease the negative effects of freight transport on the environment (air pollution, CO_2e emissions, and noise), with lower operational costs compared to ICVs [39–41]. Besides, van Duin et al. [42] concluded that EVs can perform urban delivery in an efficient way, with savings of 19% in terms of distance traveled, as well as reducing CO_2e emissions by 90%.

However, this type of vehicle has some disadvantages such as limited operational range, long charging times, and limited battery capacity [37, 39, 43]. Typically, a full-charged EV can travel between 75 and 125 miles, but the mileage can be shorter depending on external factors [44]. In fact, the most current EV models exceed 200 miles per charge, and all new models are rated for over 100 miles, with manufacturers announcing plans for even longer-range options in the near future [45]. However, real-world driving conditions often lead to significant range variability. For example, cold weather can reduce range by 20%–30% due to lower battery efficiency and increased energy use for cabin heating. Similarly, high temperatures may cause battery overheating, leading to a reduction in range of up to 20% when air conditioning is heavily used. Road quality and terrain also play a role: uphill driving and poor road surfaces increase energy demand, while downhill segments can partially offset consumption through regenerative braking. Other factors such as aggressive driving, underinflated tires, and heavier payloads further diminish range performance. On the contrary, smooth driving behavior and proper tire maintenance help improve efficiency [46]. Therefore, while battery capacity remains a primary determinant of EV range, operational and environmental variables must be carefully considered when evaluating their applicability in urban logistics systems when modeling a routing problem [9, 47].

Moreover, the fixed costs associated with EVs are significantly higher than ICVs [41], although their implementation for parcel distribution is more profitable economically and environmentally in the long-term period [48–50]. As Ding et al. [44] explain in their study, different charging techniques are currently available to recharge EVs, for instance, inductive charging, battery swapping, and conductive charging [51]. However, due to the high investment costs of the installation of charging facilities, there is a lack of charging stations for such vehicles in some cities, which causes the inclusion of this type of vehicle to require more time and investment.

5.2. Electric Modular Vehicles (EMVs). EMVs are a type of EVs that have been used for urban parcel delivery [38, 40]. EMVs have one cabin where the driver is located and the cabin can carry several modules, each one has its own battery and so they are autonomous in terms of charging and battery consumption [52]. In addition, having independent modules allows the rest of the EMV to continue the route without carrying all the modules, which means that modules can be removed if their battery level is insufficient or when there are length restrictions for vehicles in urban areas.

5.3. Autonomous Vehicles (AVs). AVs have begun to be employed and studied to support urban last-mile distribution. The literature has often focused on passenger mobility over urban delivery [53]. According to the authors in [54], autonomous ground vehicles were especially tested within pilot projects to investigate the feasibility as well as customer acceptance. The study proposed by the authors in [55] exposed that the application of this type of vehicle in freight transport presents better opportunities in terms of operational complexity compared to passenger transport because it represents greater cost-efficiency in a very competitive field, and there can be repetitive and predictable routes that would reduce engineering complexity. Experiments conducted by the authors in [56] conclude that the use of AVs can increase the efficiency of last-mile freight delivery in terms of route time by up to 30%.

5.4. Delivery Robots. Autonomous delivery robots are designed primarily to travel short distances; they can avoid obstacles located on the sidewalk autonomously. However, the length of their delivery route can be impacted by the obstacles that the robot can find on the way to the destination. While these robots can assist with last-mile delivery, they are not suitable for handling entire delivery operations, as they can only carry small- to medium-sized packages.

A case study in Xi'an city in China, demonstrated the use of delivery robots to serve areas with van access restrictions such as pedestrianized sidewalks or city campuses [57]. Similarly, in Cardiff, United Kingdom, robots are deployed to travel along sidewalks and deliver parcels to residents in urban areas [21]. These robots present a valuable solution for reducing emissions, personnel costs, urban road traffic, land use, and noise. Moreover, they can visit areas that can be restricted to vans [54, 58, 59]. The COVID-19 pandemic further highlighted their advantages, as self-driving robots can ensure social distancing, protecting both the delivery personnel and customers [21]. In addition, these robots are electronically secured, meaning that customers can only access their parcel through an individual code, ensuring security [54].

Despite these benefits, several limitations hinder the broader use of autonomous delivery roots. Their limited load capacity, speed, and operational range constrain their ability to handle larger or more complex deliveries [60]. Moreover, practical challenges arise as some customers, particularly the elderly or disabled, may be reluctant to interact with the robots, and some parcels may be too large, risky, or hazardous to be delivered by them. As a result, these robots are often used in combination with standard van deliveries to optimize the process. By combining both transportation modes, delivery efficiency improves, reducing overall travel time and costs [19]. Some experiments show that this integration can lead to cost reductions of up to 43% compared to traditional delivery methods [61].

5.5. Unmanned Aerial Vehicles (UAVs). UAVs, also referred to as drones, have become an interesting option to assist the delivery by big companies such as DHL and Amazon [62] and have also been widely studied recently as a component in freight delivery routing problems [63]. According to the authors in [64], UAVs' routing "is a potential game changer in solving the urban air mobility challenge by allowing to reshape transportation and logistics in the future" (p.1). Compared to traditional vehicle distribution, drones are more flexible and low-cost, can avoid road traffic restrictions due to congestion or accidents, are lightweight, and carbon emissions are lower [65, 66].

However, UAVs have some challenges in real-life applications: bad weather, flying restrictions, limited delivery range (10–30 km) due to their battery capacity, and payload limitations [66–70]. In some cities, there are some no-fly areas that are inaccessible by drones such as the airports, power plants, and government buildings [71]. Also, cities with dense high-rise buildings, e.g., New York in the United States of America, are very challenging for drones due to the difficulties of maneuvering [72].

According to the authors in [73], between 10% and 25% of Amazon deliveries cannot be handled by aerial drones, due to size restrictions. To address this limitation, different scenarios have been proposed in the literature introducing alternatives to take advantage of this transportation mode in urban logistics. For example, Jeong and Lee [70] explored the possibility of drones carrying multiple parcels per trip providing both pickup and delivery services to increase their utilization rate. In addition, researchers have studied the integration of drones with other transportation modes, such as trucks and delivery vans, to enhance operational effectiveness [74, 75].

Huang et al. [76] demonstrated that collaborative freight delivery using both drones and trucks can successfully reduce costs, CO_2e emissions, and delivery times. Case studies in Seattle and Buffalo, in the United States [70]; Izmir, Turkey [66]; and in Changsha, China [74] examined the use of drones in areas where customer locations are difficult to reach due to high congestion and carbon-dense environments, helping to mitigate the environmental impact of road transportation. Some studies have also explored hybrid approaches, where drones and trucks operate together to optimize logistics operations. For instance, in Changsha, drones deliver parcels directly to customers, while trucks not only handle certain deliveries but also supply drones with parcels and batteries, ensuring continuous operations [74].

5.6. Cargo Bikes. In the context of more sustainable deliveries, cargo bikes are gaining popularity in several cities. Mühlbauer and Fontaine [77] presented the use of cargo bikes as a promising alternative to conventional vans for parcel delivery in urban logistics. This transportation mode requires less parking space, and congestion can be reduced if cargo bikes use bike lanes or other road infrastructure available. Cargo bikes can have between 2 and 4 wheels, and the payload can be positioned in the front or in the back of the vehicle. Also, cargo bikes are emission-free in terms of direct CO_2e emissions, NOx, and particulate matter and emit less noise than conventional vehicles [78]. The use of cargo bikes for parcel distribution can save between 19% and 38% of CO_2e emissions, so delivery operations become more sustainable than the conventional urban parcel distribution systems [77]. Electric cargo bikes (e-cargo bikes) have also been considered; they contain electric batteries that allow a distance range of 50 km [79]. Thanks to the battery, they can be charged very fast and can be used under tough conditions for normal cargo bikes, such as steep slopes and strong winds [80]. Cargo bikes and e-cargo bikes can replace conventional delivery vans because they are able to access and supply urban areas restricted to vans such as sidewalks, narrow streets, and historic centers [81].

However, when exclusively delivering using cargo bikes, the drawbacks are related to the extensive use of public land space. Moreover, travel speed depends on the load, the distance that can be covered, the street topography, and the reduced load capacity [82]. So, this transportation mode is commonly used in the second level of two-echelon distribution systems. Cargo bikes can save up to 10% of costs [77] but should be combined with other transportation modes (e.g., delivery vans either electric or fuel-based) to transport the freight needed to be delivered to remote areas or large distances to truly benefit their advantages.

5.7. Public Transport. The use of public transport networks for both passengers and freight is also being explored in the literature, including metro lines [83, 84] and freight buses [85–88]. Case studies from cities such as Singapore, which boasts an extensive and highly efficient public transportation system [89], and Nanjing, where the underground metro network spans 378 km with 10 lines and 174 stations, highlight the potential of urban transit systems. Nanjing's metro system is considered one of the most advanced urban rail transport systems in China [90]. These studies demonstrate how integrating public transportation systems with freight services could replace the need for city freighters operated by private third-party logistics companies in inner-city areas. This integration could lead to significant reductions in logistics costs, air pollution, and traffic congestion [91].

On one hand, freight buses can pick up or deliver parcels at each location they pass, and their use can improve the accuracy of logistics services because they have fixed time schedules and can improve the utilization rate of the roads reserved for buses [86]. He and Yang [88] considered buses as a supplementary delivery alternative in parallel with trucks. It means that some parcels are delivered by buses instead of trucks to reduce the number of trucks or the number of trips by truck, leading to a reduction in delivery costs and CO_2e emissions and an increase in bus utilization. On the other hand, the use of urban rail transportation systems (e.g., metro lines) has very great advantages compared to conventional deliveries in terms of costs and service quality. However, it is important to note that the use of metro lines is supplementary and requires the use of other transportation modes as a complement for the distribution network. For instance, the authors in [84] introduced a three-stage delivery network in which trucks are in charge of transporting parcels between the supplier and the metro entry station (first stage), the second stage is the route between the metro entry station and the metro exit station (metro delivery), and the third stage corresponds to routing delivery vans from the metro exit to the delivery points.

If the public transport system is well utilized, it could be possible to also have some passengers to make crowdsourced delivery (also known as crowdshipping), which is the use of the crowd (pedestrians) for parcel delivery. Zhang et al. [92] analyzed a case study in Singapore with public transit passengers as crowdshippers. Results show that crowdshipping has a great potential to be a sustainable means for urban parcel delivery even if it is only implemented in off-peak hours: emissions and distance can be reduced by up to 17% and savings in delivery costs can reach 29% per parcel.

5.8. Mixed Transportation Modes. According to the findings from the literature, the combination of multiple modes of transportation is especially beneficial in medium and large cities with high population density and rapid, continuous growth. These cities often face challenges such as traffic congestion and access limitations across various areas. Such conditions make it difficult to maintain efficient transportation systems, which in turn can affect urban mobility and logistics.

Among the case studies analyzed are major cities such as Austin, United States, with an annual growth rate of approximately 3% [93], where the combination of cargo bikes, EVs, and ICVs was studied to improve urban logistics and reduce congestion. Chongqing, China's youngest municipality, recognized for its unique geography featuring rivers and mountains that divide the city into numerous distinct areas [94], has also been a case study in several papers. These studies have evaluated the combination of various vehicles, including EVs, drones, and trucks, to optimize distribution networks and overcome the city's complex topography. Chongqing is one of the most densely populated cities in China, with a population exceeding 18 million [34].

In cities such as these, the integration of mixed transportation networks, including vehicles that can navigate different urban environments, is a crucial strategy. These transportation systems provide more efficient access to hard-to-reach areas, ensuring smooth logistics operations. In addition, they contribute to reducing the negative impacts of congestion, offering sustainable solutions for urban mobility. This approach supports the growth of smart city infrastructure and enhances overall city resilience in the face of rapid urbanization.

There are other interesting studies that provide evidence that the combination of different transportation modes is necessary to strengthen last-mile delivery, reducing costs, time, and emissions. For example, combining electric ships with cargo bikes can cut CO_2-equivalent emissions by roughly 78% (Alewijnse and Hübl, 2021). Other promising multimodal strategies include the following: - cargo bikes supported by crowd-shipping—an environmentally friendly option that may, however, reduce delivery efficiency (Perboli et al., 2022); - autonomous vehicles working in concert with cargo bikes and pedestrian couriers (J. Li et al., 2021); - public-transport– based crowd-shipping operated in parallel with delivery vans (Zhang et al., 2023); - mixed fleets of delivery robots and vans (Chen et al., 2021; Ostermeier et al., 2023); - cargo bikes paired with vans (Simoni et al., 2018); and - truck-and-drone systems (Huang et al., 2022). Liu et al. (2023) add that close coordination between trucks and drones is a key to scaling up drone use in the last mile, offsetting drones' inherent limits in payload capacity and range.

Also, several logistics service providers such as UPS and DHL use in their fleets a mix of transportation modes for freight delivery in urban areas to add more flexibility and have access to inner-city areas with restrictions on the type of vehicles and to allow a reduction of CO_2e emissions [100, 101]. From the documents analyzed in this study, Figure 4 presents a categorization of transportation modes based on size, energy source, and autonomy level. The colored circles indicate the frequency of use of each transportation mode in the literature, showing that trucks (ICVs), delivery vans, EVs, and UAVs are among the most studied options. However, there are research opportunities regarding the use of water vehicles, urban rail transportation, public transport, AVs, and motorcycles, which remain underexplored.

The comparative analysis between the two periods (2002–2012 versus 2013–2023) reveals a clear shift in transportation trends. During 2002–2012, fuel-based and driver-operated vehicles, such as trucks and delivery vans, were predominant in logistics studies. In contrast, the last

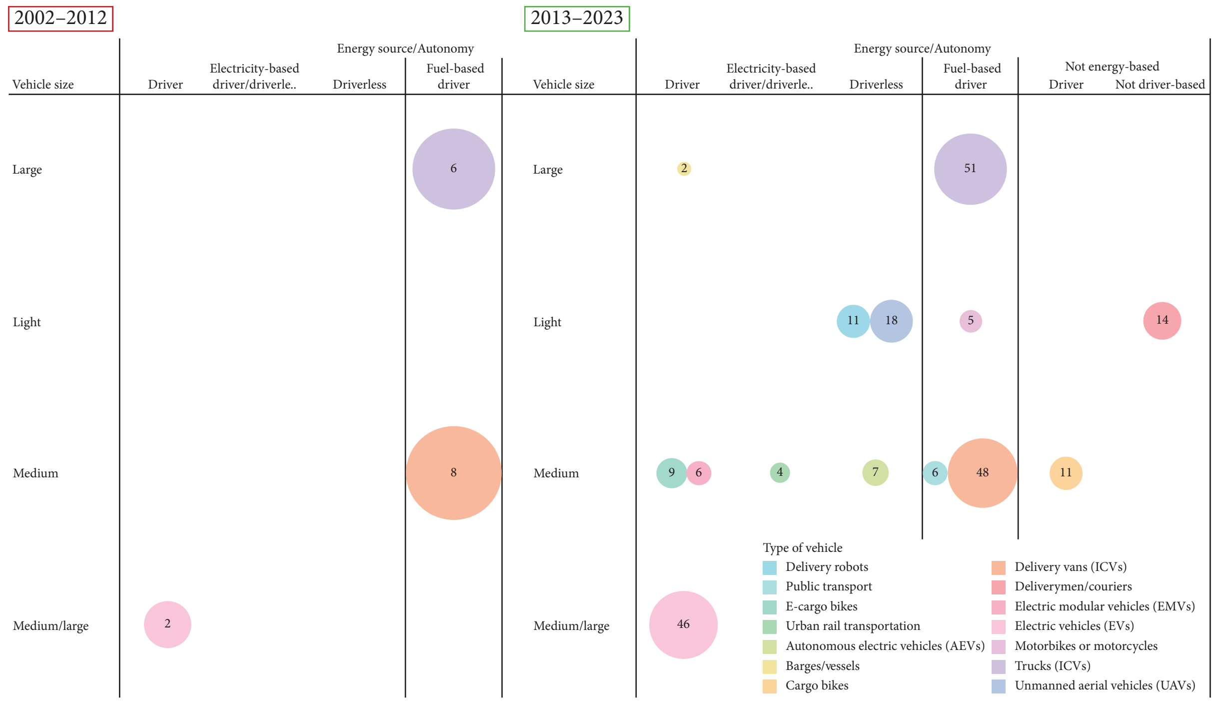

Figure 4: Evolution and classification of transportation modes by energy source, autonomy, and vehicle size: a comparative analysis (2002–2012 vs. 2013–2023).

decade (2013–2023) has seen the rise of more sustainable and autonomous technologies, including EVs, EMVs, e-cargo bikes, delivery robots, and UAVs. This evolution reflects the increasing emphasis on sustainability, automation, and efficiency in urban distribution networks. The difference in circle proportions reflects the rise in publications over time. While 2002–2012 research focused on fuel-based trucks, research between 2013 and 2023 shows growing interest in EVs, autonomous transportation modes, cargo bikes, and drones, highlighting the shift toward greener and more efficient last-mile solutions.

In addition, the selection of transportation modes in specific distribution networks depends on various factors, including the city's infrastructure, geographic characteristics (e.g., the feasibility of using ships or rail networks), public policies related to urban distribution, and access or parking restrictions in certain areas. Ensuring the optimal implementation of transportation modalities requires considering these elements to improve logistics efficiency, reduce congestion, and minimize environmental impact.

6. Performance Indicators

This section presents the findings about the performance indicators considered in the literature to measure the performance and the sustainability of the proposed scenarios. This section hence approaches to answering the last research question. Indicators to assess environmental, economic, logistics, and social issues as well as algorithmic performance are analyzed. An overview of the findings is presented in Table 4. For a detailed classification of the KPIs and their corresponding references, please refer to the Appendix and a detailed description is presented in Section 6.1.

Indicators are grouped not only by domain (economic, environmental, social, logistics, and algorithmic) but also by their underlying logic and contribution to the sustainability and operational efficiency of urban distribution systems. The selection and categorization of indicators are based on a functional coherence: each group aims to measure distinct but complementary aspects of the system. For example, while economic indicators reflect financial performance, environmental indicators assess ecological impact, and social indicators focus on human well-being and societal externalities. These dimensions, although studied separately, are inherently interconnected and support the multidimensional evaluation of the proposed scenarios.

Furthermore, measurement in this context implies more than listing indicators; it requires an understanding of how these indicators interact, complement, and occasionally contradict each other. For instance, minimizing costs may conflict with maximizing service level or reducing emissions. Therefore, the indicators selected for the analysis should be understood as part of a broader evaluative framework where trade-offs are inevitable and must be transparently addressed.

6.1. Economic Indicators. As Pugliese et al. [62] mentioned in their study that "parcel delivery is the most expensive phase of distribution logistics" (p. 488). That is why, it is very important to minimize costs without compromising the efficiency and productivity of the system. This group of

Table 4: Classification of performance indicators by algorithm performance, environmental, economic, logistics, and social.

Category	Subcategory	Indicator
Algorithm performance		CPU time, computing time, elapsed time, runtime, running time, mean ideal distance, diversification metric, gap (%), standard deviation, and computing efficiency
Environmental	Emissions	CO_2e emissions, GHG, CO, NH_3, N_2O, NOx, PM2.5, noise emissions, noise levels, and fine particle emissions
	Use of resources	Energy/fuel/electric power consumption, electric consumption, number of times EV is charged, total number of battery swaps requested, cyclist energy, battery energy, and recharged energy
Economic		Fuel consumption costs, emissions costs, carbon emissions cost, total fleet operation costs, fixed usage cost of the vehicle, maintenance costs, total distribution costs, operating costs, fixed costs, investment costs, charging costs, battery swapping costs, profits, cost improvement, cost savings, variable cost due to delays, penalty cost, cost of time window violation, total costs, drivers salary costs, customer service costs, electric delivery cost, penalty costs, facility operation costs, and load-distance costs
Logistics	Productivity	Route length, total distance traveled, real distance, travel distance, distance, net mileage, travel time, distribution time, delivery time, number of parcels/packages, parcels per route, total weight of parcels, covered customer rate, total utilization rate of the recharging station, crew size, and demand fulfillment rate
	Infrastructure	Average number of chargers, number/amount of stops, number of customers, delivery points per route, number of stations, number of shared charging stations, number of used covering locations, number of served nodes, number of intermediate depots/satellites, and number of split deliveries
	Time	Waiting/delay times, charging times, battery swapping times, EV queuing times for charging, route duration, tour time, and total working time
	Transportation modes	Fleet size, number of vehicles, road traffic flows, traffic flows on water, average utilization, vehicle loading rate, average load, number of subfleets, and number of routes/paths
Social		Disturbance, risk of accidents, average delay per customer, service delay, delays, congestion index, traffic congestion, service level, land use, occupation of the area, and customer satisfaction

indicators comprises all fixed and variable costs related to the operations of the distribution network under study. Also, it includes investment, maintenance, and operational costs of vehicle fleets, as well as vehicle fuel and energy costs, penalty costs due to delays and lost sales, savings, profits, and workers' salaries. It is important to highlight that some works consider energy costs and workers' salaries as environmental or social metrics, respectively, but we decided to keep these as economic indicators since they translate to a monetary impact for the enterprises.

It is important to note that when the indicator is the total cost, it is pertinent to be aware that it is necessary to examine which costs are being included in this indicator, since it will depend on the configuration of the distribution network, the type of decisions involved, as well as additional characteristics particular to each case study. This indicator is very useful to determine the total cost incurred by operating under such a scenario; nevertheless, a comparison between the total cost indicator of one study versus the total cost of another is not reliable if the same items were not considered in both studies. For instance, in the context of EVs, Fan [102] defined the total distribution cost as the costs of EVs' dispatch, vehicle travel, customer service, and charging operations; while for Wang et al. [113], total costs involve the opening costs and handling costs for parcel lockers and the routing costs of the EVs.

6.2. Environmental Indicators. The purpose of these indicators is to evaluate the impact on the environment of the emissions generated by the transportation modes. This impact depends significantly on the type of energy source used to power vehicles. For this reason, we can classify the environmental indicators into two subgroups. The first refers to the emission types, while the second is related to the use of resources (energy) required by the transportation modes to perform delivery activities. These are explained next.

6.2.1. Emissions. According to the authors in [29], green logistics is becoming extremely important due to its impact on the environment and society. Its aim is the minimization of carbon emissions because conventional transportation systems are unsustainable and can also affect the population's respiratory health and worsen the problem of climate change [36]. For instance, the CO_2e emissions that are generated by the fleet of vehicles comprise CO_2, methane (CH_4), and nitrous oxide (N_2O) emissions [92]. Such indicators are very important to measure the sustainability of the urban distribution networks proposed in the literature.

6.2.2. Use of Resources. This group consists of indicators to control the use of resources such as electric power, diesel, fuel, or gasoline. In addition, the study conducted by Fontaine [82] considers indicators such as cyclist's energy and the energy of the batteries that power some transportation modes such as EVs, delivery robots, UAVs, and e-cargo bikes. Moreover, the authors in [89] estimated the energy consumption based on the multiplication of the distance traveled by the vehicle and the kilowatt-hour (kWh) per mile or kilometer.

6.3. Social Indicators. Delivery activities do have a high influence on society. Social impacts of urban distribution systems can be measured in terms of the risk of accidents, the occupation of public space (land use), the congestion index or traffic congestion, or the disturbance due to noise and congestion [81]. Since customer satisfaction in last-mile distribution is mainly evaluated based on delivery time windows, the service level can be evaluated. Hence, late delivery causes customer dissatisfaction, so indicators such as average delay per customer and customer satisfaction are very important in these cases. Cao et al. [120] explained that in the VRP time windows, "the time of obtaining service for a certain customer is in the determined range, which means that the service level is good (1), otherwise it is bad (0). However, in real-life problems, time windows can be violated" (p. 2511) for various practical considerations.

Economic and productivity indicators are the most studied in the literature, while there is a lack of research that includes social indicators to assess the distribution networks. This represents a research perspective since this is a very important pillar of sustainability. The adoption and evaluation of indicators that are related to city inhabitants, drivers, delivery persons, or similar directly or indirectly related to urban distribution are key elements of a sustainable urban logistics system.

6.4. Logistics Indicators. The traditional dimensions of sustainability consider only economic, social, and environmental indicators. However, in urban transport systems, there are indicators related to logistics elements that may not perfectly suit the definition of the three previous categories. So, following the rationale proposed in [212], we also considered this fourth category, named "logistics indicators," to characterize some performance metrics that are related to the performance of the delivery operations (productivity and time), the vehicles' fleet size, and the infrastructure used to execute these activities. This is explained next.

6.4.1. Productivity. Measures of productivity of urban distribution networks are crucial for making the right strategic or planning decisions. This kind of indicator allows an overall assessment of the distribution network performance and, if there are scenarios, it is also a way to compare them to check their feasibility and possible implementation. For instance, the route length is the number of kilometers that a vehicle must travel to complete a route or tour. To analyze the global results of a distribution network, the total distance traveled is very useful. If the study is time-dependent, the total travel time, also called delivery time or distribution time, is the total time that all the fleet requires to deliver all parcels in a workday. In addition, the number of parcels delivered is a good indicator to measure the productivity of the distribution network. Finally, the covered customer rate allows decision-makers to know how many customers a route is serving and can be calculated as the number of served customers divided by the total number of customers [120]. Moreover, it is important to know how many delivery persons (crew size) are needed to perform the delivery activities.

6.4.2. Infrastructure. Since urban distribution systems require a well-designed infrastructure to operate efficiently and to serve as many customers as possible, it is important to define performance indicators that also allow the quantification and measurement of different aspects such as the number of recharging stations [213] or the number of depots or distribution centers. This group also comprises the number of customers or nodes served and the number of times the vehicles must stop delivering parcels.

6.4.3. Time. These are all indicators that are related to time-dependent parameters. Within this subgroup, there are indicators such as route duration, which is the time that a transportation mode takes to complete a route or tour. Besides, waiting times are also considered [191]. In addition, in the context of an electric VRP, Xu et al. [43] defined that the total working time includes travel time, charging time, waiting time, and service time.

6.4.4. Transportation Modes. This includes all indicators related to the use and the features of the vehicle fleet, such as fleet size, traffic flows (i.e., amount of vehicles/ships per day) [95, 214], vehicle loading rate, the number of routes per day, and the number of subfleets (e.g., number of truck versus number of drones) [76].

6.5. Algorithm Performance. Measuring the performance of algorithms that allow researchers and decision-makers to find solutions to routing problems is crucial since reaching optimality can be very computationally expensive due to the nondeterministic polynomial (NP)–hardness of these routing problems. Therefore, indicators such as central processing unit (CPU) time are considered in several papers. Finding a good solution, preferably the optimum, in a short computational time is highly desirable. Also, the gap between lower bounds and upper bounds is usually applied to compare solution approaches. Sarbijan and Behnamian [111] introduced indicators such as mean ideal distance and the diversification metric. In multiobjective optimization problems, the former computes the average distance of the Pareto solutions from the ideal point. The lower this metric, the better the algorithm's performance. The latter is the distance between the initial and final solutions of the Pareto solutions. The larger its value, the more efficient the algorithm.

6.6. Interrelation Among Indicators. Performance indicators, although organized by distinct categories, rarely operate in isolation. On the contrary, they often interact and may even conflict with one another, reflecting the inherent complexity of evaluating urban distribution systems. Understanding these interrelations is essential not only for analysis but also for effective decision-making and policy design.

First, economic and environmental indicators frequently present trade-offs. For instance, minimizing operational costs may involve using conventional vehicles instead of electric ones, which in turn increases carbon emissions. Similarly, reducing delivery times (a logistics indicator) may require a larger fleet size or more frequent trips, thus raising both economic costs and environmental impacts. These examples highlight how optimizing one dimension can produce unintended consequences in another, emphasizing the need for integrated assessment.

Second, social indicators such as service level or noise disturbance are deeply affected by logistics and economic decisions. A higher service level often demands narrower delivery windows and increased vehicle frequency, which can escalate congestion and emissions in urban areas. In addition, the occupation of public space (e.g., for loading/unloading or placing lockers) might enhance efficiency but simultaneously reduce urban livability, posing a societal dilemma between efficiency and quality of life.

Moreover, logistics indicators serve as mediators between operational objectives and sustainability outcomes. Route length, fleet size, and travel time are not only efficiency metrics but also directly influence fuel consumption, emissions, and service reliability. As such, they often act as bridging variables across economic, environmental, and social domains.

In this context, it becomes essential to interpret indicators within a multiobjective framework, where trade-offs are made explicit and can be evaluated according to stakeholder priorities. Multicriteria decision analysis (MCDA) and Pareto optimization approaches are particularly useful in addressing this complexity, as they allow decision-makers to evaluate multiple competing objectives simultaneously rather than seeking a single optimal solution.

7. Conclusions and Research Perspectives

This paper presented a comprehensive systematic literature review on urban logistics and routing problems, focusing on three main aspects: problem modeling and solution approaches, multimodal transportation, and performance indicators to assess the sustainability and efficiency of the delivery networks. The review highlights significant trends and findings from diverse case studies and identifies key methodological and technological trends shaping the field.

Recent methodological trends show a shift toward more advances and integrated approaches. While the VRP, particularly with time windows, remains the dominant modeling approach, recent studies increasingly incorporate green routing, delivery synchronization, and multimodal delivery components. Stochastic modeling remains underexplored, representing an opportunity for future research to better address real-world uncertainties such as fluctuating traffic conditions and dynamic delivery demands. Hybrid optimization techniques, including matheuristics, simheuristics, and machine learning–assisted heuristics, are becoming prominent as data availability increases in smart city settings, allowing for more efficient and adaptive decision-making processes.

The review also revealed important patterns in case study applications and data usage. Approximately 50% of the reviewed studies utilized case studies to test urban logistics models under real-world conditions, primarily located in China, the United States, and Western Europe, with developing regions underrepresented. Data sources vary significantly, ranging from empirical fleet operations to simulation-based datasets, with key input variables including vehicle types, delivery demand, fuel/energy consumption, and congestion levels. The findings consistently indicate that multimodal transportation networks, integrating EVs, drones, cargo bikes, and public transport, offer significant reductions in CO_2e emissions, costs, and congestion compared to conventional delivery methods. However, barriers to large-scale implementation persist, including infrastructure limitations, regulatory restrictions, and cost concerns related to charging stations, battery life, and operational constraints.

Different technologies in terms of transportation modes have been applied to support urban logistics networks, some are more sustainable than others, or guarantee access to restricted areas in cities. An analysis in this regard was also made, highlighting some of the advantages and disadvantages of EVs, EMVs, AVs, delivery robots, UAVs, cargo bikes, and shared public transport systems. Moreover, the combination of different transportation modes is necessary to strengthen last-mile delivery, reducing costs, time, and emissions. In addition, to ensure the implementation of the most appropriate transportation modes, it is important to analyze multiple factors such as the infrastructure of the city under study, geographic characteristics (e.g. topography and use of ships or rail networks), the public policies related to urban distribution, the access to and/or limitations in parking, and the demand of the distribution network. The integration of multimodal transportation has gained momentum, driven by environmental concerns and urban accessibility challenges. Studies show that the combination of EVs, delivery robots, drones, and shared public transport systems can enhance delivery efficiency while reducing emissions.

In terms of performance evaluation, the study presented a detailed classification of indicators used to assess the three-dimensional sustainability of urban delivery systems. A classification of five important aspects was made as follows: (1) algorithm performance, (2) environmental indicators (emissions and use of resources such as energy or fuel), (3) economic indicators, (4) logistics indicators (productivity, infrastructure, time, and transportation modalities), and (5) social indicators. In addition, the study of performance indicators has evolved to include not only economic and environmental metrics but also social sustainability indicators, such as land use, congestion levels, and customer satisfaction. The growing inclusion of social metrics represents a positive trend toward holistic assessment, though more research is needed in this area.

In response to the review findings, this study offers the following detailed conclusions regarding urban logistics research:

- The most commonly studied problem is the time window VRP, often expanded with multimodal, synchronization, or sustainability objectives.
- About half of the papers use real-world case studies, but most are limited to developed countries.
- EVs, UAVs, delivery robots, and cargo bikes are frequently evaluated as alternative transport modes, especially in combination.
- The most frequently used performance indicators are emissions, cost, energy consumption, and delivery time.
- Less than 30% of the studies include social indicators, which indicates a research gap.

Several research gaps were identified: (1) the limited use of stochastic and uncertainty-based modeling, (2) the need to diversify the geographical focus of case studies, (3) the opportunity to enhance multimodal delivery through AI and real-time optimization, and (4) the underrepresentation of social impact evaluation in logistics models.

In summary, this review provides a structured overview of the current state of urban logistics research, uncovering clear patterns in methodological preferences, technological adoption, and the evaluation of sustainability practices. The predominance of optimization-based approaches, the growing interest in hybrid heuristics, the increasing attention in multimodal transport integration, and the gradual inclusion of social indicators highlight the ongoing evolution of the field, while also exposing gaps and inconsistencies in certain areas. The thematic classification developed in this paper enables a more coherent understanding of how modeling approaches, transport technologies, and sustainability metrics interact. This framework not only facilitates comparative analysis across studies but also supports practitioners and researchers in identifying practical strategies and unexplored research avenues aligned with the goals of sustainable urban logistics systems.

Appendix

Table A1: Types of problem and the solution approach for each study.

Reference	Problem	Exact methods	Simulation	Approx algorithm	Dynamic programming	Solution approach
[102]	TDOEVRP-HERS	×		×		MIP and a hybrid adaptive large neighborhood search (HALNS)
[80]	CVRP	×		×		Genetic algorithm (GA)
[98]	MVTR-RP			×		Tailored heuristic based on a novel neighborhood search: set improvement neighborhood search (SINS)
[60]	MPLP	×		×		Hybrid Q-learning network–based method (HQM)–reinforced learning
[60]	DVRPSPD and MDVRPSPDNF	×		×		MILP and simulated annealing (SA) with path encoding and acceleration strategies
[103]	COEVRP			×		GRASP with a restricted candidate list (RCL) and SA and variable neighborhood search (VNS)
[104]	ADVRP	×		×		MILP and two-phase metaheuristic (TPH)–greedy construction algorithm and hybrid VNS-SA
[105]	MDHOTDEVRP	×		×		MIP and two-stage hybrid ant colony algorithm (TSHACA)
[87]	SARP-D	×		×		MINP and ALNS
[106]	CMEVRPTW- SCS			×		Hybrid algorithm Gaussian mixture clustering and improved multiobjective GA with Tabu search (TS) (IMOGA-TS)
[107]	Multi-facility LRP	×				Exact approach based on partitioning of the research space of the solutions of a MILP model
[70]	DRP-T	×		×		Memetic algorithm with constructive heuristic (MACH), evolutionary-based structure
[108]	2E-VRP			×		Decomposition approach combining k-means clustering and the nearest neighbor (NN) search heuristic
[109]	2E-VRP			×		Decomposition approach combining k-means clustering and the NN search heuristic to obtain initial solutions, improvement phase of relocate local search (RLS)
[44]	EVRPTW	×		×		Two-phase approach: clustering phase and mathematical model and heuristic with intelligent dispatch scheme
[60]	2E-LDVRP-MV			×		Cluster-based artificial immune algorithm (C-AIA)
[89]	CVRP	×				
[92]	VRP			×		
[94]	MD-2E-JDLRP			×		Immune algorithm (IA) and improved nondominated sorting GA-II (IA-iNSGA-II)
[50]	GVRPTW			×		Improved ant colony optimization algorithm (IACO)
[110]	DRP-HD			×		Hyperlocal–drone neighbor search heuristic (H-DNSH)
[69]	LRP-PS	×				Branch-and-price algorithm
[111]	RTCFVRP			×		Multiobjective particle swarm optimization algorithm and VNS (MOPSO-VNS)
[112]	EVRPTW			×		A two-phase heuristic approach combining a two-layer genetic algorithm (TLGA) and simulated annealing (SA)–TLGALS
[61]	MTR–RP			×		Variable neighborhood search (VNS)
[72]	TDHRP-TDRTT			×		Iterative local search (ILS)
[113]	EVCSLRPTWRS			×		Hybrid algorithm combining the Gaussian mixture clustering algorithm (GMCA) with the improved nondominated sorting GA-II (INSGA-II)
[114]	EVRPTW-DC			×		Adaptive particle swarm optimization algorithm (PSO)
[115]	LRP			×		Variable neighborhood descent (VND)
[116]	CTSP-VEW			×	×	VNS
[117]	VRP-P	×		×		Modified C&W with three local search operators
[53]	VRP	×				
[118]	GVRPTW			×		Hybrid heuristic
[119]	LRP				×	Hybrid Lagrangian relaxation and alternating direction method of multipliers (LR-ADMM) decomposition approach
[120]	GVRP-PCPS			×		Memory-based VNS
[121]	TSP			×		GA

Table A1: Continued.

Reference	Problem	Exact methods	Simulation	Approx algorithm	Dynamic programming	Solution approach
[29]	CMVRPDCDTW			×		Improved k-medoids clustering algorithm and improved multiobjective particle swarm optimization based on the dynamic insertion strategy (IMOPSO-DIS) algorithm
[122]	MDVRPTW			×		Hybrid algorithm of genetically improved set-based particle swarm optimization (S-GAIPSO)
[36]	VRP			×		Adaptive large neighborhood search (ALNS)
[123]	2E-EVRP-TW			×		VNS
[124]	MD-CVRP-OSA			×		VNS
[96]	DSVRPTW		×	×		Monte Carlo simulation and LNS
[57]	2E-VRHPD			×		ALNS
[33]	2E-VRP			×		2D-K-means, nearest neighbor heuristic (NN) with local search operators
[35]	2E-VRP			×		Combination of K-means clustering and 2-opt algorithm
[125]	VRP			×		ALNS with an embedded local search
[74]	Mo-CRPTW-mD			×		Hybrid multiobjective genetic optimization approach with Pareto local search algorithm. Initial solution is greedy-based heuristic
[8]	TSP			×	×	Hybrid metaheuristic combining ILS and dynamic programming. Branch-and-cut approach
[82]	VRPLTT			×		ALNS
[83]	VRP		×	×		Concentration-immune algorithm particle swarm optimization (C-IAPSO)
[74]	Mo-CRPTW-mD			×		Hybrid multiobjective genetic optimization approach with Pareto local search algorithm. Initial solution is greedy-based heuristic
[8]	TSP			×	×	Hybrid metaheuristic combining ILS and dynamic programming. Branch-and-cut approach
[126]	VRPTW			×		A spreadsheed-based solution that employs a multistart algorithm based on the biased-randomized version of the NN heuristic
[1]	VRPTTW			×		Simulated annealing (SA) and linear programming
[32]	2E-VRP			×		Decomposition algorithm based on the NN heuristic
[127]	EVRPTW-RS-SMBS	×		×	×	Dynamic programming–based heuristic algorithm, exact nondominated paths identification (NDPI) algorithm, multigraph based DP (MG-DP) combined with DP-based intensified LNS (DP-ILNS) to obtain a MG-DP-ILNS
[82]	VRPLTT			×		ALNS
[43]	EVRPSPD-NL- LD	×		×		MILP and ALNS
[50]	GLRP-DO	×				Branch-and-price (B&P)
[128]	VRP	×				
[30]	2E-VRPSPD-LF	×				
[129]	OMDPDTW-VRP			×		NN heuristic
[76]	VRPD			×		ACO
[59]	CSPTW-TN-DO	×		×		ALNS
[130]	DS-EVRP		×			Safe reinforcement learning method
[131]	LRP			×		Combination of the progressive hedging algorithm (PHA) and GA. Nondominated sorting genetic algorithm II (NSGA-II) and epsilon constraints methods
[132]	LRP			×		ALNS using a greedy randomized adaptive search procedure
[133]	VRP			×		Modified ACO
[97]	2E-LRP	×		×		Enhanced hybrid C&W heuristic
[27]	VRPDO	×				Branch-and-price-and-cut algorithm
[134]	VRP			×		GA
[135]	VRPTW			×		Genetic simulated annealing algorithm (combination of GA and simulated annealing algorithm)
[136]	LRP	×		×		NN heuristic and C&W
[137]	TSP			×		Differential evolution algorithm, GA, particle swarm optimization algorithm (PSO), simulated annealing (SA), ACO, artificial fish swarm algorithm (AFSA)

Table A1: Continued.

Reference	Problem	Exact methods	Simulation	Approx algorithm	Dynamic programming	Solution approach
[84]	VRPTW			×		C&W combined with Tabu search (TS)
[138]	EVRP	×				Branch-and-price-and-cut algorithm
[19]	VRPTWDR			×		ALNS
[2]	3E-CLRP			×		Methods based on continuum approximation (CA), CA-based routing cost estimation (RCE)
[139]	HFVRP-TW			×		LNS
[140]	CVRP		×	×		Giant tour best cost crossover operator (GTBCX) employed in a nondominated sorting GA- II (NSGA-II)
[141]	2E-VRPTW-CO-OD			×		ALNS
[142]	SDOVRP			×		GA
[143]	VRP		×	×		Agent-based simulation and discrete event simulation, K-nearest neighbor
[86]	PVRP	×		×		ALNS
[39]	EVRPTW-PR	×		×		VNS, VND
[144]	2E-CMDPVRP			×		Hybrid heuristic with three-dimensional K-means clustering and improved reference point–based nondominated sorting GA-III (IR-NSGA-III)
[56]	VRP			×		Based on state-of-the-art machine learning methods in combination with reinforcement learning
[81]	2E-VRP			×		LNS embedded in a heuristic rectangle/cuboid splitting
[145]	VRPTW		×			
[146]	VRPHLB			×		ALNS and an iterative first-fit decreasing (IFFD) algorithm
[77]	2E-CVRP			×		Parallelized LNS
[21]	VRPTWDR			×		Two-stage matheuristic
[147]	VRPDO			×		LNS in which a set partitioning problem is periodically used to reassemble routes
[58]	2E-LRP			×		Hybrid immune algorithm (HIA) with the introduction of two improved steps (vaccination and immunization)
[148]	LRP			×		TS-modified C&W (TS-MCWS). Sweep-based iterative greedy adaptive LNS (SIGALNS)
[95]	2E-MD-CVRP			×		
[149]	ML-VRPLC			×		Iterative best response algorithm
[79]	LRP			×		C&W
[6]	VRP			×		Agile optimization algorithm that is the combination of biased-randomized heuristics, computer parallelization techniques, and IoT/5G technologies
[150]	2E-EVRPTW-PR	×		×		The fuzzy C-mean clustering
[151]	VRPTW			×		C&W
[7]	2E-LRP		×	×		Hard and soft optimization approach
[152]	LRP, VRPTW	×				
[153]	TSP		×	×		Lin–Kernighan heuristic
[154]	VRPTW			×		LNS
[155]	LRP	×		×		MIP-based heuristic
[23]	2E-VRP-CO			×		Tailored adaptive LNS
[156]	MDVRP			×		Biased-randomized techniques integrated with a VNS (BR-VNS)
[157]	2E-LRP			×		Hybrid GA
[158]	VRPMBTW				×	A block nonlinear Gauss–Seidel framework
[159]	VRP			×		ALNS
[160]	VRP-EL			×		SA
[161]	2E-CVRP		×	×		Simheuristic, Monte Carlo simulation, and a decomposition-based heuristic based on MILP
[5]	CVRP	×				Branch-and-cut algorithm
[162]	VRPTWMD	×	×			Robust optimization (RO) approach. A tailored branch-and-cut, branch-and-cut-and-price algorithm

Table A1: Continued.

Reference	Problem	Exact methods	Simulation	Approx algorithm	Dynamic programming	Solution approach
[37]	EVRP		×	×		Improved adaptive ant colony algorithm (IACA)
[49]	VRP			×		GA
[65]	EVRP		×	×		ACO
[163]	CMDVRPTWA			×		A hybrid heuristic: K-means, C&W, and an extended nondominated sorting GA-II (E-NSGA- II)
[164]	VRP			×		Hybrid robust-stochastic approach
[165]	AVUAVRP		×	×		Two-phase hybrid heuristic algorithm (TPH) based on TS and GA
[166]	2E-CVRP			×		MILP-based decomposition algorithm
[163]	MDPVRPPD			×		A hybrid heuristic algorithm incorporating a 3D clustering and an improved multiobjective particle swarm optimization (IMOPSO)
[66]	VRP			×		TOPSIS (multicriteria decision-making) and multiobjective MILP
[167]	VRPMS	×		×		GA
[62]	VRPD	×				
[168]	VRPTW			×		Mixed-integer linear programming (MILP)
[75]	VRP		×	×		Lin–Kernighan heuristic
[169]	VRP	×				Linear programming
[170]	2E-EVRPTW-BSS	×				
[171]	VRP		×	×		Deep reinforcement learning algorithm
[172]	SCC-VRP			×		Hybridized GRASPxILS metaheuristic
[47]	EVRP-ECU	×		×		Robust optimization techniques. Heuristics based on LNS
[38]	VRP			×		Evolutionary algorithms
[40]	VRPTW			×		VNS
[24]	2E-EVRP	×		×		LNS
[17]	2E-EVRP-BSS			×		Hybrid algorithm that combines a column generation and an ALNS (CG-ALNS)
[173]	2E-TVRP			×		Savings-based algorithm followed by the VNS
[54]	LRP					
[9]	EVRPST		×	×		Simheuristic, Monte Carlo simulation with a multistart metaheuristic and with biased-randomization techniques
[174]	VRPTW			×		Heuristic based on scatter search
[38]	VRPTW			×		Memetic algorithm
[91]	VRP	×				
[175]	VRP		×	×		LANTIME metaheuristic (comprises I1 insertion heuristic, parallel insertion heuristic PI, and TS)
[67]	TSP			×	×	Iterative two-step heuristic that uses dynamic programming
[78]	VRP			×		
[176]	TDVRPCHF			×		Simplified swarm optimization algorithm
[177]	VRP		×	×		C&W for initial solutions and then TS
[88]	HFVRP, VRPPC, 2E-VRP			×		ACO
[178]	VRPSPD-D2D			×		Two honey bee-inspired metaheuristics: artificial bee colony (ABC) at the first stage; bee colony optimization (BCO) at the second stage
[179]	VRP			×		Hybrid evolutionary VND, combining the GA with a VND
[20]	VRP			×		Continuous approximation (CA) model
[176]	2E-VRP			×		ALNS
[34]	2E-CLRP			×		Cooperative approximation heuristic algorithm (facility–location phase with a Lagrangian relaxation approach, routing phase by a granular TS)

Table A1: Continued.

Reference	Problem	Exact methods	Simulation	Approx algorithm	Dynamic programming	Solution approach
[93]	LRP			×		GA and memetic algorithm
[180]	VRPTW	×		×		Memetic algorithm
[181]	MD-TEVRP-DO			×		Hybrid multipopulation GA (HMPG)
[182]	MLRPSPD			×		TS
[183]	HOEVRP	×				Integer nonlinear programming (INLP)
[184]	VRP	×				MILP
[185]	2E-CVRP		×	×		GA-based approach
[186]	VRP			×		Algorithm based on SPEA2
[187]	G-MoMaVRP					Multiobjective shortest path evolutionary algorithm (MOSPEA)
[188]	VRP			×		Straight forward algorithm
[189]	VRP	×				
[190]	VRP			×		GA and memetic algorithm
[191]	2-ECVRP	×				
[192]	2E-TVRP			×		C&W improved with a local search phase
[41]	2E-CLRP			×		Two-stage optimization process
[28]	2E-MTVRP-SS			×		ALNS
[25]	MTVRPTWR			×		Hybrid GA
[193]	LRP	×		×		GALW matheuristic
[194]	MTVRPTWMD			×		GRASP
[52]	eM-FSMVRPTW			×		GA-based approach
[195]	CVRP			×		Dijkstra algorithm
[196]	FSMVRP	×				MILP model
[197]	FSMVRPTW-EV			×		C&W
[198]	EMVRP			×		Greedy, area, and GA
[199]	MZMTVRPTW			×		Decomposition approach Unified TS
[200]	MD-CVRP	×		×		Hierarchical heuristic
[18]	VRP			×		Memetic algorithm
[201]	VRPTW			×		GA
[202]	G-FSMVRP		×	×		GA
[203]	LRP	×				MILP
[204]	VRP			×		Multiobjective differential evolutionary algorithm (MODE)
[205]	VRPTW	×		×		The Dantzig–Wolfe decomposition (or column generation)
[22]	VRP			×		Adaptive neural network trained by a SA algorithm
[206]	LRP		×	×		Monte Carlo simulation to perform a biased randomization clustering
[42]	FSMVRP			×		Sequential insertion heuristic
[207]	VRP		×			Multiagent simulation
[208]	VRP, TSP			×		Insertion heuristic with the time-dependent NN heuristic (TDNN) called TDIHDP
[16]	RVRP			×		Heuristic based on an iterative construction and improvement algorithm
[209]	VRP			×		Iterated nearest insertion (INI) and GA
[210]	TDVRP			×		TDVRP algorithm
[211]	VRP			×		GA
[31]	VRPTW			×		IMPACT algorithm

Table A2: Classification of performance indicators for each document analyzed.

Article	Environmental			Logistics			Social	Economic	Algorithm performance
	Use of resources	Emissions	Transportation modes	Infrastructure	Productivity	Time			
[33]	×	×	×		×		×	×	
[35]								×	
[96]		×			×			×	
[57]					×			×	
[32]		×	×		×				
[43]			×			×			×
[29]								×	×
[128]		×						×	
[30]	×				×			×	×
[76]			×	×	×			×	×
[59]				×			×	×	
[130]	×		×						
[131]		×						×	
[125]								×	
[126]			×			×		×	
[1]						×		×	
[127]	×	×	×		×			×	
[83]								×	
[74]							×	×	
[8]					×				×
[82]	×		×		×				
[132]			×		×			×	
[133]		×						×	
[97]								×	
[27]								×	
[134]			×	×	×				
[135]								×	
[136]					×				
[137]					×				×
[84]					×			×	×
[138]								×	
[19]						×			
[2]								×	
[139]					×			×	
[140]					×				
[141]								×	
[142]			×					×	
[216]			×					×	
[143]		×	×	×	×				
[86]								×	×
[39]			×			×			×
[216]			×			×		×	×
[56]						×			
[81]		×					×	×	
[145]		×			×	×			
[146]			×	×				×	
[77]		×						×	
[19]						×			
[79]		×	×	×		×			
[147]								×	
[58]		×						×	
[148]								×	
[95]		×	×					×	
[149]									×
[6]		×	×		×	×			
[150]								×	
[217]								×	
[151]								×	
[7]					×				

Table A2: Continued.

Article	Environmental			Logistics			Social	Economic	Algorithm performance
	Use of resources	Emissions	Transportation modes	Infrastructure	Productivity	Time			
[152]					×			×	
[153]		×					×	×	
[155]								×	
[23]			×	×	×			×	
[156]		×			×	×	×		
[157]			×		×			×	
[158]								×	×
[159]	×		×					×	×
[160]	×	×	×		×				
[161]			×		×				×
[5]						×			×
[162]								×	×
[64]									
[37]	×		×		×	×		×	×
[49]			×		×	×			
[65]		×			×		×	×	
[218]			×					×	
[164]	×	×	×						
[165]								×	
[166]			×	×	×				
[163]			×			×		×	
[66]		×						×	
[167]								×	
[62]		×	×					×	
[168]			×		×			×	
[75]	×		×			×			
[169]	×	×	×					×	
[170]	×		×					×	
[171]					×				
[172]								×	×
[47]	×		×					×	
[38]			×		×				
[24]								×	
[17]		×						×	×
[173]	×		×					×	×
[54]								×	
[9]					×				
[174]			×		×				
[40]			×		×				
[91]								×	
[175]			×			×			
[67]				×					×
[178]			×					×	
[179]			×		×			×	
[78]									
[176]					×				×
[177]					×		×		
[88]		×						×	
[20]		×						×	
[219]			×	×				×	
[34]		×	×		×			×	
[93]								×	
[213]					×			×	×
[181]			×					×	
[182]							×	×	
[183]								×	×
[184]					×			×	
[185]								×	×

Table A2: Continued.

Article	Environmental			Logistics			Social	Economic	Algorithm performance
	Use of resources	Emissions	Transportation modes	Infrastructure	Productivity	Time			
[186]		×	×			×		×	
[187]	×	×	×		×	×			
[188]			×		×			×	
[189]		×	×	×	×		×	×	
[190]					×			×	
[191]		×				×		×	
[192]		×	×						×
[41]			×	×				×	
[28]				×				×	×
[25]					×				×
[193]								×	×
[194]			×		×	×		×	
[52]			×		×				
[195]			×		×			×	
[196]		×			×			×	
[197]	×		×		×			×	×
[198]	×		×		×				
[200]	×	×	×						
[18]			×	×					
[201]			×	×					
[202]	×	×	×	×					
[203]			×						
[204]		×	×						
[205]	×	×	×						
[22]	×		×						
[206]				×					
[42]	×			×					
[207]	×			×					
[208]			×		×				
[16]		×		×					
[209]			×	×					
[210]		×	×						
[220]		×	×						
[211]		×	×						
[31]				×					

Data Availability Statement

All analysis data concerning the articles in this systematic literature review are available in the Appendix.

Disclosure

The work of the first author was carried out under a postgraduate scholarship awarded by Universidad de La Sabana, Colombia, and Kedge Business School, France.

Conflicts of Interest

The authors declare no conflicts of interest.

Funding

This work was also supported by research grants INGPHD-52-2022 and INGPHD-10-2019 from Universidad de La Sabana, Colombia.

References

[1] J. D. Cortes and Y. Suzuki, "Last-Mile Delivery Efficiency: En Route Transloading in the Parcel Delivery Industry," *International Journal of Production Research* 60, no. 9 (2022): 2983–3000, https://doi.org/10.1080/00207543.2021.1907628.

[2] M. Janjevic, D. Merchán, and M. Winkenbach, "Designing Multi-Tier, Multi-Service-Level, and Multi-Modal Last-Mile Distribution Networks for Omni-Channel Operations," *European Journal of Operational Research* 294, no. 3 (2021): 1059–1077, https://doi.org/10.1016/j.ejor.2020.08.043.

[3] L. Dablanc, "City Distribution, A Key Element of the Urban Economy: Guidelines for Practitioners," in *City Distribution and Urban Freight Transport* (Edward Elgar Publishing, 2011), 13–36, https://doi.org/10.4337/9780857932754.00007.

[4] J. Schoemaker, J. Allen, M. Huschebeck, and J. Monigl, *Quantification of Urban Freight Transport Effects I* (BESTUFS Project, 2006).

[5] H. Tahami, G. Rabadi, and M. Haouari, "Exact Approaches for Routing Capacitated Electric Vehicles," *Transportation Research Part E: Logistics and Transportation Review* 144 (2020): 102126, https://doi.org/10.1016/j.tre.2020.102126.

[6] L. Calvet, E. J. Alvarez-Palau, M. Viu, C. Castillo, P. Copado, and A. A. Juan, "Promoting Sustainable and Intelligent Freight Transportation Systems in the Barcelona Metropolitan Area," *Transportation Research Procedia* 58 (2021): 408–415, https://doi.org/10.1016/j.trpro.2021.11.055.

[7] T. Letnik, M. Mencinger, and I. Peruš, "Flexible Assignment of Loading Bays for Efficient Vehicle Routing in Urban Last Mile Delivery," *Sustainability* 12, no. 18 (2020): 7500, https://doi.org/10.3390/su12187500.

[8] R. G. Mbiadou Saleu, L. Deroussi, D. Feillet, N. Grangeon, and A. Quilliot, "The Parallel Drone Scheduling Problem With Multiple Drones and Vehicles," *European Journal of Operational Research* 300, no. 2 (2022): 571–589, https://doi.org/10.1016/j.ejor.2021.08.014.

[9] L. Reyes-Rubiano, D. Ferone, A. A. Juan, and J. Faulin, "A Simheuristic for Routing Electric Vehicles With Limited Driving Ranges and Stochastic Travel Times," *Statistics and Operations Research Transactions* 43, no. 1 (2019): 3–24, https://doi.org/10.2436/20.8080.02.77.

[10] S. M. Patella, G. Grazieschi, V. Gatta, E. Marcucci, and S. Carrese, "The Adoption of Green Vehicles in Last Mile Logistics: A Systematic Review," *Sustainability* 13, no. 1 (2020): 6–29, https://doi.org/10.3390/su13010006.

[11] V. Silva, A. Amaral, and T. Fontes, "Sustainable Urban Last-Mile Logistics: A Systematic Literature Review," *Sustainability* 15, no. 3 (2023): 2285, https://doi.org/10.3390/su15032285.

[12] P. Golinska-Dawson and K. Sethanan, "Sustainable Urban Freight for Energy-Efficient Smart Cities—Systematic Literature Review," *Energies* 16, no. 6 (2023): 2617, https://doi.org/10.3390/en16062617.

[13] D. Cook, C. Mulrow, and B. Haynes, "Systematic Reviews: Synthesis of Best Evidence for Clinical Decisions," *Annals of Internal Medicine* 126, no. 5 (1997): 376–380, https://doi.org/10.7326/0003-4819-126-5-199703010-00006.

[14] D. Tranfield, D. Denyer, and P. Smart, "Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review," *British Journal of Management* 14, no. 3 (2003): 207–222, https://doi.org/10.1111/1467-8551.00375.

[15] S. M. Hosseini-Motlagh, M. Farahmand, and M. Nouri-Harzvili, "A Multi-Path Traffic-Covering Pollution Routing Model With Simultaneous Pickup and Delivery," *Computers & Industrial Engineering* 173 (2022): 108644, https://doi.org/10.1016/j.cie.2022.108644.

[16] R. G. Conrad and M. A. Figliozzi, "The Recharging Vehicle Routing Problem," in *Proceedings of the 2011 Industrial Engineering Research Conference*, ed. T. Doolen and E. Van Aken (2011), 1–8.

[17] W. Jie, J. Yang, M. Zhang, and Y. Huang, "The Two-Echelon Capacitated Electric Vehicle Routing Problem With Battery Swapping Stations: Formulation and Efficient Methodology," *European Journal of Operational Research* 272, no. 3 (2019): 879–904, https://doi.org/10.1016/j.ejor.2018.07.002.

[18] D. Cattaruzza, N. Absi, D. Feillet, and T. Vidal, "A Memetic Algorithm for the Multi Trip Vehicle Routing Problem," *European Journal of Operational Research* 236, no. 3 (2014): 833–848, https://doi.org/10.1016/j.ejor.2013.06.012.

[19] C. Chen, E. Demir, and Y. Huang, "An Adaptive Large Neighborhood Search Heuristic for the Vehicle Routing Problem With Time Windows and Delivery Robots," *European Journal of Operational Research* 294, no. 3 (2021): 1164–1180, https://doi.org/10.1016/j.ejor.2021.02.027.

[20] W. Qi, L. Li, S. Liu, and Z.-J. M. Shen, "Shared Mobility for Last-Mile Delivery: Design, Operational Prescriptions and Environmental Impact," *Manufacturing & Service Operations Management* 20, no. 4 (2018): 737–751, https://doi.org/10.1287/msom.2017.0683.

[21] C. Chen, E. Demir, Y. Huang, and R. Qiu, "The Adoption of Self-Driving Delivery Robots in Last Mile Logistics," *Transportation Research Part E: Logistics and Transportation Review* 146 (2021): 102214, https://doi.org/10.1016/j.tre.2020.102214.

[22] G. Ćirović, D. Pamučar, and D. Božanić, "Green Logistic Vehicle Routing Problem: Routing Light Delivery Vehicles in Urban Areas Using a Neuro-Fuzzy Model," *Expert Systems with Applications* 41, no. 9 (2014): 4245–4258, https://doi.org/10.1016/j.eswa.2014.01.005.

[23] D. L. J. U. Enthoven, B. Jargalsaikhan, K. J. Roodbergen, M. A. uit het Broek, and A. H. Schrotenboer, "The Two-Echelon Vehicle Routing Problem With Covering Options: City Logistics with Cargo Bikes and Parcel Lockers," *Computers & Operations Research* 118 (2020): 104919, https://doi.org/10.1016/j.cor.2020.104919.

[24] U. Breunig, R. Baldacci, R. F. Hartl, and T. Vidal, "The Electric Two-Echelon Vehicle Routing Problem," *Computers & Operations Research* 103 (2019): 198–210, https://doi.org/10.1016/j.cor.2018.11.005.

[25] D. Cattaruzza, N. Absi, and D. Feillet, "The Multi-Trip Vehicle Routing Problem With Time Windows and Release Dates," *Transportation Science* 50, no. 2 (2016): 676–693, https://doi.org/10.1287/trsc.2015.0608.

[26] R. Cuda, G. Guastaroba, and M. G. Speranza, "A Survey on Two-Echelon Routing Problems," *Computers & Operations Research* 55 (2015): 185–199, https://doi.org/10.1016/j.cor.2014.06.008.

[27] C. Tilk, K. Olkis, and S. Irnich, "The Last-Mile Vehicle Routing Problem With Delivery Options," *Spectrum* 43, no. 4 (2021): 877–904, https://doi.org/10.1007/s00291-021-00633-0.

[28] P. Grangier, M. Gendreau, F. Lehuédé, and L. M. Rousseau, "An Adaptive Large Neighborhood Search for the Two-Echelon Multiple-Trip Vehicle Routing Problem With Satellite Synchronization," *European Journal of Operational Research* 254, no. 1 (2016): 80–91, https://doi.org/10.1016/j.ejor.2016.03.040.

[29] M. Wang, L. Miao, and C. Zhang, "Green Location-Routing Problem With Delivery Options," in *Springer Proceedings in Business and Economics* (2022), 215–228, https://doi.org/10.1007/978-3-030-75166-1_14.

[30] E. A. Yildiz and F. Altiparmak, "A Study on Green Two Echelon Vehicle Routing Problem With Simultaneous Pickup and Delivery," in *Lecture Notes on Data Engineering and Communications Technologies*, 144 (Springer Science and Business Media Deutschland GmbH, 2022), 778–793, https://doi.org/10.1007/978-3-031-10388-9_56.

[31] G. Ioannou, M. N. Kritikos, and G. P. Prastacos, "Map-Route: A GIS-Based Decision Support System for Intra-city Vehicle Routing With Time Windows," *Journal of the Operational Research Society* 53, no. 8 (2002): 842–854, https://doi.org/10.1057/palgrave.jors.2601375.

[32] A. Ramirez-Villamil, A. Jaegler, and J. R. Montoya-Torres, "Sustainable Local Pickup and Delivery: The Case of Paris," *Research in Transportation Business & Management* 45 (2022): 100692, https://doi.org/10.1016/j.rtbm.2021.100692.

[33] A. Ramírez-Villamil, J. R. Montoya-Torres, A. Jaegler, J. M. Cuevas-Torres, D. L. Cortés-Murcia, and

W. J. Guerrero, “Integrating Clustering Methodologies and Routing Optimization Algorithms for Last-Mile Parcel Delivery,” in *International Conference on Computational Logistics* (2022), 275–287, https://doi.org/10.1007/978-3-031-16579-5_19.

[34] Q. Zhao, W. Wang, and R. De Souza, “A Heterogeneous Fleet Two-Echelon Capacitated Location-Routing Model for Joint Delivery Arising in City Logistics,” *International Journal of Production Research* 56, no. 15 (2018): 5062–5080, https://doi.org/10.1080/00207543.2017.1401235.

[35] M. K. Zuhanda, S. Suwilo, O. S. Sitompul, and Mardiningsih, “A Combination K-Means Clustering and 2-opt Algorithm for Solving the Two Echelon E-Commerce Logistic Distribution,” *Logforum* 18, no. 2 (2022): 213–225, https://doi.org/10.17270/J.LOG.2022.734.

[36] S. S. Malladi, J. M. Christensen, D. Ramírez, A. Larsen, and D. Pacino, “Stochastic Fleet Mix Optimization: Evaluating Electromobility in Urban Logistics,” *Transportation Research Part E: Logistics and Transportation Review* 158 (2022): 102554, https://doi.org/10.1016/j.tre.2021.102554.

[37] Z. Zhao, X. Li, and X. Zhou, “Distribution Route Optimization for Electric Vehicles in Urban Cold Chain Logistics for Fresh Products Under Time-Varying Traffic Conditions,” *Mathematical Problems in Engineering* 2020 (2020): 1–17, https://doi.org/10.1155/2020/9864935.

[38] D. Rezgui, W. Aggoune-Mtalaa, H. Bouziri, and J. Chaouachi-Siala, “An Enhanced Evolutionary Method for Routing a Fleet of Electric Modular Vehicles,” in *2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)* (2019), 1–9, https://doi.org/10.1109/MTITS.2019.8883377.

[39] U. Bac and M. Erdem, “Optimization of Electric Vehicle Recharge Schedule and Routing Problem With Time Windows and Partial Recharge: A Comparative Study for an Urban Logistics Fleet,” *Sustainable Cities and Society* 70 (2021): 102883, https://doi.org/10.1016/j.scs.2021.102883.

[40] D. Rezgui, J. C. Siala, W. A. Mtalaa, and H. Bouziri, “A Memetic Algorithm for Fleet Size and Mix Vehicle Routing Problems With Electric Modular Vehicles,” *International Journal of Intelligent Enterprise* 6, no. 2/3/4 (2019): 138–156, https://doi.org/10.1504/IJIE.2019.101123.

[41] M. Winkenbach, P. R. Kleindorfer, and S. Spinler, “Enabling Urban Logistics Services at La Poste Through Multi-Echelon Location-Routing,” *Transportation Science* 50, no. 2 (2016): 520–540, https://doi.org/10.1287/trsc.2015.0624.

[42] J. van Duin, L. Tavasszy, and H. Quak, “Towards E(lectric)-Urban Freight: First Promising Steps in the Electric Vehicle Revolution,” *European Transport* 54 (2013): 1–19, https://www.researchgate.net/publication/268509461.

[43] W. Xu, C. Zhang, M. Cheng, and Y. Huang, “Electric Vehicle Routing Problem With Simultaneous Pickup and Delivery: Mathematical Modeling and Adaptive Large Neighborhood Search Heuristic Method,” *Energies* 15, no. 23 (2022): 9222, https://doi.org/10.3390/en15239222.

[44] N. Ding, M. Li, and J. Hao, “A Two-phase Approach to Routing a Mixed Fleet With Intermediate Depots,” *Mathematics* 11, no. 8 (2023): 1924, https://doi.org/10.3390/math11081924.

[45] United States Environmental Protection Agency, *Electric Vehicle Myths* (EPA, 2025), https://www.epa.gov/greenvehicles/electric-vehicle-myths#Myth6.

[46] Pulse Energy, “Understanding Factors that Affect Electric Vehicle (EV) Range,” (2024), https://pulseenergy.io/blog/ev-range-factors?form=MG0AV3.

[47] S. Pelletier, O. Jabali, and G. Laporte, “The Electric Vehicle Routing Problem With Energy Consumption Uncertainty,” *Transportation Research Part B: Methodological* 126 (2019): 225–255, https://doi.org/10.1016/j.trb.2019.06.006.

[48] A. Muñoz-Villamizar, C. L. Quintero-Araújo, J. R. Montoya-Torres, and J. Faulin, “Short-and Mid-Term Evaluation of the Use of Electric Vehicles in Urban Freight Transport Collaborative Networks: A Case Study,” *International Journal of Logistics Research and Applications* 22, no. 3 (2019): 229–252.

[49] B. Queck and H. C. Lau, “A Genetic Algorithm to Minimise the Number of Vehicles in the Electric Vehicle Routing Problem,” in *Lecture Notes in Computer Science* (2020), 200–214, https://doi.org/10.1007/978-3-030-59747-4_13.

[50] M. Wang, C. Zhang, M. G. H. Bell, and L. Miao, “A Branch-and-Price Algorithm for Location-Routing Problems With Pick-Up Stations in the Last-Mile Distribution System,” *European Journal of Operational Research* 303, no. 3 (2022): 1258–1276, https://doi.org/10.1016/j.ejor.2022.03.058.

[51] F. Lijun, L. Changshi, and W. Zhang, “Half-Open Time-Dependent Multi-Depot Electric Vehicle Routing Problem Considering Battery Recharging and Swapping,” *International Journal of Industrial Engineering Computations* 14, no. 1 (2023): 129–146, https://doi.org/10.5267/j.ijiec.2022.9.002.

[52] D. Rezgui, W. Aggoune-Mtalaa, and H. Bouziri, “Towards the Electrification of Urban Freight Delivery Using Modular Vehicles,” in *2015 IEEE International Conference on Service Operations And Logistics, And Informatics (SOLI)* (2015), 154–159, https://doi.org/10.1109/SOLI.2015.7367611.

[53] G. Bray and D. Cebon, “Selection of Vehicle Size and Extent of Multi-Drop Deliveries for Autonomous Goods Vehicles: An Assessment of Potential for Change,” *Transportation Research Part E: Logistics and Transportation Review* 164 (2022): 102806, https://doi.org/10.1016/j.tre.2022.102806.

[54] M.-O. Sonneberg, M. Leyerer, A. Kleinschmidt, F. Knigge, and M. H. Breitner, “Autonomous Unmanned Ground Vehicles for Urban Logistics: Optimization of Last Mile Delivery Operations,” in *.Proceedings of the 52nd Hawaii International Conference on System Sciences* (2019).

[55] R. Zarif, C. Starks, A. Sussman, and A. Kukreja, “Autonomous Trucks Lead the Way,” (2021), https://www2.deloitte.com/Us/En/Insights/Focus/Future-of-Mobility/Autonomous-Trucks-Lead-the-Way.Html.

[56] F. P. Nolte, N. Wilken, and C. Bartelt, “Rendezvous Delivery: Utilizing Autonomous Electric Vehicles to Improve the Efficiency of Last Mile Parcel Delivery in Urban Areas,” in *2021 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops)* (2021), 148–153, https://doi.org/10.1109/PerComWorkshops51409.2021.9430987.

[57] S. Yu, J. Puchinger, and S. Sun, “Van-Based Robot Hybrid Pickup and Delivery Routing Problem,” *European Journal of Operational Research* 298, no. 3 (2022): 894–914, https://doi.org/10.1016/j.ejor.2021.06.009.

[58] D. Liu, Z. Deng, W. Zhang, Y. Wang, and E. I. Kaisar, “Design of Sustainable Urban Electronic Grocery Distribution Network,” *Alexandria Engineering Journal* 60, no. 1 (2021): 145–157, https://doi.org/10.1016/j.aej.2020.06.051.

[59] V. F. Yu, P. Jodiawan, and A. A. N. P. Redi, “Crowd-Shipping Problem With Time Windows, Transshipment Nodes, and Delivery Options,” *Transportation Research Part E: Logistics and Transportation Review* 157 (2022): 102545, https://doi.org/10.1016/j.tre.2021.102545.

[60] D. Liu, H. Yang, X. Mao, V. Antonoglou, and E. I. Kaisar, "New Mobility-Assist E-Grocery Delivery Network: A Load-Dependent Two-Echelon Vehicle Routing Problem With Mixed Vehicles," *Transportation Research Record: Journal of the Transportation Research Board* 2677, no. 1 (2023): 294–310, https://doi.org/10.1177/03611981221099277.

[61] A. Heimfarth, M. Ostermeier, and A. Hübner, "A Mixed Truck and Robot Delivery Approach for the Daily Supply of Customers," *European Journal of Operational Research* 303, no. 1 (2022): 401–421, https://doi.org/10.1016/j.ejor.2022.02.028.

[62] L. D. P. Pugliese, F. Guerriero, and G. Macrina, "Using Drones for Parcels Delivery Process," *Procedia Manufacturing* 42 (2020): 488–497, https://doi.org/10.1016/j.promfg.2020.02.043.

[63] D. Rojas Viloria, E. L. Solano-Charris, A. Muñoz-Villamizar, and J. R. Montoya-Torres, "Unmanned Aerial Vehicles/Drones in Vehicle Routing Problems: A Literature Review," *International Transactions in Operational Research* 28, no. 4 (2021): 1626–1657.

[64] A. Thibbotuwawa, G. Bocewicz, P. Nielsen, and Z. Banaszak, "Unmanned Aerial Vehicle Routing Problems: A Literature Review," *Applied Sciences* 10, no. 13 (2020): 4504, https://doi.org/10.3390/app10134504.

[65] T. Li, W.-Y. Yang, Q. Shen, and H. Liu, "Research on Vehicle Routing Problem in Urban Distribution Using Unmanned Aerial Vehicles," in *CICTP 2020: Transportation Evolution Impacting Future Mobility* (2020), 4903–4914, https://doi.org/10.1061/9780784483053.408.

[66] H. G. Resat, "Design and Analysis of Novel Hybrid Multi-Objective Optimization Approach for Data-Driven Sustainable Delivery Systems," *IEEE Access* 8 (2020): 90280–90293, https://doi.org/10.1109/ACCESS.2020.2994186.

[67] R. G. M. Saleu, L. Deroussi, D. Feillet, N. Grangeon, and A. Quilliot, "An Iterative Two-Step Heuristic for the Parallel Drone Scheduling Traveling Salesman Problem," *Networks* 72, no. 4 (2018): 459–474, https://doi.org/10.1002/net.21846.

[68] S. M. Shavarani, M. G. Nejad, F. Rismanchian, and G. Izbirak, "Application of Hierarchical Facility Location Problem for Optimization of a Drone Delivery System: A Case Study of Amazon Prime Air in the City of San Francisco," *The International Journal of Advanced Manufacturing Technology* 95, no. 9–12 (2018): 3141–3153, https://doi.org/10.1007/s00170-017-1363-1.

[69] Y. Wang, Z. Wang, X. Hu, G. Xue, and X. Guan, "Truck–Drone Hybrid Routing Problem With Time-Dependent Road Travel Time," *Transportation Research Part C: Emerging Technologies* 144 (2022): 103901, https://doi.org/10.1016/j.trc.2022.103901.

[70] H. Y. Jeong and S. Lee, "Drone Routing Problem With Truck: Optimization and Quantitative Analysis," *Expert Systems With Applications* 227 (2023): 120260, https://doi.org/10.1016/j.eswa.2023.120260.

[71] Y. Liu, Q. Ye, J. Escribano-Macias, Y. Feng, E. Candela, and P. Angeloudis, "Route Planning for Last-Mile Deliveries Using Mobile Parcel Lockers: A Hybrid Q-Learning Network Approach," *Transportation Research Part E: Logistics and Transportation Review* 177 (2023): 103234, https://doi.org/10.1016/j.tre.2023.103234.

[72] Y. Wang, J. Zhe, X. Wang, Y. Sun, and H. Wang, "Collaborative Multidepot Vehicle Routing Problem With Dynamic Customer Demands and Time Windows," *Sustainability* 14, no. 11 (2022): 6709, https://doi.org/10.3390/su14116709.

[73] Forbes, (A Matter of Months Amazon's New Delivery Drone Will Start Shipping Packages, 2019), https://www.forbes.com/sites/jilliandonfro/2019/06/05/amazon-new-delivery-drone-remars-warehouse-robots-alexa-prediction/#7c0c6f7d145f.

[74] Q. Luo, G. Wu, B. Ji, L. Wang, and P. N. Suganthan, "Hybrid Multi-Objective Optimization Approach With Pareto Local Search for Collaborative Truck-Drone Routing Problems Considering Flexible Time Windows," *IEEE Transactions on Intelligent Transportation Systems* 23, no. 8 (2022): 13011–13025, https://doi.org/10.1109/TITS.2021.3119080.

[75] M. Patchou, B. Sliwa, and C. Wietfeld, "Unmanned Aerial Vehicles in Logistics: Efficiency Gains and Communication Performance of Hybrid Combinations of Ground and Aerial Vehicles," in *2019 IEEE Vehicular Networking Conference (VNC)* (2019), 1–8, https://doi.org/10.1109/VNC48660.2019.9062772.

[76] S. H. Huang, Y. H. Huang, C. A. Blazquez, and C. Y. Chen, "Solving the Vehicle Routing Problem With Drone for Delivery Services Using an Ant Colony Optimization Algorithm," *Advanced Engineering Informatics* 51 (2022): 101536, https://doi.org/10.1016/j.aei.2022.101536.

[77] F. Mühlbauer and P. Fontaine, "A Parallelised Large Neighbourhood Search Heuristic for the Asymmetric Two-Echelon Vehicle Routing Problem With Swap Containers for Cargo-Bicycles," *European Journal of Operational Research* 289, no. 2 (2021): 742–757, https://doi.org/10.1016/j.ejor.2020.07.034.

[78] A. Anderluh, V. C. Hemmelmayr, and P. C. Nolz, "Sustainable Logistics With Cargo Bikes-Methods and Applications," in *Sustainable Transportation and Smart Logistics: Decision-Making Models and Solutions* (Elsevier, 2018), 207–232, https://doi.org/10.1016/B978-0-12-814242-4.00008-9.

[79] V. Cempírek, O. Stopka, P. Meško, I. Dočkalíková, and L. Tvrdoň, "Design of Distribution Centre Location for Small E-Shop Consignments Using the Clark-Wright Method," *Transportation Research Procedia* 53 (2021): 224–233, https://doi.org/10.1016/j.trpro.2021.02.029.

[80] E. Papaioannou, C. Iliopoulou, and K. Kepaptsoglou, "Last-Mile Logistics Network Design Under E-Cargo Bikes," *Future Transportation* 3, no. 2 (2023): 403–416, https://doi.org/10.3390/futuretransp3020024.

[81] A. Anderluh, P. C. Nolz, V. C. Hemmelmayr, and T. G. Crainic, "Multi-Objective Optimization of a Two-Echelon Vehicle Routing Problem With Vehicle Synchronization and Grey Zone Customers Arising in Urban Logistics," *European Journal of Operational Research* 289, no. 3 (2021): 940–958, https://doi.org/10.1016/j.ejor.2019.07.049.

[82] P. Fontaine, "The Vehicle Routing Problem With Load-dependent Travel Times for Cargo Bicycles," *European Journal of Operational Research* 300, no. 3 (2022): 1005–1016, https://doi.org/10.1016/j.ejor.2021.09.009.

[83] K. Leng and S. Li, "Distribution Path Optimization for Intelligent Logistics Vehicles of Urban Rail Transportation Using VRP Optimization Model," *IEEE Transactions on Intelligent Transportation Systems* 23, no. 2 (2022): 1661–1669, https://doi.org/10.1109/TITS.2021.3105105.

[84] C. Zheng, Y. Gu, J. Shen, and M. Du, "Urban Logistics Delivery Route Planning Based on a Single Metro Line," *IEEE Access* 9 (2021): 50819–50830, https://doi.org/10.1109/ACCESS.2021.3069415.

[85] T. Wang, H. Shao, X. Qu, and J. Eliasson, "Consolidating Passenger and Freight Transportation in an Urban–Rural Transit System," *Fundamental Research* 4, no. 6 (2024): 1603–1612.

[86] Z. Chang, H. Chen, F. Yalaoui, and B. Dai, "Adaptive Large Neighborhood Search Algorithm for Route Planning of Freight Buses With Pickup and Delivery," *Journal of Industrial and Management Optimization* 17, no. 4 (2021): 1771–1793, https://doi.org/10.3934/jimo.2020045.

[87] R. Cheng, Y. Jiang, O. Anker Nielsen, and D. Pisinger, "An Adaptive Large Neighborhood Search Metaheuristic for a Passenger and Parcel Share-A-Ride Problem With Drones," *Transportation Research Part C: Emerging Technologies* 153 (2023): 104203, https://doi.org/10.1016/j.trc.2023.104203.

[88] Y. He and Z. Yang, "Parcel Delivery by Collaborative Use of Truck Fleets and Bus-Transit Vehicles," *Transportation Journal* 57, no. 4 (2018): 399–428, https://doi.org/10.5325/transportationj.57.4.0399.

[89] T. Cokyasar, A. Subramanyam, J. Larson, M. Stinson, and O. Sahin, "Time-Constrained Capacitated Vehicle Routing Problem in Urban E-Commerce Delivery," *Transportation Research Record: Journal of the Transportation Research Board* 2677, no. 2 (2023): 190–203, https://doi.org/10.1177/03611981221124592.

[90] X. Sun, W. Hu, X. Xue, and J. Dong, "Multi-Objective Optimization Model for Planning Metro-Based Underground Logistics System Network: Nanjing Case Study," *Journal of Industrial and Management Optimization* 19, no. 1 (2023): 170–196, https://doi.org/10.3934/jimo.2021179.

[91] Z. Chang, H. Chen, and F. Yalaoui, "Modeling and Evaluation of a City Logistics System With Freight Buses," in *Proceedings of the 8th International Conference on Operations Research and Enterprise Systems* (2019), 292–298, https://doi.org/10.5220/0007362502920298.

[92] M. Zhang, L. Cheah, and C. Courcoubetis, "Exploring the Potential Impact of Crowdshipping Using Public Transport in Singapore," *Transportation Research Record: Journal of the Transportation Research Board* 2677, no. 2 (2023): 173–189, https://doi.org/10.1177/03611981221123246.

[93] M. D. Simoni, P. Bujanovic, S. D. Boyles, and E. Kutanoglu, "Urban Consolidation Solutions for Parcel Delivery Considering Location, Fleet and Route Choice," *Case Studies on Transport Policy* 6, no. 1 (2018): 112–124, https://doi.org/10.1016/j.cstp.2017.11.002.

[94] J. Du, X. Wang, X. Wu, F. Zhou, and L. Zhou, "Multi-Objective Optimization for Two-Echelon Joint Delivery Location Routing Problem Considering Carbon Emission Under Online Shopping," *Transportation Letters* 15, no. 8 (2023): 907–925, https://doi.org/10.1080/19427867.2022.2112857.

[95] B. Alewijnse and A. Hübl, "Minimising Total Costs of a Two-Echelon Multi-Depot Capacitated Vehicle Routing Problem (2E-MD-CVRP) That Describes the Utilisation of the Amsterdam City Canal Network for Last Mile Parcel Delivery," *IFIP Advances in Information and Communication Technology* 633 (2021): 603–612, https://doi.org/10.1007/978-3-030-85910-7_64.

[96] G. Perboli, M. Rosano, and Q. Wei, "A Simulation-Optimization Approach for the Management of the On-Demand Parcel Delivery in Sharing Economy," *IEEE Transactions on Intelligent Transportation Systems* 23, no. 8 (2022): 10570–10582, https://doi.org/10.1109/TITS.2021.3094851.

[97] J. Li, H. Ensafian, M. G. H. Bell, and D. G. Geers, "Deploying Autonomous Mobile Lockers in a Two-Echelon Parcel Operation," *Transportation Research Part C: Emerging Technologies* 128 (2021): 103155, https://doi.org/10.1016/j.trc.2021.103155.

[98] M. Ostermeier, A. Heimfarth, and A. Hübner, "The Multi-Vehicle Truck-and-Robot Routing Problem for Last-Mile Delivery," *European Journal of Operational Research* 310, no. 2 (2023): 680–697, https://doi.org/10.1016/j.ejor.2023.03.031.

[99] Y.-Q. Liu, J. Han, Y. Zhang, Y. Li, and T. Jiang, "Multivisit Drone-Vehicle Routing Problem With Simultaneous Pickup and Delivery Considering No-Fly Zones," *Discrete Dynamics in Nature and Society* 2023 (2023): 1–21, https://doi.org/10.1155/2023/1183764.

[100] DHL, "2022 Annual Report," (2022), https://www.dpdhl.com/en/sustainability/our-approach/sustainability-reports.html.

[101] UPS, "Global Reporting Initiative," (2022), https://about.ups.com/content/dam/upsstories/images/social-impact/reporting/2022-reporting/2022%20UPS%20GRI%20Report.pdf.

[102] L. Fan, "A Hybrid Adaptive Large Neighborhood Search for Time-dependent Open Electric Vehicle Routing Problem With Hybrid Energy Replenishment Strategies," *PLoS One* 18, no. 9 (2023): e0291473, https://doi.org/10.1371/journal.pone.0291473.

[103] T. Stamadianos, N. A. Kyriakakis, M. Marinaki, and Y. Marinakis, "A Hybrid Simulated Annealing and Variable Neighborhood Search Algorithm for the Close-Open Electric Vehicle Routing Problem," *Annals of Mathematics and Artificial Intelligence* (2023): https://doi.org/10.1007/s10472-023-09858-x.

[104] N. Moradi, İ. Sadati, and B. Çatay, "Last Mile Delivery Routing Problem Using Autonomous Electric Vehicles," *Computers & Industrial Engineering* 184 (2023): 109552, https://doi.org/10.1016/j.cie.2023.109552.

[105] L. Fan, "A Two-Stage Hybrid Ant Colony Algorithm for Multi-Depot Half-Open Time-dependent Electric Vehicle Routing Problem," *Complex & Intelligent Systems* 10, no. 2 (2023): 2107–2128, https://doi.org/10.1007/s40747-023-01259-1.

[106] H. Wang, M. Li, Z. Wang, et al., "Heterogeneous Fleets for Green Vehicle Routing Problem With Traffic Restrictions," *IEEE Transactions on Intelligent Transportation Systems* 24, no. 8 (2023): 8667–8676, https://doi.org/10.1109/TITS.2022.3197424.

[107] A. Sciomachen and M. Truvolo, "An Exact Approach for Selecting Pickup-Delivery Stations in Urban Areas to Reduce Distribution Emission Costs," *Mathematics* 11, no. 8 (2023): 1876, https://doi.org/10.3390/math11081876.

[108] A. Ramirez-Villamil, J. R. Montoya-Torres, and A. Jaegler, "Urban Logistics through River: A Two-Echelon Distribution Model," *Applied Sciences* 13, no. 12 (2023): 7259, https://doi.org/10.3390/app13127259.

[109] A. Ramírez-Villamil, J. R. Montoya-Torres, A. Jaegler, and J. M. Cuevas-Torres, "Reconfiguration of Last-Mile Supply Chain for Parcel Delivery Using Machine Learning and Routing Optimization," *Computers & Industrial Engineering* 184 (2023): 109604, https://doi.org/10.1016/j.cie.2023.109604.

[110] M. Pachayappan and B. Sundarakani, "Drone Delivery Logistics Model for On-Demand Hyperlocal Market," *International Journal of Logistics Research and Applications* 26, no. 12 (2023): 1728–1760, https://doi.org/10.1080/13675567.2022.2107189.

[111] M. Salehi Sarbijan and J. Behnamian, "Real-Time Collaborative Feeder Vehicle Routing Problem With Flexible Time Windows," *Swarm and Evolutionary Computation* 75 (2022): 101201, https://doi.org/10.1016/j.swevo.2022.101201.

[112] J. Li, Z. Liu, and X. Wang, "Public Charging Station Localization and Route Planning of Electric Vehicles

Considering the Operational Strategy: A Bi-level Optimizing Approach," *Sustainable Cities and Society* 87 (2022): 104153, https://doi.org/10.1016/j.scs.2022.104153.

[113] Y. Wang, J. Zhou, Y. Sun, X. Wang, J. Zhe, and H. Wang, "Electric Vehicle Charging Station Location-Routing Problem With Time Windows and Resource Sharing," *Sustainability* 14, no. 18 (2022): 11681, https://doi.org/10.3390/su141811681.

[114] N. Ding, J. Yang, Z. Han, and J. Hao, "Electric-Vehicle Routing Planning Based on the Law of Electric Energy Consumption," *Mathematics* 10, no. 17 (2022): 3099, https://doi.org/10.3390/math10173099.

[115] M. E. Bruni and S. Khodaparasti, "A Variable Neighborhood Descent Matheuristic for the Drone Routing Problem with Beehives Sharing," *Sustainability* 14, no. 16 (2022): 9978, https://doi.org/10.3390/su14169978.

[116] X. Meng, J. Li, M. Zhou, and X. Dai, "A Dynamic Colored Traveling Salesman Problem with Varying Edge Weights," *IEEE Transactions on Intelligent Transportation Systems* 23, no. 8 (2022): 13549–13558, https://doi.org/10.1109/TITS.2021.3125721.

[117] L. Wehbi, T. Bektaş, and Ç. Iris, "Optimising Vehicle and On-Foot Porter Routing in Urban Logistics," *Transportation Research Part D: Transport and Environment* 109 (2022): 103371, https://doi.org/10.1016/j.trd.2022.103371.

[118] Y. Niu, Z. Yang, R. Wen, J. Xiao, and S. Zhang, "Solving the Green Open Vehicle Routing Problem Using a Membrane-Inspired Hybrid Algorithm," *Sustainability* 14, no. 14 (2022): 8661, https://doi.org/10.3390/su14148661.

[119] S. Yang, L. Ning, L. Tong, and P. Shang, "Integrated Electric Logistics Vehicle Recharging Station Location–Routing Problem With Mixed Backhauls and Recharging Strategies," *Transportation Research Part C: Emerging Technologies* 140 (2022): 103695, https://doi.org/10.1016/j.trc.2022.103695.

[120] L. Cao, C. Ye, R. Cheng, and Z. k. Wang, "Memory-Based Variable Neighborhood Search for Green Vehicle Routing Problem With Passing-By Drivers: A Comprehensive Perspective," *Complex & Intelligent Systems* 8, no. 3 (2022): 2507–2525, https://doi.org/10.1007/s40747-022-00661-5.

[121] I. C. Lin, T. H. Lin, and S. H. Chang, "A Decision System for Routing Problems and Rescheduling Issues Using Unmanned Aerial Vehicles," *Applied Sciences* 12, no. 12 (2022): 6140, https://doi.org/10.3390/app12126140.

[122] M. Zhang and B. Yang, "Swarm Robots Cooperative and Persistent Distribution Modeling and Optimization Based on the Smart Community Logistics Service Framework," *Algorithms* 15, no. 2 (2022): 39, https://doi.org/10.3390/a15020039.

[123] M. A. Akbay, C. B. Kalayci, C. Blum, and O. Polat, "Variable Neighborhood Search for the Two-Echelon Electric Vehicle Routing Problem With Time Windows," *Applied Sciences* 12, no. 3 (2022): 1014, https://doi.org/10.3390/app12031014.

[124] Y. Tao, C. Lin, and L. Wei, "Metaheuristics for a Large-Scale Vehicle Routing Problem of Same-Day Delivery in E-Commerce Logistics System," *Journal of Advanced Transportation* 2022 (2022): 1–15, https://doi.org/10.1155/2022/8253175.

[125] C. Friedrich and R. Elbert, "Adaptive Large Neighborhood Search for Vehicle Routing Problems With Transshipment Facilities Arising in City Logistics," *Computers & Operations Research* 137 (2022): 105491, https://doi.org/10.1016/j.cor.2021.105491.

[126] J. G. Sanabria-Rey, E. L. Solano-Charris, C. A. Vega-Mejía, and C. L. Quintero-Araújo, "Solving Last-Mile Deliveries for Dairy Products Using a Biased Randomization-Based Spreadsheet. A Case Study," *American Journal of Mathematical and Management Sciences* 41, no. 1 (2022): 51–69, https://doi.org/10.1080/01966324.2021.1910886.

[127] R. Raeesi and K. G. Zografos, "Coordinated Routing of Electric Commercial Vehicles With Intra-Route Recharging and En-Route Battery Swapping," *European Journal of Operational Research* 301, no. 1 (2022): 82–109, https://doi.org/10.1016/j.ejor.2021.09.037.

[128] K. Fan, Y. Tian, L. Yao, and R. Qiu, "Urban Logistics Vehicle Routing Problem Under the Carbon Trading Market," in *Lecture Notes on Data Engineering and Communications Technologies*, 145 (Springer Science and Business Media Deutschland GmbH, 2022), 340–352, https://doi.org/10.1007/978-3-031-10385-8_25.

[129] M. Karaoğlu and G. Kara, "Two-Stage Heuristic Algorithm Proposal for Urban E-Commerce Deliveries," *Asia Pacific Journal of Operational Research* 39, no. 03 (2022): https://doi.org/10.1142/S0217595921500342.

[130] R. Basso, B. Kulcsár, I. Sanchez-Diaz, and X. Qu, "Dynamic Stochastic Electric Vehicle Routing With Safe Reinforcement Learning," *Transportation Research Part E: Logistics and Transportation Review* 157 (2022): 102496, https://doi.org/10.1016/j.tre.2021.102496.

[131] K. Alamatsaz, A. Ahmadi, and S. M. J. Mirzapour Al-e-hashem, "A Multiobjective Model for the Green Capacitated Location-Routing Problem Considering Drivers' Satisfaction and Time Window With Uncertain Demand," *Environmental Science and Pollution Research* 29, no. 4 (2022): 5052–5071, https://doi.org/10.1007/s11356-021-15907-x.

[132] I. Azcuy, N. Agatz, and R. Giesen, "Designing Integrated Urban Delivery Systems Using Public Transport," *Transportation Research Part E: Logistics and Transportation Review* 156 (2021): 102525, https://doi.org/10.1016/j.tre.2021.102525.

[133] R. Juvvala and S. P. Sarmah, "Evaluation of Policy Options Supporting Electric Vehicles in City Logistics: A Case Study," *Sustainable Cities and Society* 74 (2021): 103209, https://doi.org/10.1016/j.scs.2021.103209.

[134] X. Yuan, J. Zhu, Y. Li, H. Huang, and M. Wu, "An Enhanced Genetic Algorithm for Unmanned Aerial Vehicle Logistics Scheduling," *IET Communications* 15, no. 10 (2021): 1402–1411, https://doi.org/10.1049/cmu2.12106.

[135] X. Hou, Y. Ji, W. Liu, J. Han, J. Zhang, and C. He, "Research on Logistics Distribution Routing Problem of Unmanned Vehicles Based on Genetic Simulated Annealing Algorithm," in *2021 2nd International Conference on Artificial Intelligence and Information Systems* (2021), 1–7, https://doi.org/10.1145/3469213.3470241.

[136] T. Settey, J. Gnap, D. Beňová, M. Pavličko, and O. Blažeková, "The Growth of E-Commerce Due to COVID-19 and the Need for Urban Logistics Centers Using Electric Vehicles: Bratislava Case Study," *Sustainability* 13, no. 10 (2021): 5357, https://doi.org/10.3390/su13105357.

[137] M. Soumya Krishnan and E. R. Vimina, "E-Commerce Logistic Route Optimization Deciphered Through Meta-Heuristic Algorithms by Solving TSP," *Lecture Notes in Electrical Engineering* 733 (2021): 419–436, https://doi.org/10.1007/978-981-33-4909-4_32.

[138] A. M. Florio, N. Absi, and D. Feillet, "Routing Electric Vehicles on Congested Street Networks," *Transportation Science* 55, no. 1 (2021): 238–256, https://doi.org/10.1287/TRSC.2020.1004.

[139] T. Ayu and Nahry, "Optimizing the Heterogeneous Fleet Vehicle Routing Problem With Time Window on Urban Last Mile Delivery," *IOP Conference Series: Earth and Environmental Science* 830, no. 1 (2021): 012100, https://doi.org/10.1088/1755-1315/830/1/012100.

[140] M. Sajid, J. Singh, R. A. Haidri, et al., "A Novel Algorithm for Capacitated Vehicle Routing Problem for Smart Cities," *Symmetry* 13, no. 10 (2021): 1923, https://doi.org/10.3390/sym13101923.

[141] V. F. Yu, P. Jodiawan, M. L. Hou, and A. Gunawan, "Design of a Two-Echelon Freight Distribution System in Last-Mile Logistics Considering Covering Locations and Occasional Drivers," *Transportation Research Part E: Logistics and Transportation Review* 154 (2021): 102461, https://doi.org/10.1016/j.tre.2021.102461.

[142] T. Rattanamanee, "A Genetic Algorithm for Split Delivery Open Vehicle Routing Problem With Physical Workload Consideration," in *2021 Research, Invention, and Innovation Congress: Innovation Electricals and Electronics (RI2C)*, 2021, 1–4, https://doi.org/10.1109/RI2C51727.2021.9559769.

[143] M. Trott, N. F. Baur, M. Auf der Landwehr, J. Rieck, and C. von Viebahn, "Evaluating the Role of Commercial Parking Bays for Urban Stakeholders on Last-Mile Deliveries–A Consideration of Various Sustainability Aspects," *Journal of Cleaner Production* 312 (2021): 127462, https://doi.org/10.1016/j.jclepro.2021.127462.

[144] Y. Wang, Q. Li, X. Guan, M. Xu, Y. Liu, and H. Wang, "Two-Echelon Collaborative Multi-Depot Multi-Period Vehicle Routing Problem," *Expert Systems with Applications* 167 (2021): 114201, https://doi.org/10.1016/j.eswa.2020.114201.

[145] G. Napoli, S. Micari, G. Dispenza, L. Andaloro, V. Antonucci, and A. Polimeni, "Freight Distribution With Electric Vehicles: A Case Study in Sicily. RES, Infrastructures and Vehicle Routing," *Transport Engineer* 3 (2021): 100047, https://doi.org/10.1016/j.treng.2021.100047.

[146] J. Grabenschweiger, K. F. Doerner, R. F. Hartl, and M. W. P. Savelsbergh, "The Vehicle Routing Problem With Heterogeneous Locker Boxes," *Central European Journal of Operations Research* 29, no. 1 (2021): 113–142, https://doi.org/10.1007/s10100-020-00725-2.

[147] D. Dumez, F. Lehuédé, and O. Péton, "A Large Neighborhood Search Approach to the Vehicle Routing Problem With Delivery Options," *Transportation Research Part B: Methodological* 144 (2021): 103–132, https://doi.org/10.1016/j.trb.2020.11.012.

[148] A. Aghalari, D. E. Salamah, C. Marino, and M. Marufuzzaman, "Electric Vehicles Fast Charger Location-Routing Problem Under Ambient Temperature," *Annals of Operations Research* 324, no. 1-2 (2021): 721–759, https://doi.org/10.1007/s10479-021-04375-8.

[149] W. Joe and H. C. Lau, "Coordinating Multi-Party Vehicle Routing With Location Congestion via Iterative Best Response," in *Lecture Notes in Computer Science* (2021), 72–88, https://doi.org/10.1007/978-3-030-82254-5_5.

[150] L. Caggiani, A. Colovic, L. P. Prencipe, and M. Ottomanelli, "A Green Logistics Solution for Last-Mile Deliveries Considering E-Vans and E-Cargo Bikes," *Transportation Research Procedia* 52 (2021): 75–82, https://doi.org/10.1016/j.trpro.2021.01.010.

[151] C. Cao, X. Zhang, and Z. Guo, "Vehicle Routing Problem With Time Windows Arising in Urban Delivery," *Journal of Physics: Conference Series* 1626, no. 1 (2020): 012097, https://doi.org/10.1088/1742-6596/1626/1/012097.

[152] M. Leyerer, M. O. Sonneberg, M. Heumann, and M. H. Breitner, "Shortening the Last Mile in Urban Areas: Optimizing a Smart Logistics Concept for E-Grocery Operations," *Smart Cities* 3, no. 3 (2020): 585–603, https://doi.org/10.3390/smartcities3030031.

[153] A. Mor, M. G. Speranza, and J. M. Viegas, "Efficient Loading and Unloading Operations via a Booking System," *Transportation Research Part E: Logistics and Transportation Review* 141 (2020): 102040, https://doi.org/10.1016/j.tre.2020.102040.

[154] N. Rincon-Garcia, B. Waterson, T. J. Cherrett, and F. Salazar-Arrieta, "A Metaheuristic for the Time-Dependent Vehicle Routing Problem Considering Driving Hours Regulations–An Application in City Logistics," *Transportation Research Part A: Policy and Practice* 137 (2020): 429–446, https://doi.org/10.1016/j.tra.2018.10.033.

[155] J. Guerrero-Lorente, A. F. Gabor, and E. Ponce-Cueto, "Omnichannel Logistics Network Design With Integrated Customer Preference for Deliveries and Returns," *Computers & Industrial Engineering* 144 (2020): 106433, https://doi.org/10.1016/j.cie.2020.106433.

[156] L. Reyes-Rubiano, L. Calvet, A. A. Juan, J. Faulin, and L. Bové, "A Biased-Randomized Variable Neighborhood Search for Sustainable Multi-Depot Vehicle Routing Problems," *Journal of Heuristics* 26, no. 3 (2020): 401–422, https://doi.org/10.1007/s10732-018-9366-0.

[157] L. Yan, M. Grifoll, and P. Zheng, "Model and Algorithm of Two-Stage Distribution Location Routing With Hard Time Window for City Cold-Chain Logistics," *Applied Sciences* 10, no. 7 (2020): 2564, https://doi.org/10.3390/app10072564.

[158] S. Yang, L. Ning, P. Shang, and L. Carol) Tong, "Augmented Lagrangian Relaxation Approach for Logistics Vehicle Routing Problem With Mixed Backhauls and Time Windows," *Transportation Research Part E: Logistics and Transportation Review* 135 (2020): 101891, https://doi.org/10.1016/j.tre.2020.101891.

[159] R. Eshtehadi, E. Demir, and Y. Huang, "Solving the Vehicle Routing Problem With Multi-Compartment Vehicles for City Logistics," *Computers & Operations Research* 115 (2020): 104859, https://doi.org/10.1016/j.cor.2019.104859.

[160] K. Lee, J. Chae, B. Song, and D. Choi, "A Model for Sustainable Courier Services: Vehicle Routing with Exclusive Lanes," *Sustainability* 12, no. 3 (2020): 1077, https://doi.org/10.3390/su12031077.

[161] A. Ramírez-Villamil, J. R. Montoya-Torres, and A. Jaegler, "A Simheuristic for the Stochastic Two- Echelon Capacitated Vehicle Routing Problem," in *Winter Simulation Conference (WSC)* (2020), 1276–1287, https://doi.org/10.1109/WSC48552.2020.9383860.

[162] J. De La Vega, P. Munari, and R. Morabito, "Exact Approaches to the Robust Vehicle Routing Problem With Time Windows and Multiple Deliverymen," *Computers & Operations Research* 124 (2020): 105062, https://doi.org/10.1016/j.cor.2020.105062.

[163] Y. Wang, S. Zhang, X. Guan, et al., "Collaborative Multi-Depot Logistics Network Design With Time Window Assignment," *Expert Systems with Applications* 140 (2020): 112910, https://doi.org/10.1016/j.eswa.2019.112910.

[164] H. Shahmoradi-Moghadam, O. Samani, and J. Schönberger, "A Hybrid Robust-Stochastic Optimization Approach for the Noise Pollution Routing Problem With a Heterogeneous Vehicle Fleet," in *Lecture Notes in Logistics* (Springer Science and Business Media B.V, 2020), 124–134, https://doi.org/10.1007/978-3-030-44783-0_12.

[165] Y. Li, M. K. Lim, Y. Tan, S. Y. Lee, and M. L. Tseng, "Sharing Economy to Improve Routing for Urban Logistics Distribution Using Electric Vehicles," *Resources, Conservation and Recycling* 153 (2020): 104585, https://doi.org/10.1016/j.resconrec.2019.104585.

[166] A. Ramirez-Villamil, J. R. Montoya-Torres, and A. Jaegler, "Solving an Urban Goods Distribution Problem as the 2E-CVRP Model Using a MILP-Based Decomposition Approach," *Communications in Computer and Information Science* 1274 (2020): 153–164, https://doi.org/10.1007/978-3-030-61834-6_14.

[167] P. Deng, G. Amirjamshidi, and M. Roorda, "A Vehicle Routing Problem With Movement Synchronization of Drones, Sidewalk Robots, or Foot-Walkers," *Transportation Research Procedia* 46 (2020): 29–36, https://doi.org/10.1016/j.trpro.2020.03.160.

[168] A. Doğan, İ. Bilici, O. K. Demiral, M. S. Erdoğan, and Ö. Kabadurmuş, "Building a Decision Support System for Vehicle Routing Problem: A Real-Life Case Study From Turkey," in *Lecture Notes in Mechanical Engineering* (2020), 661–675, https://doi.org/10.1007/978-3-030-31343-2_57.

[169] A. K. Yudha and S. Starita, "Nighttime Vehicle Routing for Sustainable Urban Logistics," in *2019 17th International Conference on ICT and Knowledge Engineering (ICT&KE)* (2019), 1–6, https://doi.org/10.1109/ICTKE47035.2019.8966825.

[170] D. Wang, H. Zhou, and R. Feng, "A Two-Echelon Vehicle Routing Problem Involving Electric Vehicles With Time Windows," *Journal of Physics: Conference Series* 1324, no. 1 (2019): 012071, https://doi.org/10.1088/1742-6596/1324/1/012071.

[171] J. J. Q. Yu, W. Yu, and J. Gu, "Online Vehicle Routing With Neural Combinatorial Optimization and Deep Reinforcement Learning," *IEEE Transactions on Intelligent Transportation Systems* 20, no. 10 (2019): 3806–3817, https://doi.org/10.1109/TITS.2019.2909109.

[172] A. F. Torres-Ramos, N. Labadie, N. Velasco, and J. R. Montoya-Torres, "A Graspxils for the Shared Customer Collaboration Vehicle Routing Problem," *IFAC-PapersOnLine* 52, no. 13 (2019): 2608–2613, https://doi.org/10.1016/j.ifacol.2019.11.600.

[173] H. Li, M. Bai, and J. Chen, "The Two-Echelon Time-Constrained Vehicle Routing Problem With Second-Echelon Vehicle Fleet Mix," in *Proceedings of International Conference on Computers and Industrial Engineering* (2019), 1–23.

[174] B. Ulusoy and M. Turkay, "Route Balancing Vehicle Routing Problem with Time Windows for Urban Logistics," in *2019 International Symposium on Advanced Electrical and Communication Technologies (ISAECT)* (2019), 1–6, https://doi.org/10.1109/ISAECT47714.2019.9069732.

[175] P. O. Groß, J. F. Ehmke, and D. C. Mattfeld, "Cost-Efficient and Reliable City Logistics Vehicle Routing With Satellite Locations Under Travel Time Uncertainty," *Transportation Research Procedia* 37 (2019): 83–90, https://doi.org/10.1016/j.trpro.2018.12.169.

[176] C.-L. Huang, Y.-Z. Jiang, S.-Y. Tan, W.-C. Yeh, V. Y. Y. Chung, and C.-M. Lai, "Simplified Swarm Optimization for the Time Dependent Competitive Vehicle Routing Problem With Heterogeneous Fleet," in *2018 IEEE Congress on Evolutionary Computation (CEC)* (2018), 1–8, https://doi.org/10.1109/CEC.2018.8477687.

[177] P. Alvarez, I. Lerga, A. Serrano-Hernandez, and J. Faulin, "The Impact of Traffic Congestion When Optimising Delivery Routes in Real Time. A Case Study in Spain," *International Journal of Logistics Research and Applications* 21, no. 5 (2018): 529–541, https://doi.org/10.1080/13675567.2018.1457634.

[178] M. Marinelli, A. Colovic, and M. Dell'Orco, "A Novel Dynamic Programming Approach for Two-Echelon Capacitated Vehicle Routing Problem in City Logistics With Environmental Considerations," *Transportation Research Procedia* 30 (2018): 147–156, https://doi.org/10.1016/j.trpro.2018.09.017.

[179] D. Rezgui, H. Bouziri, W. Aggoune-Mtalaa, and J. C. Siala, "A Hybrid Evolutionary Algorithm for Smart Freight Delivery With Electric Modular Vehicles," in *2018 IEEE/ACS 15th International Conference on Computer Systems and Applications (AICCSA)* (2018), 1–8, https://doi.org/10.1109/AICCSA.2018.8612861.

[180] D. Rezgui, J. Chaouachi Siala, W. Aggoune-Mtalaa, and H. Bouziri, "Application of a Variable Neighborhood Search Algorithm to a Fleet Size and Mix Vehicle Routing Problem With Electric Modular Vehicles," *Computers & Industrial Engineering* 130 (2019): 537–550, https://doi.org/10.1016/j.cie.2019.03.001.

[181] L. Zhou, R. Baldacci, D. Vigo, and X. Wang, "A Multi-Depot Two-Echelon Vehicle Routing Problem With Delivery Options Arising in the Last Mile Distribution," *European Journal of Operational Research* 265, no. 2 (2018): 765–778, https://doi.org/10.1016/j.ejor.2017.08.011.

[182] X. Wang, F. Yang, and D. Lu, "Multi-Objective Location-Routing Problem With Simultaneous Pickup and Delivery for Urban Distribution," *Journal of Intelligent and Fuzzy Systems* 35, no. 4 (2018): 3987–4000, https://doi.org/10.3233/JIFS-169721.

[183] B. Ma, D. Hu, and Q. Sun, "Research on Route Optimization of Pure Electric Vehicle Under Joint Distribution Mode in City," in *COTA International Conference of Transportation Professionals* (2018), 400–408, https://doi.org/10.1061/9780784481523.040.

[184] S. M. Mirhedayatian and S. Yan, "A Framework to Evaluate Policy Options for Supporting Electric Vehicles in Urban Freight Transport," *Transportation Research Part D: Transport and Environment* 58 (2018): 22–38, https://doi.org/10.1016/j.trd.2017.11.007.

[185] K. Wang, S. Lan, and Y. Zhao, "A Genetic-Algorithm-Based Approach to the Two-Echelon Capacitated Vehicle Routing Problem With Stochastic Demands in Logistics Service," *Journal of the Operational Research Society* 68, no. 11 (2017): 1409–1421, https://doi.org/10.1057/s41274-016-0170-7.

[186] M. Wasiak, M. Jacyna, K. Lewczuk, and E. Szczepański, "The Method for Evaluation of Efficiency of the Concept of Centrally Managed Distribution in Cities," *Transport* 32, no. 4 (2017): 348–357, https://doi.org/10.3846/16484142.2017.1345005.

[187] A. Gupta, C. K. Heng, Y. S. Ong, P. S. Tan, and A. N. Zhang, "A Generic Framework for Multi-Criteria Decision Support in Eco-Friendly Urban Logistics Systems," *Expert Systems with Applications* 71 (2017): 288–300, https://doi.org/10.1016/j.eswa.2016.09.033.

[188] N. Q. Chinh, H. C. Kim, S. Jiang, and N. Zhang, "Collaborative Vehicle Routing Problem for Urban Last-Mile Logistics," in *2016 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2016-Conference Proceedings* (2017), 1531–1536, https://doi.org/10.1109/SMC.2016.7844456.

[189] R. A. Santana, R. D. A. Rosa, H. F. Astoures, D. S. D. Silva, and D. Siqueira Da Silva, "Planning the Distribution of

Goods in the Context of City Logistics Considering Split Deliveries With Access and Time Restrictions," *International Journal of Logistics Systems and Management* 28, no. 4 (2017): 507–527, https://doi.org/10.1504/IJLSM.2017.087789.
[190] A. M. S. Asih, B. M. Sopha, Y. Khairunnisa, H. E. Gunawan, and Y. Karuniawati, "Heterogeneous Vehicle Routing Delivery on Collaborative Distribution Using Genetic Algorithm—The Case of Yogyakarta City," in *2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)* (2017), 1432–1436, https://doi.org/10.1109/IEEM.2017.8290129.
[191] M. Esmaili and R. Sahraeian, "A New Bi-Objective Model for a Two-Echelon Capacitated Vehicle Routing Problem for Perishable Products With the Environmental Factor," *International Journal of Engineering, Transactions A: Basics* 30, no. 4 (2017): 523–531, https://doi.org/10.5829/idosi.ije.2017.30.04a.10.
[192] H. Li, J. Yuan, T. Lv, and X. Chang, "The Two-Echelon Time-Constrained Vehicle Routing Problem in Linehaul-Delivery Systems Considering Carbon Dioxide Emissions," *Transportation Research Part D: Transport and Environment* 49 (2016): 231–245, https://doi.org/10.1016/j.trd.2016.10.002.
[193] P. Gianessi, L. Alfandari, L. Létocart, and R. Wolfler Calvo, "The Multicommodity-Ring Location Routing Problem," *Transportation Science* 50, no. 2 (2016): 541–558, https://doi.org/10.1287/trsc.2015.0600.
[194] J. F. d. Souza Neto and V. Pureza, "Modeling and Solving a Rich Vehicle Routing Problem for the Delivery of Goods in Urban Areas," *Pesquisa Operacional* 36, no. 3 (2016): 421–446, https://doi.org/10.1590/0101-7438.2016.036.03.0421.
[195] A. Ochoa-Ortíz, F. Ornelas-Zapata, L. Margain-Fuentes, et al., "Capacitated Vehicle Routing Problem for PSS Uses Based on Ubiquitous Computing: An Emerging Markets Approach," *Dyna* 82, no. 191 (2015): 20–26, https://doi.org/10.15446/dyna.v82n191.51141.
[196] A. Moutaoukil, G. Neubert, and R. Derrouiche, "Urban Freight Distribution: The Impact of Delivery Time on Sustainability," *IFAC-PapersOnLine* 48, no. 3 (2015): 2368–2373, https://doi.org/10.1016/j.ifacol.2015.06.442.
[197] P. Lebeau, C. De Cauwer, J. Van Mierlo, C. Macharis, W. Verbeke, and T. Coosemans, "Conventional, Hybrid, or Electric Vehicles: Which Technology for an Urban Distribution Centre?" *The Scientific World Journal* 2015, no. 1 (2015): 302867, https://doi.org/10.1155/2015/302867.
[198] L. Amodeo, D. Lamari, G. Musolino, et al., "An Ex-Ante Evaluation of Last-Mile Freight Distribution Services for City Logistics," *WIT Transactions on The Built Environment* 1 (2015): 291–302, https://doi.org/10.2495/UT150231.
[199] T. G. Crainic, Y. Gajpal, and M. Gendreau, "Multi-Zone Multi-Trip Vehicle Routing Problem With Time Windows," *INFOR: Information Systems and Operational Research* 53, no. 2 (2015): 49–67, https://doi.org/10.3138/infor.53.2.49.
[200] A. Muñoz-Villamizar, J. R. Montoya-Torres, and C. A. Vega-Mejía, "Non-Collaborative Versus Collaborative Last-Mile Delivery in Urban Systems With Stochastic Demands," *Procedia CIRP* 30 (2015): 263–268, https://doi.org/10.1016/j.procir.2015.02.147.
[201] A. Polimeni and A. Vitetta, "Vehicle Routing in Urban Areas: An Optimal Approach With Cost Function Calibration," *Transportation Business: Transport Dynamics* 2, no. 1 (2014): 1–19, https://doi.org/10.1080/23249935.2013.826747.
[202] D. Zhang, X. Lu, S. Li, and F. Jin, "An Optimization Model on Fleet Size and Mixed Vehicle Routing Problem Considering CO_2 Emissions Cost and its Algorithm" (2014), 2715–2725, https://doi.org/10.1061/9780784413623.260.
[203] A. F. Muñoz-Villamizar, J. R. Montoya-Torres, and N. Herazo-Padilla, "Mathematical Programming Modeling and Resolution of the Location-Routing Problem in Urban Logistics," *Ingeniería y Universidad* 18, no. 2 (2014): 271–289, https://doi.org/10.11144/Javeriana.IYU18-2.mpmr.
[204] A. Javadi, M. J. Tarokh, and S. Piroozfar, "Solving a Multi-Objective Vehicle Scheduling-Routing of Interurban Transportation Fleet With the Purpose of Minimizing Delays by Using the Differential Evolutionary Algorithm," *Uncertain Supply Chain Management* 2, no. 3 (2014): 125–136, https://doi.org/10.5267/j.uscm.2014.5.005.
[205] A. G. Qureshi, E. Taniguchi, R. G. Thompson, and J. S. E. Teo, "Application of Exact Route Optimization for the Evaluation of a City Logistics Truck Ban Scheme," *International Journal on the Unity of the Sciences* 18, no. 2 (2014): 117–132, https://doi.org/10.1080/12265934.2014.930672.
[206] A. Muñoz-Villamizar, J. R. Montoya-Torres, A. A. Juan, and J. Cáceres-Cruz, "A Simulation-Based Algorithm for the Integrated Location and Routing Problem in Urban Logistics," in *2013 Winter Simulation Conference (WSC)* (2013), 2032–2041, https://doi.org/10.1109/WSC.2013.6721581.
[207] J. S. E. Teo, E. Taniguchi, and A. G. Qureshi, "Evaluation of Distance-Based and Cordon-Based Urban Freight Road Pricing in E-Commerce Environment With Multiagent Model," *Transportation Research Record: Journal of the Transportation Research Board* 2269, no. 1 (2012): 127–134, https://doi.org/10.3141/2269-15.
[208] J. F. Ehmke, A. Steinert, and D. C. Mattfeld, "Advanced Routing for City Logistics Service Providers Based on Time-Dependent Travel Times," *Journal of Computational Science* 3, no. 4 (2012): 193–205, https://doi.org/10.1016/j.jocs.2012.01.006.
[209] A. Polimeni, F. Russo, and A. Vitetta, "Demand and Routing Models for Urban Goods Movement Simulation," *European Transport/Trasporti Europei* 46 (2010): 3–23.
[210] R. G. Conrad and M. A. Figliozzi, "Algorithms to Quantify Impact of Congestion on Time-Dependent Real-World Urban Freight Distribution Networks," *Transportation Research Record: Journal of the Transportation Research Board* 2168, no. 1 (2010): 104–113, https://doi.org/10.3141/2168-13.
[211] T. Van Rooijen, B. Groothedde, and J. C. Gerdessen, "Quantifying the Effects of Community Level Regulation on City Logistics," *Innovations in City Logistics* (2008): 387–400.
[212] J. Camargo Pérez, M. H. Carrillo, and J. R. Montoya-Torres, "Multi-Criteria Approaches for Urban Passenger Transport Systems: A Literature Review," *Annals of Operations Research* 226, no. 1 (2015): 69–87, https://doi.org/10.1007/s10479-014-1681-8.
[213] D. Rezgui, J. C. Siala, W. Aggoune-Mtalaa, and H. Bouziri, "Towards Smart Urban Freight Distribution Using Fleets of Modular Electric Vehicles," in *Lecture Notes in Networks and Systems*, 37 (Springer, 2018), 602–612, https://doi.org/10.1007/978-3-319-74500-8_55.
[214] C. E. Schmidt, A. C. L. Silva, M. Darvish, and L. C. Coelho, "Time-Dependent Fleet Size and Mix Multi-Depot Vehicle Routing Problem," *International Journal of Production Economics* 255 (2023): 108653, https://doi.org/10.1016/j.ijpe.2022.108653.
[215] Y. Wang, J. Zhou, Y. Sun, J. Fan, Z. Wang, and H. Wang, "Collaborative Multidepot Electric Vehicle Routing Problem With Time Windows and Shared Charging Stations," *Expert*

Systems with Applications 219 (2023): 119654, https://doi.org/10.1016/j.eswa.2023.119654.

[216] Y. Wang, S. Zhang, X. Guan, J. Fan, H. Wang, and Y. Liu, "Cooperation and Profit Allocation for Two-Echelon Logistics Pickup and Delivery Problems With State–Space–Time Networks," *Applied Soft Computing* 109 (2021): 107528, https://doi.org/10.1016/j.asoc.2021.107528.

[217] B. Oliveira, A. G. Ramos, and J. P. De Sousa, "A Generic Mathematical Formulation for Two-Echelon Distribution Systems Based on Mobile Depots," *Transportation Research Procedia* 52 (2021): 99–106, https://doi.org/10.1016/j.trpro.2021.01.090.

[218] Y. Wang, Q. Li, X. Guan, J. Fan, Y. Liu, and H. Wang, "Collaboration and Resource Sharing in the Multidepot Multiperiod Vehicle Routing Problem With Pickups and Deliveries," *Sustainability* 12, no. 15 (2020): 5966, https://doi.org/10.3390/su12155966.

[219] Y. Huang, M. Savelsbergh, and L. Zhao, "Designing Logistics Systems for Home Delivery in Densely Populated Urban Areas," *Transportation Research Part B: Methodological* 115 (2018): 95–125, https://doi.org/10.1016/j.trb.2018.07.006.

[220] P. Matis, "Heuristics for the Solution of a Very Large Street Routing Problem With Mixed Transportation Mode," *Communications—Scientific letters of the University of Zilina* 11, no. 3 (2009): 20–24, https://doi.org/10.26552/com.c.2009.3.20-24.