drones

Review

Last-Mile Drone Delivery: Past, Present, and Future

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Abstract: Sustainable green products and services garner more attention from companies and enterprises that aim to succeed and grow in highly competitive markets by imposing less harms on the environment and ecosystems. Last-mile delivery from local distribution centers to customers plays an essential role in the retail business. Retail companies are leaning towards implementing green, efficient transportation methods, such as drones, in their last-mile delivery operations to conserve ecosystems. Accordingly, researchers have documented numerous research findings on last-mile drone delivery in recent years. This literature review selected a collection of articles mostly from 2011 to 2022 and reviewed them in terms of key technical challenges, such as routing, cargo distribution optimization, battery management, data communication, and environmental protection. These challenges are interrelated in a sense of achieving eco-friendly, efficient, lean, last-mile drone delivery. The selection of these technical challenges is based on the top challenges discussed in the literature.

Keywords: drone; last-mile drone delivery; routing; cargo distribution optimization

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1. Introduction

Transporting goods by sea, land/ground, and air requires sustainable logistics involving different vehicles to deliver parcels from one location to another. For instance, sea transportation uses ships and boats, land/ground transportation uses railroad trains, trucks, cars, and bikes, and air transportation uses airplanes and drones. Last-mile delivery operations mostly use trucks. In fact, trucks are the most employed tool in urban logistics. However, utilizing trucks in last-mile delivery has limitations, such as being unable to provide deliveries to some rural regions that are hard to reach by truck, consuming gasoline that leads to air pollution, being unable to deliver parcels in a timely manner due to traffic jams, etc. A potential eco-friendly vehicle in last-mile delivery is a bicycle. Retail companies such as DoorDash [1,2] and UberEats [3,4] use bicycles to deliver parcels to urban customers. However, bicycle delivery has drawbacks, such as exposing the bicycle riders to traffic hazards, requiring longer delivery times, and having limited cargo capacities. Generally, bicycle delivery is good for neighborhoods, but it may not be efficient in urban areas [5].

The invention of the drone technology [6] enabled the use of drones in last-mile delivery to complement the existing transportation methods. Abraham Karem [6] is the inventor of drone technology. He was passionate about aircraft and started building prototype aircraft when he was a teenager. He immigrated to the United States of America in the 1970s and later founded a company, Leading Systems Inc., in his home garage [6]. He started manufacturing his first drone named Albatross, followed by the more advanced Amber [7], which became the predecessor of the famed Predator drone [8] that brought him the "Drone father" designation. The propulsion system of a drone consists of motors, electronic speed controllers, and propellers, which allow the drone to fly and maneuver in the air. Hassanalian and Abdelkefi [9] categorized the drone types in terms of their weights, characteristics, and capabilities. Based on the propulsion system and the structural design, there are four major types of drones; multi-rotor drones [10], fixed-wing drones [11], single-rotor helicopter [12,13], and fixed-wing hybrid VTOL (Vertical Take-Off and Landing) drones [14]. Drones [15,16] benefit global industries by increasing work efficiency and productivity, decreasing workload and production costs, improving accuracy and repeatability, refining service and customer relations, and resolving security issues on a vast scale.

The Internet and digital transformation allowed more retail companies to use electronic commerce, or e-commerce [17]. E-Commerce has been the primary method of shopping, especially during the 2019–2021 pandemic, when more than half of the world population had to stay at home [18]. This is the primary reason global parcel volume increased from 87 billion in 2018 to more than 126 billion in 2020 and is predicted to reach 200 billion by 2025 [19]. In 2019, UPS, FedEx, and Amazon only delivered about 11.2 billion packages in the United States of America (USA).

Trucks are the primary transportation method for last-mile delivery. Fossil-fuel trucks cause noise and air pollution, traffic jams, cluttered parking spots, traffic accidents, higher delivery costs, and other unforeseen ground vehicle issues. Delivery trucks [20] are about 4% of vehicles on the USA roads; they cause about 50% of the nitrogen oxide emissions, 60% of the fine particulates, and 7% of all greenhouse gas emissions in the USA. Hence, many retail companies, such as Amazon, Alphabet Wing, Walmart, UPS, etc., lean toward using the drone technology as a sustainable transportation method as it offers eco-friendly, faster delivery with lower operating costs and less human involvements [21–26]. Other companies, such as Mercedes-Benz, started collaborating with the drone manufacturer Matternet to implement the on-demand delivery of e-commerce products using electric vans and drones [27]. Besides delivering standard parcels, drones are also used in food delivery [1,4,28–33], vaccine delivery [31,34–37], and the delivery of other lifesaving supplies in disaster relief operations [37]. However, utilizing drones in last-mile delivery has numerous challenges, such as reducing delivery costs, increasing energy efficiency, lowering environmental harms, tracking parcel deliveries, preventing sporadic delays in deliveries, staying on track with advanced technologies, etc.

The aim of this study is to provide a constructive survey of recently published research findings on the topics of last-mile drone delivery. The research findings are evaluated with respect to key technical challenges, such as routing, cargo distribution optimization, battery management, data communication, and environmental protection. The selection of these technical challenges is based on the top challenges discussed in the literature.

The remainder of this paper is structured as follows. Section 2 describes the selection criteria of publications and the key technical challenges of last-mile drone delivery. Sections 3–7 present the literature review analysis of the selected publications by highlighting advancements and future opportunities with respect to each key technical challenge. Section 8 provides the summary of the study.

2. Methodology

The survey methodology involved journal articles, books, book chapters, and conference proceedings from online sources such as Elsevier, IEEE, MDPI, Springer, and others, obtained by searching on the Google Scholar website with keywords such as “last-mile drone delivery”, “unmanned aerial vehicle logistics”, “vehicle routing problem”, “the Internet of drone things”, “drone fleet”, “urban delivery”, “cyber-physical systems and UAV”, “traveling salesman problem”, “optimizing fuel consumption in logistics”, and “drone battery swapping/charging station”. Afterward, publications, mainly from 2011 to 2022, were selected for this review article. Furthermore, key technical challenges shown in Figure 1, such as routing, cargo distribution optimization, battery management, data communication, and environmental protection, were considered for the literature review analysis as they were the top challenges discussed in the literature. The analysis involved the evaluation of the selected publications with respect to the key technical challenges shown in Figure 1.

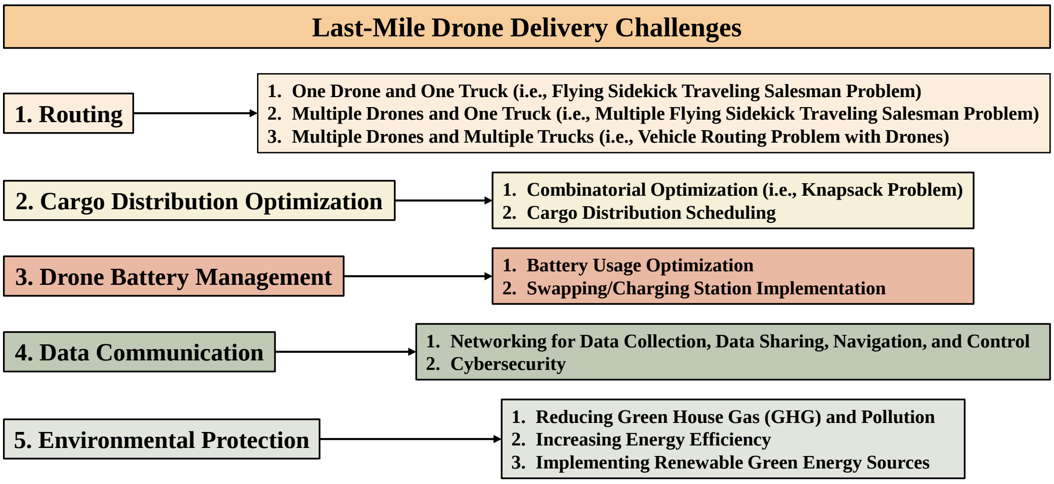

Figure 1. This figure illustrates last-mile drone delivery challenges.

Routing is an essential challenge to address as it aims to find optimum delivery routes that make last-mile drone delivery economically, operationally feasible. Trucks are necessary to carry drones and supplies as well as parcels in last-mile drone delivery. Therefore, last-mile drone delivery routing should consider routes for both drones and trucks. Depending on drone-and-truck arrangements, last-mile drone delivery routing may involve one drone and one truck (i.e., The Flying Sidekick Travelling Salesman Problem [38,39]), multiple drones and one truck (i.e., The Multiple Flying Sidekicks Travelling Salesman Problem [40–42]), or multiple drones and multiple trucks (i.e., Vehicle Routing Problem with Trucks and Drones [37,43,44]).

Cargo distribution optimization is a critical challenge to address as it offers proper distribution of parcels among delivery trucks, drones, bicycles, and robots for last-mile delivery. Delivery vehicles have different cargo capacity limits, safety ratings, reliability levels, eco ratings, and energy consumption. On the other side, parcels have different sizes, weights, destinations, urgency levels, priorities, safe-handling requirements, and costs [45–48]. Hence, assigning parcels to delivery vehicles requires proper cargo distribution to optimize the target performances of last-mile delivery with respect to budget limits, time constraints, or any other restrictions on the delivery operation. Cargo distribution optimization may involve combinatorial optimization (i.e., Knapsack Problem (KP) [49–52], Bin Packing Problem (BPP) [47,51,53,54]), and cargo distribution scheduling [55–57].

Drone battery management is another key challenge to address as it aims to achieve energy efficiency and reliability. Battery management in last-mile drone delivery may involve battery charging/replacing strategies [37,55,58–61] or battery consumption optimization [49,58,62–65] through adjusting the drone operation settings and conditions to save more energy for longer battery consumption.

Data communication is an essential challenge to address as it enables data collection, data sharing, coordination, navigation, and control during the last-mile drone delivery operation. Data communication can be device-to-device, device-to-human, human-to-device, or human-to-human. Communication challenges may encompass cybersecurity [66–69] and networking [5,18,26,45,50,53,56,59,67,70–80] via flying ad-hoc networks [77], cellular networks [71–73], the Global Positioning System [69,81], etc.

Environmental protection in last-mile drone delivery is a critical challenge to address as it promotes eco-friendly strategies to preserve the environment and ecosystems. Environmental protection can be achieved in various ways, such as reducing pollution and carbon footprints [21,82–85], improving the energy efficiency of the delivery operation [49,63,64,72,80,86,87], implementing renewable green energy sources [88–90], etc.

Figure 2 shows trends in the selected publications from 2011 to 2022 with respect to the technical challenges of last-mile drone delivery. There is a growing trend of publications that address drone battery management since 2018. In addition, the routing problem remains a hot topic among publications from 2011 to 2022. Cargo distribution optimization, data communication, and environmental protection have been drawing attention from time to time. Sections 3–7 present the literature review analysis of the selected publications by highlighting advancements and future opportunities with respect to each key technical challenge.

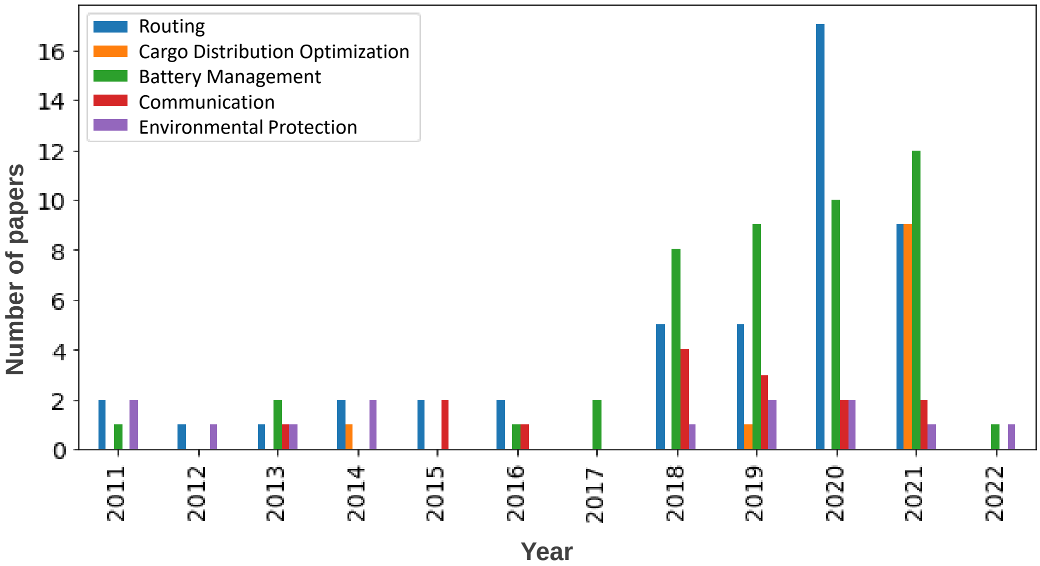

Figure 2. This figure illustrates trends in the selected publications from 2011 to 2022.

3. Routing

3.1. Advancements

Routing is an essential challenge to address as it aims to find optimum delivery routes that make last-mile drone delivery economically and operationally feasible. Trucks are necessary to carry drones and supplies as well as parcels in last-mile drone delivery. Therefore, last-mile drone delivery routing should consider routes for both drones and trucks. Depending on drone-and-truck arrangements, last-mile drone delivery routing may involve one drone and one truck, multiple drones and one truck, or multiple drones and multiple trucks.

Long before utilizing drones in last-mile delivery, Dantzig and Ramser [91] introduced the vehicle routing problem (VRP) in 1959 to find the optimal set of routes for a fleet of vehicles to deliver to a given group of customers. They were concerned with the optimal route of a fleet of gasoline delivery trucks between the storage of petroleum products to stations. The goal of the VRP is to minimize the total route a fleet should travel. Clarke and Write [92] enhanced the VRP algorithm proposed by Dantzig and Ramser [91] by using a compelling greedy perspective called the "savings algorithm".

A novel solution that extends the classic Clarke-and-Wright algorithm [92] is a mathematical model developed by Karak and Abdelghany [39] to solve the Hybrid Vehicle-Drone Routing Problem (HVDRP). They set three experiments to examine the capability of their proposed model to solve different vehicle-drone routing problems. They developed three heuristics, the hybrid Clarke and Wright heuristic (HCWH), the vehicle-driven heuristic (VDH), and the drone-driven heuristic (DDH), for solving HVDRP.

Murray and Chu [38] extended the HVDRP model [39] and introduced the Flying Sidekick Traveling Salesman Problem (FSTSP) in 2015 to find optimal routing and scheduling for multiple drones and a truck. In operations research, the makespan is the time taken between the start and the end of work. If the makespan of the truck exceeds that of the drone, minimal improvement may be possible, given that solutions are initialized to assign all drone-eligible customers to drones. Therefore, the ongoing strategy focuses on the drone to monitor whether its makespan surpasses the truck. If so, reducing the drone makespan is considered by shifting customers to the delivery truck.

Gonzalez-R et al. [93] introduced a mathematical model, an iterated greedy heuristic method, using a simulated annealing (SA) algorithm to optimize the truck-and-drone delivery routes. The model works with one truck and one drone. During the package delivery, the drone will come back to the truck to swap/recharge the battery when needed as the truck is a battery swap station for the drone as well. This means that the drone needs to calculate the remaining battery life, and, if the drone needs new batteries, it will join the truck at the next truck stop where the truck delivers a package. If the truck reaches the stop sooner than the drone, it will wait for the drone to join and vice versa. They also considered that drones could have multi-drop routes, which will help drones deliver to multiple customers by eliminating unnecessary travel to the truck. There is no limitation on the battery swap operation for drones, and each time drone will leave the truck with full batteries and/or a newly assigned delivery task.

Es Yurek and Ozmutlu [94] work on FSTSP to reduce the completion time of last-mile delivery. They proposed an iterative algorithm based on the decomposition approach. In the first step, they find the truck route and determine which customer is eligible for drone delivery based on weight, travel distance, and accessibility. In the second step, a mixed-integer linear programming model is used to optimize the drone route by fixing the routing and the assignment decisions made in the first stage. Lemardelé et al. [95] investigated two delivery methods—FSTSP and a method with ground autonomous delivery devices (GADDs). They suggested that the cost of drones with a truck is minimal in smaller areas with less dense locations. However, in dense areas, it is more justifiable to use the GADD method to reduce the cost of the operation. Salama and Srinivas [78] studied last-mile delivery with multiple drones and a single truck, which is a multiple-drone VRP. They proposed to divide the customer sites into clusters, establish a dispatch point in each group for the truck to launch the delivery drones, and optimize the truck route for the dispatch points. The truck stops at each dispatch point, and drones start their deliveries to customers; meanwhile, the truck does deliveries to its assigned customers. They used an unsupervised machine learning heuristic algorithm to minimize the total delivery cost and time.

Kitjacharoenchai et al. [44] extended FSTSP [38] to include multiple drones and multiple trucks in the model that is referred to as the Two Echelon Vehicle Routing Problem with Drones (2EVRPD). The study aims to find optimized routes for drones and trucks while minimizing delivery time. Moshref-Javadi et al. [42,96] presented an extension of HVDRP [39] to optimize last-mile delivery routes, where both drones and trucks work simultaneously. A truck acts as a mobile depot, while drones deliver packages to customers, one customer per dispatch due to its weight limit. Trucks can also deliver parcels to multiple customers. This synchronized system is used to minimize customer waiting time. Bakir and Tiniç [70] introduced another extension of HVDRP [39] where the drones are allowed to be flexible, which means drones can connect to all the trucks in the system. They called it Vehicle Routing Problem with Flexible Drone (VRPFD) and tried to find a set of routes for a fleet of drones and trucks working simultaneously in the system. They also allowed trucks to visit an exact location more than one time. They also suggested that flexible drone utilization reduced the makespan by up to 12.12%, with an average of 5.39%.

Shavarani et al. [79] stated that using a drone fleet in last-mile delivery would reduce the waiting time and the transportation cost. They developed a multi-objective mathematical model to find optimum locations for depots in the vicinity of customer locations. The customers closest to the depot have higher priorities for receiving the delivery services. Thus, the overall travel distance can be reduced, followed by reduced costs.

As last-mile delivery in urban areas directly influences customers, retail companies regard it as a powerful tool for attracting more consumers. Drones with intelligent routing capabilities would benefit last-mile delivery by offering eco-friendly, lean, reliable, fast, and sustainable delivery services. In particular, the implementation of flying sidekick drones and trucks in last-mile delivery, as illustrated in Figure 3, would help reduce the overall operation cost, fuel consumption, and environmental harms.

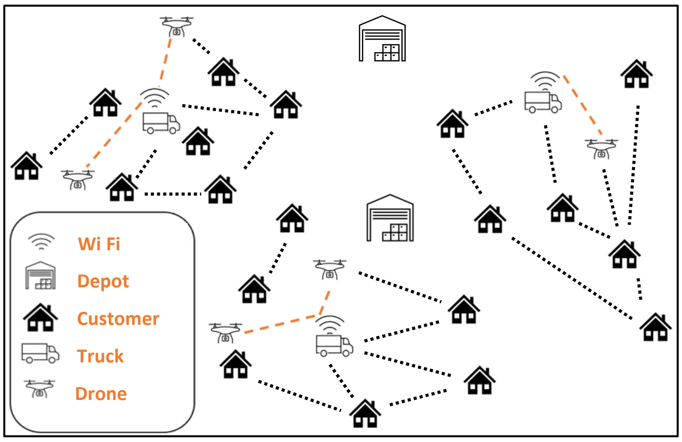

Figure 3. This figure illustrates flying sidekick drones and trucks in last-mile delivery.

3.2. Opportunities

Based on FSTSP [38], Murray and Raj [40] documented an exciting study on multiple Flying Sidekick Traveling Salesman Problem (mFSTSP). They explained that, because of the complex nature of the routing problem, they could not rely on mixed-integer linear programming (MILP). Perhaps, a practical solution can be achieved by using a heuristic approach. Murray and Raj, as well as other researchers [38,40,42,44,70], mostly focused on optimizing the delivery routes to minimize the total delivery time of the truck-and-drone fleet. There are some research opportunities to optimize the delivery routes with respect to other targets, such as energy efficiency, customer satisfaction, etc.

Sacramento et al. [43] formulated a mathematical model similar to FSTSP [38] with additional constraints. They used time limit control for the capacitated multiple-truck cases to minimize the distribution cost. They noticed that using small aircraft, such as drones, has obvious advantages over the truck-only distribution of goods. However, their model only looked at fuel costs of the distribution and no other factors, such as cargo capacities, maintenance, driver salaries, other operational expenses, etc.

As vehicle routing is an open-ended problem, researchers are still exploring new heuristic/metaheuristic algorithms or new linear/nonlinear optimization techniques to advance the last-mile drone delivery operation. Moreover, drones still experience some logistic challenges when delivering items to customer places. They can deliver items to accessible places, such as the front door or the back yard of a house. However, such delivery approaches may pose security concerns as the delivered items may be left unattended. In addition, drones cannot deliver packages to mailboxes or apartment buildings. Therefore, last-mile drone delivery needs more research and development to find secure, diverse ways to deliver items to diverse customer places.

4. Cargo Distribution Optimization

4.1. Advancements

Cargo distribution optimization is a critical challenge to address as it offers proper distribution of parcels among delivery trucks, drones, bicycles, and robots for last-mile delivery. Delivery vehicles have different cargo capacity limits, safety ratings, reliability levels, and energy consumption. On the other side, parcels have different sizes, weights, destinations, urgency levels, priorities, safe-handling requirements, and costs [45–48]. Cargo distribution optimization may involve combinatorial optimization (i.e., Knapsack Problem (KP) [49–52], Bin Packing Problem (BPP) [47,51,53,54]), and cargo distribution scheduling [55–57].

Vehicle routing and cargo distribution among delivery vehicles are major optimization problems in supply-chain management [45]. Naumov and Pawluś [51] reviewed last-mile delivery in urban zones with restrictions on motorized vehicles and the use of cargo bicycles in those zones. They focused on efficient packing, routing, and speed limitations that depend on the cargo load. The Traveling Salesman Problem (TSP) and the Knapsack Problem (KP) were involved in minimizing the distance and maximizing the specific bicycle cargo. This study considered a number of homogenous bicycles and a number of packages with different weights and sizes. KP deals with assigning packages to bicycles, and TSP deals with optimizing the route of each bicycle. They used three algorithms to optimize packaging and routing problems. The first algorithm is the Bin-Pack-3D method that consists of two steps. The first step finds optimum package-cargo combinations, and the second step optimizes the bicycle delivery routes. The second algorithm is the Multiple Traveling Salesman Problem (MTSP), which finds every possible path for all bicycles and selects the most feasible route for each bicycle. The third algorithm, the Capacitated Traveling Salesman Problem (CTSP), finds service stations with delivery bicycles, whereas each bicycle has a limited cargo capacity. They compared the three algorithms and found that the three algorithms produced almost identical results in terms of the overall delivery time and distance.

Sorbelli et al. [56] introduced the Multiple-Drone-Delivery Scheduling Problem (MDSP) that involves drones assisted by trucks. This study aimed to search for the optimal scheduling of drones to use their maximum battery life by ensuring that the battery power does not deplete during delivery. The study involved KP in managing a set of delivery tasks to maximize profit by considering the drone energy consumption and the cargo capacity limits of drones. Correspondingly, Zhang [49] examined the practicality of using automated delivery robots to deliver packages with different weights and sizes. The presented approach [49] consists of three steps. The first step is to use the Generalized Linear Model (GLM) to fit the total volume of packages for distribution cycles. The second step is to solve a routing problem for delivery robots by using a three-dimensional KP concept. The third step uses a mixed-integer linear programming model to optimize the total distance and the energy required by each delivery robot. The proposed approach demonstrated that using delivery robots is more practical and efficient.

Parcel priority is another parameter to consider in cargo distribution and scheduling [97]. Deplano et al. [52] proposed a mixed-integer linear programming model for the multiple heterogeneous KP with realistic container loading constraints and the priority of bins/parcels. Yildiz [50] compared exact KP methods with approximate KP methods. Exact KP methods are time-consuming because of the NP-hard (non-deterministic polynomial-time hard) nature of the problem. Therefore, the study focused on a deep reinforcement learning model as an approximate KP method. It involved a neural net with fully connected layers. The experimental results demonstrated that the proposed approximate KP method was about 40 times faster than the exact KP methods.

Capacity in logistics is the amount of physical space, assets, and employees available to carry, store, and deliver packages. Warehouses, trucks, drones, and employees are examples of last-mile drone delivery capacity elements. Predicting the next-day package volume is an important capacity planning problem [54]. Fadda et al. [53] introduced a machine-learning model to predict the next-day distribution volume and the number of vehicles needed to distribute parcels using historical data. They utilized machine learning methods to predict demand based on historical data. They clustered the customer locations and assigned a fleet to each cluster based on the distribution volume of each cluster by Tactical Capacity Planning (TCP).

Implementing cargo distribution optimization concepts in last-mile delivery helps retail companies gain more profits as it aims to optimize the cargo distribution process as well as scheduling/planning. Although researchers proposed numerous brute-force methods as well as heuristic methods for cargo distribution optimization and scheduling/planning, there is always room for advancements to make the cargo distribution operation more eco-friendly, more efficient, and more profitable.

4.2. Opportunities

Delivery vehicles have different cargo capacity limits, safety ratings, reliability levels, eco ratings, and energy consumption. On the other side, parcels have different sizes, weights, destinations, urgency levels, priorities, safe-handling requirements, and costs [45–48]. Hence, assigning parcels to delivery vehicles requires proper cargo distribution to optimize the target performances of last-mile delivery with respect to budget limits, time constraints, or any other restrictions on the delivery operation. In addition, forecasting the future parcel volumes is a challenging problem to solve for cargo distribution scheduling as it involves various levels of uncertainty.

Last-mile delivery now tends to use various delivery vehicles, such as trucks, drones, bicycles, mobile robots, etc. Therefore, cargo distribution optimization with heterogeneous delivery vehicles needs more accurate linear/nonlinear mathematical models for optimization and further investigation, so that different types of delivery vehicles may effectively complement each other in certain situations. Furthermore, the aspect of unusual parcel shapes is underestimated in cargo distribution optimization. Handling parcels with unusual shapes in a safe, secure, timely manner adds new complexities to cargo distribution and scheduling.

5. Battery Management

5.1. Advancements

Drone battery management is another key challenge to address as it aims to achieve energy efficiency and reliability. Battery management in last-mile drone delivery may involve (1) battery consumption optimization [49,58,62–65] through adjusting the drone operation settings and conditions to save more energy for longer battery consumption or (2) battery charging/replacing strategies [37,55,58–61].

Drone battery consumption is the topic of several studies. It depends on variables such as the parcel weight, the drone speed, flight routes, weather conditions, altitudes, depot locations, energy saving modes, and other drone operating conditions [98]. Overall, battery consumption optimization focuses on route optimization, drone-speed-and-altitude optimization, cargo weight optimization, and delivery scheduling based on weather forecasting.

To achieve optimum battery power consumption, drone routes and dispatch locations can be optimized for greater energy efficiency. Raj and Murray [41] studied the effect of drone speed on power consumption. In general, drone power consumption depends on the cargo weight, the speed, and the weather condition. Raj and Murray [41] proposed an algorithm that checks and adjusts the tradeoff between the speed and the travel distance. They tried to minimize the total delivery time for both trucks and drones. The results indicated that trucks would have shorter routes and fewer customers than that of drones.

Torabbeigi et al. [57] focused on the Battery Consumption Rate (BCR), a function of the drone payload. They considered lightweight parcels in the study and identified that about 60% of deliveries would fail, in drone delivery, if the weight of the parcels were not considered in BCR. Dispatch location optimization is another approach to decreasing BCR. Salama and Srinivas [78] worked on last-mile delivery with multiple drones and a truck. They clustered customer locations and optimized drone dispatch points. The approach showed a reduction in the overall cost and the delivery time. BCR is also crucial for sensor data collection. Yuan et al. [80] proposed an Actor-Critic-based Deep Stochastic Online Scheduling (AC-DSOS) algorithm that limits the drone hovering space to consume less energy during the sensor data collection process. Moreover, Kim et al. [99] focused on the atmospheric temperature and its effect on the drone battery depletion. They proposed an optimization model that helps schedule deliveries under uncertain battery durations. The model aims to minimize the total operating cost and the probability of not completing the scheduled flights.

Researchers suggest various battery charging/replacing strategies. For example, battery stations can be added to the service routes, so that drones can stop by and recharge/replace their batteries. Generally, battery stations can accommodate three ways of replenishing drone batteries as illustrated in Figure 4: Battery swapping [100]; Contact-based battery recharging [59]; Wireless battery recharging [88].

Figure 4. This figure illustrates the three types of battery replenishing stations for drones.

The battery swapping process needs a human operator. Galkin et al. [100] introduced the use of cellular networks for drones and suggested that a drone fleet can be used as a flying infrastructure to serve the cellular network users when the regular infrastructure is busy. A significant challenge, in this case, is the battery limitation problem. They suggested three solutions to the problem. The first solution involves drone swapping. This means that when a working drone needs recharging, a new drone takes up its work to allow the other drone to return to the charging station to recharge using a contact-based charger. The second solution is similar to the first one in terms of drone swapping. However, the battery charging stations are replaced by battery replacing stations that require human operators to replace the drone batteries using mechanical tools. The third solution is similar to the first solution, but it uses non-contact wireless chargers to recharge drone batteries. Asadi and Nurre Pinkley [55] also worked on battery swap stations and proposed a model that uses battery swap stations to reduce the recharging burden and the wait time. They proposed a stochastic Scheduling, Allocation, and Inventory Replenishment Problem (SAIRP) to solve for battery swap stations. They also considered that recharging causes battery degradation. With the Markov Decision Process (MDP), they defined a two-dimensional state space that shows the number of full batteries and their average capacities. In addition, a two-dimensional action space indicates the number of batteries charged/discharged and the number of batteries replaced. Results illustrated that MDP suffers from the high dimensionality of the problem. Therefore, they implemented reinforcement learning (RL) methods that demonstrate highly competitive performances in finding an optimality gap, satisfying the demand gap, and reducing the computational time.

Raciti et al. [59] studied the contact-based charging stations installed on the roofs of buildings. They stated that a drone has a limited battery life; therefore, having a network of recharge stations on the tops of buildings would help achieve more operation hours. They also suggested that, as different types of drones require different charging pads, it is better to use multi-pad technology to charge various drones. They simulated the proposed idea in the Simulink software and demonstrated its effectiveness.

Faraci et al. [88] introduced a green wireless charging station for a drone fleet. The recharging station harvests energy from the wind so that a wireless power transfer system charges drones with the harvested energy. This study aims to optimize the number of drones based on the availability of wind energy for the seamless operation of a drone fleet.

5.2. Opportunities

Battery management in last-mile drone delivery involves optimizing the drone operation to save more energy and the logistics of battery recharging or replacing. New machine learning methods that monitor the drone battery consumption to figure out optimum drone operation settings in conjunction with weather forecasting could be a potential future direction for solving battery consumption problems. The logistics of battery recharging or replacing still needs more research to improve the battery lifetime performances in terms of reliability, durability, and longevity. In addition, improving the battery capacity and lifetime using advanced materials and finding alternative energy sources that are renewable are potential topics to study.

As drones use electric power to fly, their operation depends on the battery capacity and the recharging/replacement arrangements. Researchers are still searching for new materials and methods to increase the battery capacity and lifetime. For instance, Galkin et al. [100] investigated new technologies in building batteries that have more lifecycle to reduce the burden of recharging.

On the other hand, researchers are still trying to optimize the logistics of the drone battery recharging/replacement process. Figure 4 illustrates three types of recharging/replacing stations used for drones: a battery swapping station, a contact-based recharging station, and a wireless recharging station. The battery swap station requires a human operator to replace the depleted batteries of drones with new ones and recharge the depleted batteries. A drone would spend minimal time at the battery swap station as it does not need to wait for recharging. However, the wait time depends on the number of drones in line, the availability of charged batteries, and the human operator's skill. The contact-based charging station has a recharging pad compatible with different types of drones. The waiting time depends on the number of drones in the recharging line, the number of recharging pads, and the drone recharging time. The wireless charging station provides an electromagnetic field for wireless recharging. A drone should hover in the electromagnetic field of a wireless recharging station to get recharged. This recharging method is fast and efficient as the recharging process can be done autonomously.

A limitation of the battery swap station and the contact-based station is that a drone needs to finish its delivery service before going to the charging station without any parcel. However, the wireless charging station can accommodate wireless recharging for drones with parcels, so that a drone can recharge itself before, during, or after the delivery service. The wireless charging station offers greater efficiency in terms of time and logistics. The future work may focus on identifying optimum locations of wireless recharging stations for a drone fleet in a specific region. In addition, wireless recharging relies on the data communication between drones as well as between wireless recharging stations and drones.

6. Data Communication

6.1. Advancements

Data communication is an essential challenge to address as it enables data collection, data sharing, coordination, navigation, and control during the last-mile drone delivery operation. Data communication can be device-to-device, device-to-human, human-to-device, or human-to-human. Communication challenges mainly involve cybersecurity [66–69] and networking [5,18,26,45,50,53,56,59,67,70–80] via flying ad-hoc networks (FANETs) [77], cellular networks [71–73], the Global Positioning System (GPS) [69,81], etc.

The Internet of Things (IoT) is the interconnection through the Internet of computing devices embedded in things that people use. It has immense future potential and draws the attention of various industries [67,74–76]. The IoT enabled ubiquitous computing that involves cloud computing and fog/edge computing [31,69,75] as well as ubiquitous sensing or ubiquitous geo-sensing [75,101] that involves omnipresent sensor networks and their ability to probe geographic phenomena in real-time. A domestic ubiquitous computing environment might interconnect lighting and environmental control systems with personal biometric monitors woven into the clothing of the environment, so that the illumination and the heating conditions can be modulated continuously and imperceptibly. Industrial cloud computing stores data and has the computing power for data analytics and decision-making. It serves as a data center over the Internet with various computing tools for analyzing data. This platform receives data from devices, analyzes the data, and provides a clear data visualization for humans.

The Internet of Drones (IoD) [31,66,68,69,73,88,102] is a new term derived from IoT for interconnected drones that share data, central computing systems, and human operators for data analysis and decision-making. A drone may experience unpredictable situations during its operation; therefore, it needs to sense the environment, analyze the data, and make autonomous decisions. Drones that consist of sensors, actuators, drive mechanisms, propellers, electronics, and digital control systems enable smart services by pushing the boundaries of technological realms. Gharibi et al. [73] discussed using three types of networks for the IoD. The three types of networks include the air traffic control network, the Internet, and a cellular network. They suggested that their model could be utilized in package delivery, search and rescue, traffic monitoring, and other applications. In a comprehensive review, Abualigah [102] focused on the applications, deployment, and integration of the IoD. Figure 5 illustrates that the IoD is enabled by secure data communication for navigation, coordination, data sharing, and control.

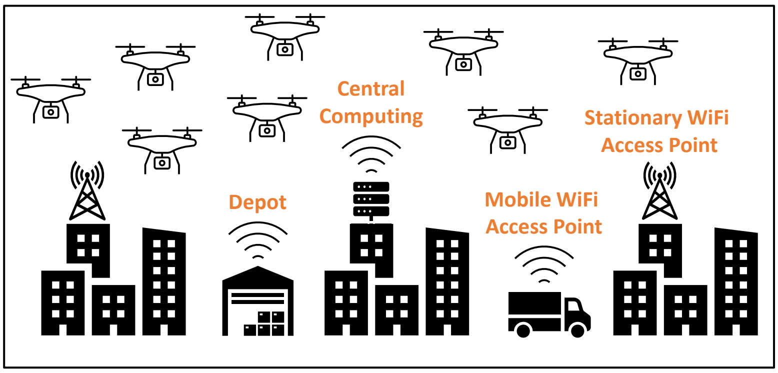

Figure 5. The Internet of Drones (IoD) uses secure data communication for navigation, coordination, data sharing, and control.

The cybersecurity of the IoD is crucial for protecting information and preventing cyber threats that target IoD hardware and software. Choudhary et al. [68] classified and discussed possible cyberthreats and vulnerabilities in data communication networks. Various cybersecurity tools are used to maintain the required level of security. Al-Garadi et al. [67] stated that standard cybersecurity tools such as data encryption/decryption, user authentication, and user access control are not enough for IoD cybersecurity. They studied the use of machine learning and deep learning in cybersecurity, discussed possible vulnerabilities of each cybersecurity tool, and suggested potential research areas for future improvements in IoD cybersecurity. Abdelmaboud [66] additionally discussed the privacy and security challenges in global resource management, sensor communication, coordination, scheduling, and drone distribution and deployment.

Nayyar [77] compared various routing protocols in the work entitled to Flying Adhoc Networks (FANETs). The aim was to find which protocol can perform well in dynamic environments. The observations suggested that the Hybrid Wireless Mesh Protocol (HWMP) and the Optimized Link State Routing Protocol (OLSR) perform well in unpredictable and dynamic environments. Challita et al. [72] proposed a reinforcement learning model to optimize the routes of drones interconnected via cellular connections based on the Echo State Network (ESN) cells. They suggested that every drone builds a map of its own and shares it with other drones to reduce the load on the ground network and wireless transmission delays. Cao et al. [86] developed a Deep Reinforcement Learning (DRL) method for drones to collect data from IoT nodes that cannot send data to the central server due to their remote locations. They arranged for a drone to hover over an IoT wireless transmitter to harvest data from the IoT node. They used DRL for a drone to find its optimum hovering path over each IoT node to optimize the battery power consumption of the drone and the IoT transmitter. Goudarzi et al. [74] also mathematically formulated the drone path planning problem for sensor data collection using drones and the Internet of Things (IoT). They first developed a cost function to have a scalable system. They present a formula to overcome a significant issue; path smoothing. As drones do not need to fly exactly over each sensor, they utilize Bezier Curves (BCs) to generate smoothed paths for drones. They used a Lyapunov vector controller to achieve a drone circular motion. They tested their model using MATLAB. The simulation results demonstrated that drones could find the shortest path and follow the circular path using the Lyapunov function within the data access point zone.

Campion et al. [71] reviewed the current state of drone swarm communication and suggested using cellular networks [71–73] as the communication infrastructure of drone swarms. They classified the swarm communication variants into infrastructure-based swarm architecture and the Flying Adhoc NETwork (FANET) architecture [69].

Akagi et al. [81] emphasized that drones use Global Positioning Signals (GPS) to measure their current locations. They suggested that drones need alternative ways to navigate the environment and avoid collisions. Hence, Akagi et al. [81] obtained measurements from multiple sources, including GPS, magnetometers, and cameras. A drone is assumed to receive sporadic GPS measurements that are shared with the swarm. In addition, they proposed a centralized extended Kalman filter to estimate the state of the drone swarm using a line-of-sight measurement camera.

6.2. Opportunities

A data communication network is vulnerable to various cyberthreats. Hence, the IoD networks need more intelligent, reliable cybersecurity tools to deal with cyberattacks that are getting more sophisticated and harder to prevent. Moreover, the reliability of wireless networks and the causes of network disruptions with proper resolutions are potential topics to study. For instance, Nayyar et al. [69] stated that drones have GPS connectivity, but only sometimes. A disruption in the GPS connectivity negatively affects the drone operation. Fog computing or edge computing can provide distributed local computing if cloud computing is not accessible. Perhaps, fog computing may help drones operate autonomously with little or no GPS connection to satellites and ground servers, which may allow drones to update themselves and perform ground, air, and underwater operations.

Another area of research may focus on the possibility of including the customers in the data communication during the delivery operation. Notifying the customers with live tracking data and getting necessary feedback from the customers for coordination and arrangements would offer benefits in many ways.

As last-mile drone delivery garners more attention, the IoT and the IoD will grow along with breakthrough advancements in unmanned aircraft, cyber-physical systems, data analytics, artificial intelligence, data communication, distributed computing, and cybersecurity.

7. Environmental Protection

7.1. Advancements

Environmental protection in last-mile drone delivery is a critical challenge to address as it promotes eco-friendly strategies to preserve the environment and ecosystems. Environmental protection can be achieved in various ways, such as reducing pollution and carbon footprints [21,82–85], improving the energy efficiency of the delivery operation [49,63,64,72,80,86,87], implementing renewable green power sources [88–90], etc.

Trucks are necessary to carry drones and supplies as well as parcels in last-mile drone delivery. However, trucks mostly use fossil-based fuels that cause the Green-House Gas (GHG). Edenhofer et al. [103] reported in 2014 that transportation produces 14% of the global GHG and 95% of the world transportation energy is from fossil fuels. Figure 6 depicts a pie chart of global GHG emissions by economic sectors using the data reported by Edenhofer et al. [103]. Due to the adverse effects of GHG on the environment, reducing

GHG is a critical problem to solve. This problem also matters to retail businesses as they use trucks that consume fossil fuels for transportation and delivery.

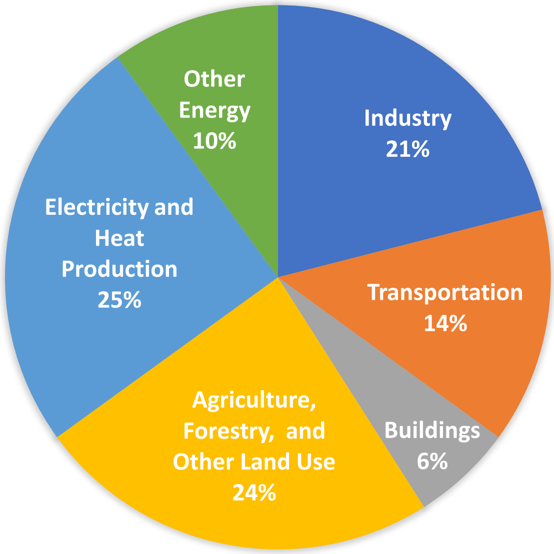

Figure 6. This figure depicts a pie chart of global GHG emissions by economic sectors.

The Green Vehicle Routing Problem (GVRP) is a variant of TSP and VRP, which aims to reduce fossil fuel consumption by reducing the vehicle travel distance, the speed, and the cargo weight. Kuo and Wang [104] proposed a tabu-search algorithm for saving vehicle fuel consumption by reducing the vehicle weight. They demonstrated that the heavier the vehicle is, the more energy it needs to move. Heavier vehicles have greater inertia and higher rolling resistance, which increases fuel consumption. Likewise, Xiao et al. [105] claimed that the vehicle fuel-consumption rate is based on the weight and the distance traveled. They developed a simulated-annealing algorithm with a hybrid exchange rule and experimentally demonstrated that the method can reduce the fuel consumption by 5% with a little more than 2% increase in the travel distance. MirHassani and Mohammadyari [85] used a gravitational search algorithm to minimize the vehicle fuel consumption by reducing the travel distance and the vehicle load.

The relationship between the vehicle speed and the fuel consumption was studied by Bektaş and Laporte [82] for heavy-duty delivery vehicles. They reported that speeds above 40 km/h negatively impact the fuel efficiency. Franceschetti et al. [83] studied the time-dependent pollution routing problem to determine optimum vehicle speeds with a cost function that considers GHG emissions, traffic congestions, and driver costs. Koç et al. [84] studied a heterogeneous fleet vehicle routing problem based on the pollution-routing problem (PRP) presented by Bektaş and Laporte [82] and proposed a hybrid evolutionary metaheuristic model. They examined the proposed model to measure the trade-offs between various cost indicators, such as the vehicle cost, the travel distance, fuel consumption, GHG emissions, and the driver cost. The results indicated that using a heterogeneous fleet without vehicle speed optimization enables a further reduction in the total cost rather than a homogeneous fleet with vehicle speed optimization.

Drones help reduce GHG emissions in last-mile delivery. Dukkanci et al. [63] proposed a model that involves multiple drones and trucks, where trucks are used as the mobile launch spots of drones. They called the model the Energy-minimizing and Range-constrained Drone Delivery Problem (ERDDP). This model considers mobile launch points from a potential set of sites, finds travel routes for drones to do deliveries, and optimizes the drone speed to do more deliveries with each battery charge cycle. Chiang et al. [62] studied the effects of drones on GHG emissions and the delivery operation cost. Their computational results strongly support the notion that using delivery drones in last-mile delivery would save the overall cost by reducing the delivery time and the number of delivery vehicles. An interesting study conducted by Stolaroff et al. [87] demonstrated a comparison between drone delivery and truck delivery. They concluded that the impact of last-mile delivery by drones on the environment is lower than that of the urban truck delivery. The results suggested that drone delivery may reduce GHG emissions and the energy consumption of the delivery operation.

Alternative energy sources, such as biofuels, renewable natural gas, electricity, and hydrogen fuels, help reduce GHG emissions. A study by Liu, et al. [89] compared Hydrogen Fuel Cell Electric Vehicles (HFCEVs) to conventional fossil fuel vehicles. They stated that the production and the transportation of the hydrogen fuel use 5–33% less fossil fuel energy and produce 15–45% less GHG emissions. Ugurlu [90] compared different types of hydrogen fuels and found that gaseous hydrogen produces less GHG emissions compared to liquid hydrogen.

With each click on an online order, the customer and the company are responsible for the carbon footprint of the online order. Many solutions would help customers and companies reduce their carbon footprints. On the customer end, people can combine all their purchases into just one order and have all the products shipped in one package. On the vendor end, they can implement eco-friendly vehicles, such as drones, with optimized passes to play their roles in reducing carbon footprints. In general, a large portion of parcels are light enough for delivery vehicles such as drones. For example, 86% of Amazon parcels weigh under 5 pounds [106]. Hence, drones can deliver such lightweight parcels by reducing the number of trucks and truck routes in last-mile drone delivery. The energy needed for drones is 94% less than the energy needed for delivery trucks [64].

7.2. Opportunities

Sustainable green products and services garner more attention from companies and enterprises that aim to succeed and grow in highly competitive markets where environmental conservation is critical. Environmental conservation in last-mile drone delivery can be achieved in various ways, such as reducing pollution and GHG emissions, improving the energy efficiency of the delivery operation, implementing renewable green power sources, etc.

The main delivery vehicles in last-mile drone delivery are drones and trucks. Although drones use the electric power that is renewable, the production and the disposal of their batteries may pose harms to the environment and ecosystems. Trucks are necessary to carry drones and supplies as well as parcels for last-mile drone delivery. However, fossil-fueled trucks produce harmful pollution and GHG emissions as they use fossil fuels that are not renewable. Moreover, the production of fossil fuels poses dire harms to the environment.

Routing, cargo distribution optimization, battery management, and data communication for the last-mile drone delivery operation have concerted effects on the environment and ecosystems. Therefore, the current practices and technologies in last-mile drone delivery need to be upgraded or new practices and new technologies should be implemented to conserve ecosystems.

8. Summary

Last-mile delivery from local distribution centers to customers plays an essential role in the retail business. Retail companies are leaning towards implementing green, efficient transportation methods, such as drones, in their last-mile delivery operations to conserve ecosystems. Thus, researchers have documented numerous research findings on last-mile drone delivery in recent years. This study selected a collection of articles mostly from 2011 to 2022 and reviewed them in terms of key technical challenges, such as routing, cargo distribution optimization, battery management, data communication, and environmental protection. The routing problem remained a hot topic among publications from 2011 to 2022. There is a growing trend of publications that address drone battery management since 2018. Cargo distribution optimization, data communication, and environmental protection have been drawing attention from time to time. These challenges are interrelated in a sense of achieving eco-friendly, efficient, lean, last-mile drone delivery.

The main delivery vehicles in last-mile drone delivery are drones and trucks. Drones use the electric power that is renewable, but the production and the disposal of their batteries may pose harms to the environment and ecosystems. Furthermore, trucks are necessary to carry drones and supplies as well as parcels for last-mile drone delivery, but fossil-fueled trucks produce harmful pollution and GHG emissions as they use fossil fuels that are not renewable.

Last-mile delivery now tends to use various delivery vehicles, such as trucks, drones, bicycles, mobile robots, etc. Therefore, last-mile delivery with heterogeneous delivery vehicles needs more accurate linear/nonlinear mathematical models for optimization and further investigation, so that different types of delivery vehicles may effectively complement each other in certain situations.

As the key technical challenges are open-ended problems, researchers are still exploring new heuristic/metaheuristic routing algorithms, new linear/nonlinear cargo distribution optimization techniques, new renewable power sources, and new advanced communication methods to advance the last-mile drone delivery operation. Moreover, drones still experience some logistic challenges when delivering items to customer places. They can deliver items to accessible places, such as the front door or the back yard of a house. However, such delivery approaches may pose security concerns as the delivered items may be left unattended. In addition, drones cannot deliver packages to mailboxes or apartment buildings. Therefore, last-mile drone delivery needs more research and development to find secure, diverse ways to deliver items to diverse customer places.

The efforts to address the key technical challenges of last-mile drone delivery, such as routing, cargo distribution optimization, battery management, and data communication, have concerted effects on the environment and ecosystems. Hence, the current practices and technologies in last-mile drone delivery need to be upgraded or new practices and new technologies should be implemented to conserve the ecosystems.

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