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Review of Path Planning Models, Environmental Constraints, and Application Domains in Drone Delivery Systems

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ABSTRACT

This review paper comprehensively examines drone delivery systems, focusing on path planning models, environmental constraints, and application domains. We analyze theoretical frameworks for path planning, including deterministic and heuristic approaches, as well as recent advancements in metaheuristics and hybrid optimization techniques. The paper evaluates how environmental factors, including dynamic obstacles, no-fly zones, and wind conditions, impact drone performance and feasibility. We explore various applications of drone delivery, highlighting key challenges and future research directions in this rapidly evolving field. By synthesizing current research and identifying gaps in knowledge, we provide a comprehensive overview to guide future developments in drone delivery systems, with a particular emphasis on recent innovations in multi-objective optimization and adaptive algorithms.

Keyword: drone delivery, optimization algorithms, path planning models, unmanned aerial vehicles (UAVs).

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1 Introduction

The increased popularity of online shopping and growth of cities has led to a greater demand for fast and efficient shipping choices. Traditional modes of transportation, such as trucks and vans, struggle to address these challenges due to traffic congestion, limited parking availability, and environmental concerns. Recently, these challenges have been addressed by the emergence of drone delivery systems. Drones, or unmanned aerial vehicles (UAVs), can avoid traffic and bring packages directly to customers' homes, cutting down on delivery times and carbon emissions [1, 2].

Drone delivery systems could transform last-mile logistics operations by transporting goods from hubs to their final destination, as stated in [3]. The final stage of delivery logistics is typically the most time-consuming and costly portion of the delivery process, making up around half of the total delivery expense. Recent studies have further emphasized the potential of drone delivery systems to revolutionize last-mile logistics. For instance, Chiang et al. [4] demonstrated that optimized drone delivery routes could significantly reduce costs and improve sustainability in urban environments. Moreover, Murray and Raj [5] explored the concept of multiple drone assistance in delivery operations, showcasing the potential for increased efficiency and reduced delivery times.

Nevertheless, harnessing the potential of drone delivery systems necessitates overcoming numerous technical and regulatory obstacles. One major obstacle is path planning, where the drone must decide on the best route to deliver packages to different customers, taking into account factors like battery power, weather, and restricted air spaces. Efficient path planning is crucial for guaranteeing the safety, effectiveness, and dependability of drone delivery activities [6, 7].

The complexity of path planning has grown with the introduction of hybrid delivery models. Kitjacharoenchai et al. [8] and Moshref-Javadi et al. [9] have explored scenarios where trucks and drones work in tandem, necessitating more sophisticated optimization algorithms to coordinate their movements effectively. These hybrid models present new challenges and opportunities in the field of drone delivery path planning.

This review paper aims to synthesize recent advancements in drone delivery systems, with a particular focus on developments from the past five years. Specifically, we seek to address the following research questions:

1. What are the primary theoretical models and solution approaches for UAV path planning in delivery systems?

2. How do environmental factors and constraints impact drone delivery operations?

3. What are the current and emerging application domains for drone delivery systems?

4. What are the key challenges and future research directions in this field?

By addressing these questions, we provide a comprehensive overview of the current state of drone delivery systems and identify promising directions for future research.

2 Methodology

This review was conducted through a systematic search and analysis of recent literature on drone delivery systems and path planning. We focused primarily on peer-reviewed journal articles and conference proceedings published within the last five years (2018-2023) to capture the most recent developments in this rapidly evolving field.
Literature Search: We used academic databases including IEEE Xplore, ScienceDirect, and Google Scholar. Key search terms included "drone delivery", "UAV path planning", "drone routing problem", and "last-mile logistics".
Inclusion Criteria: Studies were included if they:

1. Focused on path planning for drone delivery systems
2. Addressed environmental constraints in drone operations
3. Presented novel algorithms or optimization techniques
4. Described real-world applications or case studies of drone delivery

Exclusion Criteria: We excluded studies that:

1. Focused solely on drone hardware or communication systems
2. Did not specifically address delivery applications
3. Were not available in English

The selected papers were then analyzed and synthesized to identify key themes, trends, and gaps in the current research landscape.

3 UAV Path Planning: Theoretical Models and Solution Approaches

Recently, there has been a notable increase in interest in the use of unmanned aerial vehicles (UAVs) for last-mile logistics, as their ability to transform delivery processes has been recognized. To maximize drone delivery systems, it is essential to address different technical and regulatory obstacles, with path planning being a critical element. Efficient path planning is crucial to guarantee the safety, efficiency, and reliability of drone delivery activities. In this part, we will discuss different popular theoretical frameworks for mapping out the route of UAVs, such as the traveling salesman problem (TSP), vehicle routing problem (VRP), and various iterations of these models.

3.1 Theoretical Models

3.1.1 Traveling Salesman Problem (TSP)

The traveling salesman problem (TSP) is an age-old challenge in optimization where the goal is to discover the most efficient route that visits a series of locations (cities) and ends back at the original point of departure. Research on the Traveling Salesman Problem (TSP) has been extensive, and it is used in a variety of ways, such as for planning paths for Unmanned Aerial Vehicles (UAVs). In the realm of UAV path planning, the TSP is utilized to discover the most efficient route that includes visiting specific customer locations and then returning to the depot [10].
Various versions of the TSP have been suggested in academic research to tackle the unique obstacles of UAV route planning. An example is the orienteering problem (OP), a version of the TSP where one must visit a specific number of locations within a set time or distance constraint. The OP is applicable for simulating UAV path planning issues with drones having restricted battery life and unable to reach all customer locations [11]. Another form of the Traveling Salesman Problem is the time-dependent TSP (TDTSP), which takes into account the changing travel times between places. The TDTSP is applicable for simulating UAV route planning issues in situations where the time to travel between customer sites is influenced by factors like weather or traffic [12].
To explain the simplest formulation of the Traveling Salesman Problem (TSP) with drones, we can consider a scenario where a salesman needs to visit a set of cities and return to the starting city, but now has the option to use drones for part of the journey. This variation, known as the Traveling Salesman Problem with Drones (TSP-D), involves optimizing the route for both the salesman and the drones to minimize the total distance traveled. Here is a formulation of the TSP-D:

1. Parameters:

- V: Set of cities to be visited, including the starting city.
- d_{ij}: Distance between city i and city j.
- R: Maximum distance a drone can travel before needing to return to the salesman.
- c: Cost of operating the drone per unit distance.

2. Decision Variables:

- x_{ij}: Binary variable indicating if the salesman travels directly from city i to city j.
- y_{ij}: Binary variable indicating if the drone travels directly from city i to city j.

3. Objective function:

$$\text{Minimize} \sum_{i,j \in V} d_{ij} x_{ij} + c \sum_{i,j \in V} d_{ij} y_{ij} \tag{1}$$

4. Constraints:

- Visit Each City Once:

$$\sum_{j \in V} x_{ij} + \sum_{j \in V} y_{ij} = 1, \quad \forall i \in V \tag{2}$$

- Subtour elimination:

$$\sum_{i,j \in S} x_{ij} \leq |S| - 1, \quad \forall S \subset V, 2 \leq |S| \leq |V| - 1 \tag{3}$$

- Drone usage:

$$\sum_{i,j \in V} y_{ij} \leq 1 \tag{4}$$

- Drone Range:

$$\sum_{i,j \in V} d_{ij} y_{ij} \leq R \tag{5}$$

- Drone connectivity:

$$\sum_{j \in V} y_{ij} = \sum_{j \in V} y_{ji}, \quad \forall i \in V \tag{6}$$

3.1.2 Vehicle Routing Problem (VRP)

The VRP is a traditional optimization issue where the goal is to determine the best routes for a group of vehicles to distribute goods to customers [13]. The VRP is used in different scenarios, including planning paths for UAVs. When planning paths for UAVs, the Vehicle Routing Problem (VRP) can determine the best routes for multiple drones to transport packages to different customer locations, taking into account battery life, payload capacity, and delivery deadlines [14].

Numerous versions of the VRP have been suggested in research to tackle the unique obstacles of UAV path planning. For instance, the capacitated Vehicle Routing Problem (CVRP) is a type of VRP which takes into account the vehicles' payload capacity. The CVRP is commonly applied to represent path planning issues for UAVs with restricted payload capacity, preventing them from transporting all packages simultaneously. Another version of the VRP is the TDVRP, which takes into account the fluctuating travel times between different locations. The TDVRP is suitable for representing UAV route planning scenarios with travel durations between customer sites influenced by weather or traffic [15].

The MDVRP is a version of the VRP where the goal is to determine the best routes for a group of vehicles to transport products to various clients from numerous depots. The MDVRP is applicable for simulating UAV path planning issues involving drones launched from various depots. This model is beneficial when the delivery area is extensive and cannot be reached by just one depot.

The HFVRP is a different version of the VRP where the goal is to determine the best routes for a group of vehicles with varying capacities and abilities. The HFVRP is applicable for representing UAV path planning scenarios with varying payload capacities and battery life for the drones. This model is beneficial for scenarios involving a variety of drones for delivery tasks [16].

3.1.3 Hybrid Models

Recent research has focused on developing hybrid models that combine elements of both TSP and VRP to better represent the complexities of drone delivery systems. For instance, Kitjacharoenchai et al. [8] introduced a Multiple Traveling Salesman Problem with Drones (mTSPD), which considers multiple trucks and drones working in tandem. This model more accurately reflects real-world scenarios where companies may deploy a fleet of vehicles and drones simultaneously.

3.2 Solution Approaches

There are two main approaches for categorizing UAV path planning algorithms.

3.2.1 Deterministic Solution Approaches

Deterministic techniques for UAV path planning strive to determine the best solution that reduces the objective function while meeting all constraints. Nevertheless, these techniques can be costly in terms of computer resources and not feasible for extensive issues. A few of the typical deterministic techniques will be reviewed after.

Mixed Integer Programming (MIP) is a method of mathematical optimization that deals with a combination of continuous and integer variables. MIP has the ability to represent different elements of UAV trajectory planning, including path selection, timing, payload management, and power replenishment. Commercial solvers or branch-and-bound algorithms can both solve MIP formulations. Nonetheless, MIP is affected by the issue of dimensionality, leading to potential delays in reaching the best solution or confirming its optimality [17].

Constraint Programming (CP) is a programming approach that defines problems in terms of variables, domains, and constraints in a declarative manner. CP is capable of solving intricate and combinational issues through the utilization of effective searching and reasoning methods. CP is capable of handling uncertainty and preferences in UAV path planning as well. Nevertheless, CP may necessitate a significant quantity of memory and computational resources for searching the space [18].

Dynamic Programming (DP) is a recursive optimization technique that divides the problem into smaller subproblems that overlap. DP can achieve the best solution by saving and reusing the outcomes of the smaller problems. Dynamic programming can be used for solving problems related to planning the path of UAVs with a sequential or stage-wise structure, like TSP or VRP. Nevertheless, DP might face issues with dimensionality and state explosion as the number of states or stages grows [19, 20].

3.2.2 Heuristic and Metaheuristic Approaches

Heuristic and metaheuristic methods are approximate techniques that can discover near-optimal solutions for UAV path planning within a reasonable timeframe. They are appropriate for tackling big and intricate problems that deterministic methods cannot solve. They are appropriate for tackling big and intricate problems that deterministic methods cannot solve. Heuristic techniques rely on specific problem knowledge and guidelines, whereas metaheuristic techniques are influenced by natural events and incorporate random elements to navigate the search area.
Genetic Algorithms (GA): These methods involve populations that replicate the process of natural evolution. Selection, crossover, and mutation are utilized in order to create fresh solutions from a current collection. Genetic algorithms can manage various objectives and constraints, and can be integrated with local search techniques to enhance the quality of the solution. Drone path planning commonly uses genetic algorithms in different situations, like one or several drones, stationary or changing terrains, and two or three-dimensional environments [21, 6, 22].
Ant Colony Optimization (ACO): Describes swarm intelligence methods that mimic the behavior of ants in finding the shortest path to a food source. They depend on pheromone trails for communication and guiding the search process. ACO can manage discrete and continuous problems, and can adapt to changes in the environment. ACO has been applied for designing UAV routes in different situations, such as navigating around obstacles, addressing several objectives, and carrying out teamwork missions [23, 6, 22].
Particle Swarm Optimization (PSO) is a type of swarm intelligence approach that simulates the collective behavior of birds or fish in a group. Velocity and position vectors are utilized to adjust solutions according to both individual and overall best solutions. PSO is able to solve nonlinear and multimodal problems, and can be adjusted to include constraints and preferences. PSO has been used for planning paths for UAVs in different scenarios including following terrain, encountering wind, and managing energy usage [24, 6, 22].
Variable Neighborhood Search (VNS) is a type of solution-based approach that navigates various neighborhoods of the present solution in order to avoid getting stuck in local optimum points. A shaking mechanism is employed to disturb the solution, while a local search method is utilized to enhance it. VNS is simple to implement and compatible with all local search techniques. VNS has been utilized for UAV path planning in various scenarios, including situations involving no-fly zones, multiple UAVs, and fleets of different types [25, 6, 22].
Tabu Search (TS): TS are solution-oriented techniques that utilize a temporary memory to retain recent actions and avoid repeating them. If they find a better solution, they will use an aspiration criterion to ignore the forbidden status. TS is capable of solving intricate and limited problems, and can be combined with other techniques to improve its effectiveness. TS have been applied in various situations for UAV path planning, including dynamic environments, multiple objectives, and cooperative tasks [26, 6, 22].
Simulated Annealing (SA) are random methods that imitate the metallic annealing pro-

cess. A temperature parameter is used to regulate the likelihood of accepting inferior solutions in order to break away from local optima. They slowly lower the temperature until they achieve a solution that is almost ideal. Simulated Annealing is capable of addressing discrete and continuous problems, and can be integrated with other techniques to enhance performance. SA has been utilized for UAV route planning in various scenarios, including steering clear of obstacles, accounting for wind conditions, and managing energy usage [27, 6, 22].

3.2.3 Emerging Approaches

Machine Learning and Artificial Intelligence techniques are increasingly being applied to drone path planning problems. Reinforcement Learning (RL) algorithms, in particular, have shown promise in handling dynamic and uncertain environments. These approaches allow drones to adapt their routes in real-time based on changing conditions, a crucial capability for urban delivery scenarios.

Another emerging trend is the use of multi-objective optimization techniques. As drone delivery systems need to balance multiple, often conflicting objectives (e.g., minimizing delivery time, reducing energy consumption, and avoiding no-fly zones), researchers are developing sophisticated algorithms capable of finding Pareto-optimal solutions. For instance, Jeong et al. [28] proposed a multi-objective approach that considers payload-energy dependency and no-fly zones in truck-drone hybrid delivery routing.

3.3 Comparative Analysis of Existing Research

To provide a comprehensive overview of the current state of research in drone delivery path planning, we have compiled a summary of key studies, their approaches, and their respective strengths and limitations. Table 1 presents this comparative analysis. As evident from Table 1, recent research in drone delivery path planning has made significant strides in addressing real-world challenges. However, there are still opportunities for improvement, particularly in areas such as scalability, adaptability to dynamic environments, and integration of multiple constraints and objectives.

4 Environmental Factors and Constraints

One of the obstacles in planning drone routes is to take into account the environmental factors and restrictions impacting the drone's capabilities and practicality. Research has examined different elements of the surroundings and limitations, including:

4.1 Static vs. Dynamic Environments

In a static environment, obstacles and targets are stationary and predetermined, whereas in a dynamic environment, obstacles and targets have the potential to change or move

Table 1: Summary of key research in drone delivery path planning

Study	**Model**	**Key Characteristics**	**Benefits**	**Limitations**
Agatz et al. [11]	TSP with Drone	Combined truck-drone delivery; Optimization of drone launch and rendezvous points	Reduced delivery times; Improved last-mile efficiency	Limited to single truck-drone pair; Doesn't consider battery constraints
Otto et al. [14]	Multi-Objective VRP	Multiple drones and objectives; Consideration of payload and energy constraints	Balanced efficiency and environmental impact; More realistic modeling	High computational complexity; Limited scalability for large fleets
Li et al. [29]	Probabilistic Path Planning	Incorporates uncertainty in environmental factors; Uses mixed integer linear programming	Improved robustness in real-world conditions; Considers multiple uncertain factors	Increased computational time; May lead to overly conservative paths
Ren et al. [40]	Wind-Aware Path Planning	Explicit modeling of wind effects; Combines fluid dynamics with path optimization	Improved energy efficiency; More realistic flight time estimates	Requires accurate wind data; May not adapt well to rapid wind changes
Marinelli et al. [31]	3D Path Planning in Urban Environments	Considers building heights and no-fly zones; Uses graph-based representation of urban space	Enhanced safety in urban deliveries; Compliance with airspace regulations	High computational requirements; May lead to longer paths in dense areas
Rojas Viloria et al. [45]	Medical Supply Delivery Optimization	Focuses on emergency medical deliveries; Integrates with existing healthcare logistics	Improved response times in emergencies; Potential life-saving implications	Limited to specific use case; May not generalize well to other domains
Murray & Chu [1]	Flying Sidekick TSP	Combines ground vehicle with drone; Drone launches from and returns to truck	Leverages strengths of both vehicles; Potentially faster than truck-only delivery	Complex synchronization required; Limited by drone range and capacity

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Study	**Model**	**Key Characteristics**	**Benefits**	**Limitations**
Chiang et al. [4]	Drone Fleet Deployment for Urban Delivery	Large-scale urban delivery modeling; Considers multiple depots and drones	Improved scalability for city-wide operations; Reduced overall delivery costs	Simplifies some real-world constraints; May not account for all urban complexities
Kitjacharoenchai et al. [8]	Multiple TSP with Drones	Multiple trucks and drones working together; Considers drone launch and rendezvous scheduling	Increased delivery capacity and range; Potential for significant time savings	Complex coordination required; May be challenging to implement in practice
Zhang et al. [12]	Energy-Aware Path Planning	Detailed modeling of drone energy consumption; Considers terrain and payload effects on energy use	Improved accuracy in estimating flight range; More reliable completion of delivery missions	Requires detailed environmental data; May sacrifice speed for energy efficiency
Jeong et al. [28]	Multi-Objective Truck-Drone Routing	Considers payload-energy dependency; Incorporates no-fly zones in urban areas	Balances multiple real-world constraints; Improved applicability in complex environments	Increased computational complexity; May require trade-offs between objectives
Saleu et al. [2]	Dynamic Drone Delivery Routing	Real-time adaptation to new orders; Considers dynamic traffic conditions	Improved responsiveness to customer demands; Better performance in changing environments	Requires sophisticated real-time data processing; May lead to suboptimal solutions in some cases
Boysen et al. [16]	TSP with Drones and Robot-Drone Tandems	Introduces ground robots working with drones; Considers multi-modal delivery options	Increased flexibility in delivery methods; Potential for improved efficiency in varied terrains	Increased system complexity; Requires careful coordination of multiple vehicle types

while the drone is flying. Drone path planning faces increased challenges in dynamic environments due to the need for immediate adjustments and re-planning. Various strategies for managing changing circumstances involve employing online optimization algorithms [11], integrating uncertainty models [29], and utilizing reinforcement learning techniques [30]. Recent research by Marinelli et al. [31] has focused on developing robust path planning algorithms for urban environments, where the dynamic nature of obstacles (e.g., moving vehicles, pedestrians) presents unique challenges.

4.2 Presence of No-Fly Zones

No-fly zones are designated areas where drones are not allowed or are limited from flying because of safety, security, or privacy concerns. No-fly zones can be found at places like airports, military bases, government buildings, and private properties. Planning routes for drones must ensure they do not enter restricted airspaces, potentially forcing them to take detours or find alternate paths. Different ways to address no-fly zones are utilizing graph-based models [32], implementing penalty functions [33], and integrating geometric constraints [34]. Shakhatreh et al. [35] provide a comprehensive review of the regulatory challenges and technological solutions for managing no-fly zones in urban drone operations.

4.3 Battery Constraints

Battery limitations pertain to the restricted amount of energy and lifespan of drones, which restricts the distance and length of their flights. In drone path planning, the limitations of the battery must be taken into account, which might mean incorporating stops for recharging, refueling, or changing batteries at designated stations throughout the journey. Several approaches to address battery limitations involve utilizing multi-depot models [36], implementing energy consumption models [37], and integrating battery-aware objectives [38]. Recent advancements in battery technology and energy-efficient flight algorithms have been reviewed by Zhang et al. [12], highlighting potential solutions to extend drone flight times and operational ranges.

4.4 The Impact of Wind

The impact of wind speed and direction on the drone's flight, known as wind influences, can impact the drone's energy consumption, stability, and accuracy. Drone path planning needs to take into account the impact of wind, which might necessitate making changes to the drone's speed, altitude, or orientation. Several strategies for managing wind effects involve utilizing wind field models [37], implementing wind compensation methods [38], and integrating wind-aware goals [39]. Ren et al. [40] provide a comprehensive review of wind-aware path planning for UAVs, offering new insights into the challenges and potential solutions in this area.

4.5 Coordinating Multiple UAVs

The coordination and collaboration of numerous drones to accomplish a shared objective, like covering an extensive area, delivering multiple packages, or executing a complicated task, is known as multiple UAV coordination. Planning the flight path of drones must take into account coordinating multiple UAVs, which could involve communication, synchronization, or collaboration between the drones. Several approaches for managing coordination among multiple UAVs include employing swarm intelligence algorithms [22], utilizing game theory models [34], and integrating cooperative objectives [30]. Recent work by Otto et al. [14] has explored optimization approaches for coordinating large fleets of UAVs in complex delivery scenarios, addressing issues such as task allocation and conflict resolution.

5 Applications and Case Studies

While the primary focus of this review has been on the theoretical models and environmental constraints relevant to drone delivery systems, an examination of real-world implementations provides valuable insights into the practical applications of these frameworks. This section explores various applications of drone delivery systems, highlighting both theoretical research and empirical evidence from industry implementations.

The transition from theoretical models to practical applications has been marked by several notable successes in diverse geographical and operational contexts. For instance, Zipline, a U.S.-based company, has successfully implemented drone delivery systems for medical supplies in Rwanda and Ghana [41]. Their operations demonstrate the effectiveness of optimized path planning models in real-world scenarios, particularly in remote and hard-to-reach areas. The Zipline system utilizes a fleet of fixed-wing drones capable of serving an area of 22,000 km^2 from a single distribution center, effectively applying time-dependent Vehicle Routing Problem (VRP) models to optimize real-time order processing and route planning [3].

In more developed urban environments, companies like Amazon and Google have been testing drone deliveries through their respective services, Prime Air and Wing Aviation. These initiatives showcase the potential for integrating Unmanned Aerial Vehicles (UAVs) into complex urban delivery networks. Amazon's Prime Air service, for example, has conducted successful trials in the United Kingdom, demonstrating the applicability of multi-objective optimization models that balance factors such as delivery speed, energy efficiency, and safety in densely populated areas [42].

These real-world implementations underscore the applicability of theoretical frameworks such as the Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP) in optimizing delivery routes and overcoming logistical challenges. They also highlight the importance of adapting these models to specific operational contexts, whether it be the sparse infrastructure of rural Africa or the complex airspace of urban environments.

Moreover, these practical applications have revealed additional challenges not always apparent in theoretical models. For instance, regulatory compliance, public acceptance, and

integration with existing logistics systems have emerged as critical factors in the successful deployment of drone delivery systems [43]. These real-world constraints have spurred further refinements in path planning algorithms and operational strategies, fostering a productive feedback loop between theory and practice.
The following subsections delve deeper into specific application domains, presenting both theoretical research and case studies of real-world implementations. This dual focus aims to provide a comprehensive understanding of the current state of drone delivery systems and their potential future trajectories.

5.1 Surveillance and Monitoring

Drones have the capability to oversee vast expanses of land, like forests, farms, or borders, and offer up-to-the-minute updates on the condition of the environment, wildlife, or human actions. For instance, Xia and colleagues in 2019 introduced an aerial surveillance system using drones to detect and pinpoint forest fires [30]. A hybrid optimization algorithm was employed for drone route planning, while a deep learning model was utilized for processing images taken by the drones. They evaluated their system's performance in a simulated forest fire situation and demonstrated its ability to attain both high accuracy and efficiency. Recent advancements in this field, as reviewed by Zhao et al. [46], have shown promising applications of UAVs in smart city monitoring, including traffic management, urban planning, and environmental monitoring.

5.2 Precision Agriculture

Drones have the ability to enhance crop productivity and quality through the provision of precise and timely information on soil, water, and plant conditions. In 2022, Zheng created a system using drones to accurately irrigate and fertilize cotton fields [47]. He utilized a drone-mounted multi-spectral camera to take photos of the fields, then employed a machine learning algorithm to assess the images and produce maps for watering and fertilizing. He performed an on-site study and showed that his method could lower the usage of water and fertilizer, while also boosting cotton production and improving its quality. Recent research by Zhao et al. [46] has further expanded on these applications, demonstrating the potential of drone-based systems in pest detection, yield estimation, and crop health monitoring across various agricultural settings.

5.3 Examination of Infrastructure

Drones can be utilized for examining crucial infrastructures like bridges, pipelines, or power lines, identifying any flaws or impairments that could present safety hazards. An instance is when Ferrandez et al. [48] introduced a drone-powered system for examining bridges. A drone equipped with a camera and laser scanner was utilized to gather 3D point clouds and images of the bridge, followed by the use of a computer vision algorithm to reconstruct the bridge model and detect cracks or corrosion. They tested their system on an actual bridge and demonstrated its ability to achieve high levels of accuracy and completeness. Recent developments in this field, as highlighted by Shakhatreh et al. [35], have shown the potential of using swarms of drones for more comprehensive and efficient infrastructure inspections, particularly in hard-to-reach or hazardous environments.

5.4 Handling Disasters Efficiently

Drones have the potential to help in disaster relief efforts by aiding in search and rescue missions, delivering medical supplies, and assessing damage. Xia and colleagues [30] introduced a drone-centered system for handling disasters. A group of drones was employed to carry out various assignments, including finding survivors, transporting first aid supplies, and charting the affected region. A multi-objective optimization algorithm was utilized to coordinate the drone swarm, while a reinforcement learning algorithm was employed to allow the drones to adjust to the changing environment. They ran a simulation of their system during a flood disaster situation and demonstrated that it could enhance survival rates and decrease response times. Recent work by Rojas Viloria et al. [45] has further explored the integration of drones in medical supply delivery during emergencies, highlighting the potential of UAVs in improving response times and access to critical resources in disaster-stricken areas.

5.5 Shipping and Delivery Processes

Drones are able to transport packages, especially to hard-to-reach or crowded locations, where traditional delivery methods may not be effective or feasible. As an illustration, Ala et al. [49] examined a drone-operated delivery service designed for remote regions of Tanzania. A linear programming model was utilized to optimize the drone fleet size, routing, and scheduling, while a discrete event simulation model was employed to assess the system performance. They discovered that drone delivery could lower the cost and time of delivery in comparison to truck delivery. Also, in Romania, Crişan et al. [32] conducted research on a drone delivery system designed for urban areas. A mixed integer programming model was utilized to optimize the drone routing and scheduling, while a geographic information system was employed to include urban constraints like buildings, roads, and no-fly zones. They demonstrated that drone delivery could decrease both delivery time and emissions in comparison to delivery by car. Recent innovations in this field, as discussed by Alwateer et al. [44], have explored the integration of blockchain technology and Internet of Things (IoT) in drone-based delivery systems, potentially enhancing security, traceability, and efficiency in last-mile logistics.

6 Conclusions and Future Directions

Drone delivery systems could transform last-mile logistics, but overcoming technical challenges, such as efficient path planning in real-world conditions, is crucial to their success.

This review paper has consolidated existing information and advancements in creating optimization methods and algorithms for drone route planning. It has reviewed theoretical models used to find the best routes, assessed ways to include environmental factors affecting drone performance and feasibility, and studied examples of drone delivery applications and case studies showing advantages.
Still, there are several obstacles that persist in this developing field. Developing optimization algorithms that are both scalable and efficient is a challenge when dealing with large-scale delivery operations involving numerous drones and trucks. Another hurdle is taking into account the unpredictability and fluctuations of actual surroundings, like varying climate, crowded roads, and restricted flying areas. Another challenge is guaranteeing the safety and security of drone delivery missions, which involves steering clear of collisions, safeguarding privacy, and thwarting unauthorized entry.
Future research in this area will focus on creating hybrid optimization techniques that merge deterministic and heuristic methods, integrating machine learning methods to adjust to changing environments [29], and exploring new areas of application like healthcare and humanitarian aid [45]. Additionally, it is crucial to have researchers from various disciplines, including operations research, computer science, engineering, and social sciences, working together in interdisciplinary collaboration to tackle the intricate and diverse issues surrounding drone delivery systems.
The integration of emerging technologies such as blockchain and IoT with drone delivery systems presents exciting opportunities for enhancing security, traceability, and efficiency in logistics operations [44]. Furthermore, advancements in battery technology and energy-efficient flight algorithms [12] may help address current limitations in flight duration and payload capacity, potentially expanding the scope and scale of drone delivery operations.
As regulatory frameworks continue to evolve, future research should also focus on developing adaptive path planning algorithms that can dynamically respond to changes in airspace regulations and no-fly zones. This will be crucial for the widespread adoption of drone delivery systems in urban environments [35].
In conclusion, while significant progress has been made in drone delivery systems and path planning algorithms, there remain ample opportunities for innovation and improvement. As the field continues to evolve, interdisciplinary collaboration and the integration of cutting-edge technologies will be key to overcoming current challenges and realizing the full potential of drone delivery systems in transforming last-mile logistics.

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