SURVEY

Hybrid Truck-Drone Delivery Systems: A Systematic Literature Review

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ABSTRACT Owing to the continued development of e-commerce, logisticians now have an outstanding obligation to tackle last-mile delivery challenges. A number of logistics providers have suggested the incorporation of drones with trucks to provide a more flexible delivery system. This paper analyzes the content of 95 publications related to hybrid truck-drone delivery systems (HTDDS) in the context of last-mile delivery. First, a brief overview of the potential implementation of drone delivery systems is presented, including their integration with other vehicles. The overview aims to demonstrate the operational characteristics of such systems and their implications. Then, the surveyed literature is classified based on vehicles roles, system configuration, problem formulation, and solution methods. In relation to this research, several key findings and potential research directions are discussed. Despite the high level of interest in HTDDS research, it is still in its early phases and requires improvements in various areas. The payload capacity, speed, range, and energy consumption are all factors that must be considered in the modeling of drone characteristics. Almost all studies identify customer requests before the delivery operation begins. However, customer demands for immediate delivery present an opportunity for real-time optimization to provide solutions for e-commerce activities. Environmental issues are developing, as the last-mile delivery problem is regarded as the most polluting portion of the supply chain. Thus, more consideration should be given to the environmental impact of HTDDS. Finally, research on drone routing related to air traffic management has received relatively little attention.

INDEX TERMS Drones, hybrid truck-drone delivery systems, last-mile delivery, routing.

I. INTRODUCTION
A. BACKGROUND

The e-commerce market, defined as the transaction of goods and services through an electronic communication channel [1], has witnessed a rapid increase due to its convenience and the wide range of offered products and services. In 2019, retail e-commerce sales reached $3.53 trillion worldwide, and it is forecasted to increase by $6.54 trillion by 2022 [2]. The continuous rise in the demand for e-commerce markets has impacted the logistics and transportation industry. Logistics providers need to adjust their strategies to manage the increased volume of packages and provide low-cost and on-time services. Undoubtedly, the last-mile delivery (LMD)

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problem, referred to as delivering goods from e-retailers hubs to their final destinations [3], is one of the main issues that logistics providers need to tackle. It is the most expensive, most polluting, and least efficient part of the e-commerce supply chain, accounting for 13%-75% of the total supply chain cost [4], [5]. In a 2020 survey on identifying the most significant challenges to LMD, 35% of retailers and manufacturers stated that reducing logistics costs is the main obstacle in providing efficient LMD services [6]. Additionally, environmental reports urge logistics providers to shift to eco-friendly solutions, where carbon dioxide emissions from freight transportation account for 30% of transportation-related carbon emissions [7]. The transportation industry must look for alternatives to tackle LMD hurdles such as high cost, ecological impact, and the complexity of supply chain performance. Businesses have begun competing to develop

new technologies and test different delivery methods, such as autonomous vehicles like robots and drones, to expedite deliveries and satisfy customers while reducing logistics costs and achieving real improvements in LMD practices.

One of the recently emerging technologies for resolving the LMD problem is autonomous delivery robots. Robots are self-driving road vehicles that travel on predetermined and regulated sequences to reach customers who unload the vehicle and get their packages [8]. They travel at a pedestrian pace of approximately 6km/h on sidewalks, significantly slowing their delivery speed but allowing them to transport heavy cargo of up to 10kg. They are also subjected to a low level of security rules, but they must rely on existing road networks [9]. Drones or unmanned aerial vehicles (UAVs) have recently been suggested as a means of performing last-mile deliveries, as they have several advantages compared to traditional delivery vehicles. In addition, they may move in three dimensions and are not physically bound to a pre-defined, static, and limited-capacity road network. This permits UAVs to be used for delivery in regions where road infrastructure is lacking, such as rural areas and islands [10]. Add to that, drones are not influenced by traffic congestion and can fly at varying heights [11]. Thus, drones are allowed to move at more consistent and higher average speeds, which can significantly shorten delivery times, particularly in congested metropolitan areas. Both delivery systems (drones and robots) are mathematically similar but differ mostly in particular characteristics such as payload, costs, operational ranges, regulations, and handling of traffic management.

The deployment of drones has received a lot of attention [12], due to the increased need for commercial drones for faster delivery. The market size of the global drone delivery service is estimated to reach $1.68 billion by 2023 [13]. A considerable number of technology companies such as UPS [14], Matternet [15], Flirtey [16], Amazon [17], Alphabet's Wing [18], and Zipline [16], are focusing on the development of drones to support logistics providers' needs for LMD. For example, UPS became the first Federal Aviation Administration (FAA)-approved nationwide drone aviation company to operate commercial drones in campus settings such as hospitals and universities [19]. Also, UPS has a partnership with Matternet to launch a drone on a college campus in the US [20]. Google provided public drone delivery services through its subsidiary company, Alphabet's Wing, which received an air carrier certificate from the FAA to provide drone services to the public [21]. It has launched the first air service in North Canberra, Australia, allowing customers to place food, beverages, and pharmacy items through mobile apps and have them delivered directly to their homes within minutes [22]. Through a study conducted by Amazon, 86% of their customers' orders weigh less than five pounds [23], which has driven Amazon to develop an Amazon Prime Air drone aiming to deliver five-pound packages within a 15-mile radius in 30 minutes [24]. Zipline drones have flown more than one million kilometers in Rwanda, conveying more than 13,000 medical parcels for emergency medicine [25]. Zipline is now extending its drone technology to Ghana in response to the current Covid-19 pandemic. It allows contactless drone delivery to transport Covid-19 test samples and therefore help healthcare authorities to react quickly to the pandemic and save lives [26]. Flirtey has also provided aid kits and emergency medication delivery in Australia and New Zealand [16]. Drone delivery has the potential to decrease delivery costs, avoid the congestion of traditional road networks, reduce carbon emissions, and increase customer satisfaction by reducing the number of missed deliveries caused by delivery delays [27].

B. RESEARCH SIGNIFICANCE AND MOTIVATION

This section provides a brief review of potential drone delivery systems in last-mile operations and discusses the significance and the different challenges entailed by such systems. We present the potential implementation of drone delivery systems adopted by companies such as Amazon, UPS, and others. These implementations differ in terms of their operational characteristics. Table 1 outlines several potential applications of drones in the LMD based on whether they operate independently or in conjunction with other vehicles such as trucks, trains, etc. Drones are launched from a fixed location like a fulfillment center in the first scenario, while they are released from a mobile vehicle, demonstrating a launch from a moving location in the second case. In addition, the operational characteristics of the drones along with the implementation of these delivery systems are presented.

Despite the advantages of drones, three major restrictions limit the performance of a drone-based delivery system. First, drone payloads are limited in terms of permitted size and overall weight of shipment [28]. Second, due to the restricted capacity of existing battery technology, drone operations are often hindered by short flight duration constraints [11]. This means that batteries must be recharged or replaced after each drone route. Third, the existing technology and regulations restrict the complete dynamic and coordinated control of multiple drone-based delivery models [29]. Furthermore, the FAA has established restrictions that limit the use of drones for commercial purposes when flying in airspace such as keeping the drone within the visual line of sight [30]. Thus, the use of drones for commercial purposes will tremendously benefit businesses but will still enact significant limits.

A recent research avenue is to integrate drones with traditional delivery methods such as trucks to form hybrid truck-drone delivery systems (HTDDS). With the combination of the two delivery methods, the advantages of the truck, such as long-range travel capability and high load capacity, can offset the disadvantages of drones and vice versa [31]. Figure 1 depicts an example of the HTDDS configuration. In general, the truck departs from the depot to launch the drone at a specific node, which could be a customer node or any non-customer node (drone station, a point along the truck's path, etc.). Afterward. the drone delivers to customers and finally returns to the truck for recharging, maintenance,

and replenishment. This operation is repeated until all customer deliveries are fulfilled.
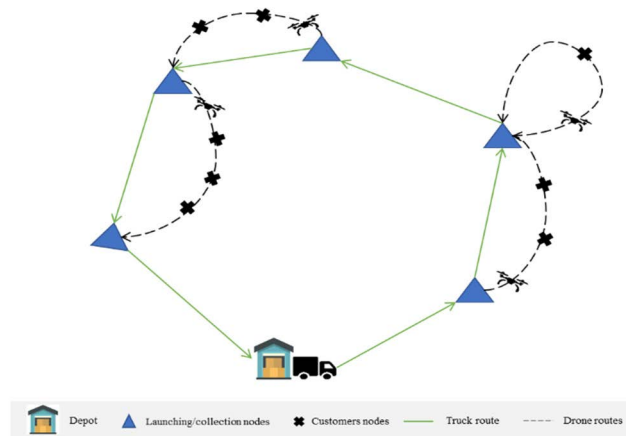

FIGURE 1. Illustration of HTDDS.

Exploring HTDDS is undeniably attracting academicians and practitioners. UPS has reported that truck-drone systems could save up to $50 million per year by only cutting a mile off per day for every driver's route [32]. In addition, Amazon has received a patent for a combined truck-drone system in which the truck serves as a mobile facility for launching, receiving, and maintaining the drone [33]. Several applications mentioned in Table 1 reveal that unlike in traditional vehicle routing problems (VRPs), the depot from which we route deliveries no longer needs to be in one location and can move as we deliver. Furthermore, the number of deliveries made by drones varies. For instance, Amazon airborne fulfillment center [34] handles multiple drones [35], all carried out by a moving system. In this case, the system also requires proper parcel transfer scheduling and an appropriate optimization of routing for both system components. Therefore, it is more important than ever to pay attention to the design challenges of drone systems. Integrating drone technology with conventional vehicles (e.g., trucks) would undoubtedly increase the difficulty of optimizing the delivery system.

Other researchers have conducted reviews of HTDDS research [11], [36], [37], [38], [39], [40], [41], [42], [43], [44]. For example, Otto *et al.* [40] conducted a thorough analysis of the drone literature, concentrating mostly on civil applications. In addition, only 15 articles on integrated operations between vehicles and drones in transportation are examined. Similarly, Khoufi *et al.* [41] covered drone path optimization problems as well as surveillance and monitoring problems. However, they analyzed a small number of studies in the context of transportation and delivery. Macrina *et al.* [43] surveyed 63 publications that focus on routing problems for package delivery while providing a classification of the drone routing problems based on their descriptions and solution methods only. Chung *et al.* [37] reviewed the state of the art of drone operations (DO) and drone-truck combined operations (DTCO) in civil applications. The authors focused on optimization issues, including mathematical models, solution

approaches, vehicle synchronization, and challenges to DO and DTCO implementation. The authors surveyed 68 papers on DTCO in a variety of fields, including agriculture, security, disaster management, entertainment and media, transportation and logistics, and other areas. A total of 43 articles in the reviewed literature are concerned with the application of transportation and logistics. Poikonen and Campbell [36] identified future directions in the research of drone optimization. They also provided ways to improve modeling in the context of drone capabilities and suggested alternative delivery modes. Rojas Viloria *et al.* [38] presented a literature review of 79 publications on the characterization of routing problems using drones in applications such as parcel delivery, surveillance, entertainment, military, and internal logistics. The surveyed literature is divided into categories based on the goal function, solution strategy, and constraints. Among the 79 articles, there are 25 related to package delivery using drones in combination with vehicles such as trucks, unmanned ground vehicles, motorcycles, and others. Thus, there is no extensive discussion in the field of HTDDS. Similarly, Cheikhrouhou and Khoufi [39] reviewed the recent contributions regarding ground vehicles and UAVs, with a focus on the application fields such as transportation and delivery, data collection, search and rescue, multi-robot task allocation, and scheduling. For each contribution, they discussed optimization approaches like exact methods and metaheuristics to solve routing problems such as the multiple traveling salesman problem (mTSP). However, there is no detailed review of HTDDS as the paper presents a brief review of them. Boysen *et al.* [11] recorded the several delivery concepts methodically in a concise notation scheme, analyzed the relevant decision problems, and examined previous research on operations research approaches for tackling these challenges. Hence, their focus is not on drone operations solely. Add to that, the literature on drone delivery is classified based on whether it is merely on drone operations or in conjunction with other vehicles, as well as solution methods. Li *et al.* [42] reviewed the integration of ground vehicles and UAV forming a two-echelon network. The authors classified two-echelon network routing challenges depending on the characteristics of the routing problems. The categorization supplied is limited and considers features such as number of drones, payload capacity of drones, time window, objective function and solution methodologies. Finally, Moshref-Javadi and Winkenbach [44] provided a comprehensive review of the real-world applications of drones in the logistics industry. They also reviewed the relevant drone-based logistics systems and their associated operational planning problems. In particular, the systematic review covers a variety of application areas such as emergency services, healthcare services, e-commerce, disaster relief, food distribution, and others.

Although a great number of survey papers have been conducted, none of the available contributions provide a systematic classification approach for distinguishing HTDDS models based on their detailed system configurations (number of vehicles, role of vehicle, and model description),

TABLE 1. Potential applications of drones in the last mile.

Delivery system	Potential application	Drone characteristics				Implementation	
		Speed	Payload capacity	Range	Delivery time	Yes	No
Drone delivery from a fixed location	Amazon prime air delivery drone [24, 45]	50 mph	5 lbs	16 km	13 minutes	Cambridge, UK	-
	Matternet drone [15]	25 mph	4.4 lbs	12.5 miles	15 minutes	College campus	-
	Alphabet's Wing drone [46]	70 mph	3.3 lbs	12 miles	-	North Canberra, Australia	-
Drone delivery system from a moving location	UPS truck-drone system [47]	-	10 lbs	-	30 minutes (total flight time)	Rwanda	-
	Amazon train-mounted mobile hubs for drone delivery [48]	-	Single delivery	-	-	-	patent
	Amazon airborne fulfillment center [34]	-	10 lbs	-	10 minutes	-	patent
	Workhorse and horsefly truck-drone system [49]	45 mph	10 lbs	-	25 minutes (total flight time)	Virginia, US	-
	Amazon truck-drone system [50]	50 mph	5 lbs	16 km	-	-	patent

operational characteristics, and solution methods. It is critical to review the literature on HTDDS methods primarily in the area of LMD, as a substantial amount of scholarly research has accumulated on this system in recent years. Generally, drones have emerged as an innovative and realistic business alternative for LMD due to their recent technological breakthroughs. When compared to a traditional LMD operation using a vehicle, a drone offers competitive advantages such as reduced cost structure, faster delivery time, better reach in low-infrastructure areas, and lower carbon emissions. When drone operations are combined with truck operations, they provide superior performance [51]. HTDDS problems are viewed as extended versions of the VRP. Considering the availability and location of customers, the possibility of rerouting shipments, drone power limitations, and other operational factors, the routing and/or scheduling problems have become more dynamic and, therefore, more challenging to address. Thus, there is a need to better understand the resulting system challenges and the solution techniques needed for solving HTDDS problems efficiently.

The purpose of this paper is to provide a comprehensive review of the current state of the art of HTDDS models with an emphasis on routing problems. The review paper follows a systematic research methodology to conduct a thorough examination of the literature on HTDDS models. In specific, we first categorize the reviewed literature using multiple ways ranging from the number of trucks, the number of drones, and the roles of both vehicles, as well as the type of operation between them. Furthermore, the study examines HTDDS optimization models in-depth and provides extensively referenced objective functions and model constraints. The approaches to solving the HTDDS models are also being evaluated. Finally, we explore the research gaps in the HTDDS modeling literature and outline future research directions. In addition, the extent of HTDDS models' application in real life is discussed by highlighting the roadblocks to employing existing HTDDS models in real life.

The remainder of the paper is structured as follows: In section 2, the methodology of the systematic literature review is presented. Section 3 provides the state of the art of HTDDS research and summarizes papers based on the roles of vehicles and system configuration. Section 4 classifies the evaluated literature based on objective function and model constraints and parameters, while section 5 classifies it based on solution methods. Section 6 states research gaps and recommendations as well as barriers to the real-world application of HTDDS. Finally, the review is concluded.

II. METHODOLOGY

In this paper, we follow the methodology suggested by Tranfield *et al.* [52] for conducting a systematic review. Figure 2 shows the main stages of the systematic review methodology. Each of the three stages is provided in detail below:

- Planning the review: Through looking at the technological initiatives of HTDDS in the industry, HTDDS is viewed as being of high importance to academicians and researchers, owing to the increased modeling challenges that this system can have. These challenges include the drone's flying time, load capacity, battery capacity, number of customers, drone's and truck's roles and their numbers, etc. This emphasizes the significance of designing effective solutions methods capable of achieving high-quality outcomes to withstand the system's actual application use. As a result, this paper systematically synthesizes the existing literature and addresses the following questions:
  RQ1: How are trucks and drones integrated to form a delivery system in the literature of HTDDS?
  RQ2: How HTDDS optimization problems are modeled in the literature?
  RQ3: What solution approaches are used to solve the related optimization problems?
  RQ4: To what extent are the developed models and solution methods applicable in real-life situations?

- Conduct the review: Given that the introduction of the HTDDS is relatively new, the time period of the literature review is from 2015 to 2021. The search keywords are (("truck" OR "vehicle") AND ("drone" OR "unmanned aerial vehicle" OR "UAV" OR "unmanned aircraft" OR "unmanned aerial system" OR "UAS") AND ("last mile" OR "delivery" OR "logistics") AND "rout*").
- The publications have been collected from Scopus, Science Direct, and IEEE Xplore databases, focusing on peer-reviewed articles, conference papers, and book chapters. Each database resulted in a separate list, and the total number of generated studies was 579 papers. In specific, the number of studies found in Scopus, IEEE Xplore, and ScienceDirect databases is 388, 99, and 92, respectively. A total of 268 duplicates were removed from the combined list, and 144 studies were chosen based on the relevance of the title. Following that, the selected studies were reviewed based on the abstract, resulting in 120 articles. The content of the paper is then examined using the following criteria: focus on the application of the HTDDS in LMD; routing considerations of the HTDD; the availability of solution methods including exact and heuristic solutions; and the availability of numerical results. On the other hand, studies that only focus on drone delivery systems are excluded from the list of surveyed studies. We also considered the quality of the publications and excluded those deemed to be of substandard quality. The examination of the content generated a list of 89 publications. Further, all references from the selected studies were reviewed to guarantee thoroughness, and the few missing from the initial search were included in the final list. As a result, six papers were added and the content of 95 critical studies is to be reviewed.
- Reporting and dissemination: the articles are initially classified based on different aspects. Then, a discussion of the major findings, research gaps, and the main roadblocks to implementing HTDDS in real life is presented. Finally, we discuss potential future research directions.

Figure 3 depicts the growing interest in this research field, emphasizing the need to highlight future directions of HTDDS deployment in LMD. There is a slow realization of this area of research in the first two years, followed by a moderate increase in the following three years. The number of publications has increased dramatically in the last two years, indicating that scholars have a great interest in HTDDS optimization problems.

III. REVIEW OF HTDDS BASED ON PROBLEM TYPES AND CONFIGURATION

In this section, the surveyed literature is examined based on the variants of optimization problems, which are then classified according to the vehicles' roles. Further, we categorize the HTDDS literature based on the number of trucks

and drones used in the delivery system, as their number and synchronicity influence system configuration.
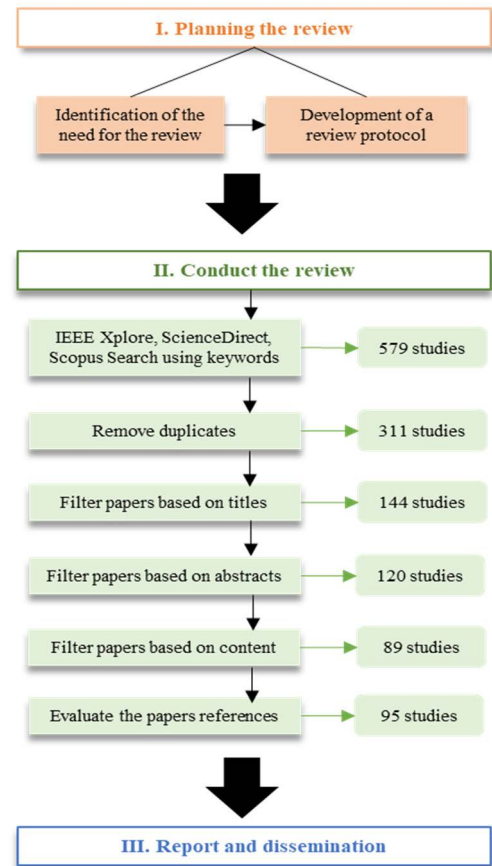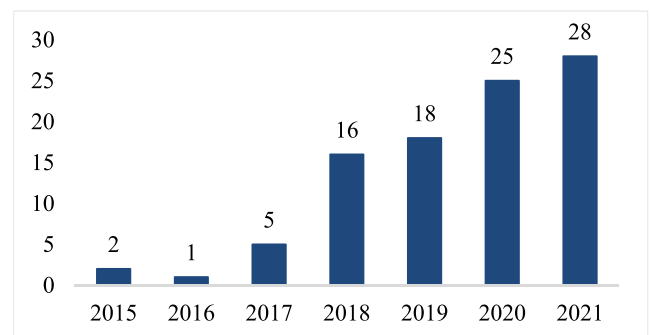

FIGURE 2. Research methodology.

FIGURE 3. Number of publications per year.

A. REVIEW BASED ON VEHICLES ROLES

The surveyed literature presents different ways of integrating trucks and drones to form a delivery system. The two vehicles can collaborate similarly or differently in order to reach the end customer. The level of collaboration arises from the responsibility of the truck to support the drone in terms of launching, collecting, maintaining, and replenishing it with delivery packages. Drones can either deliver

to customers or resupply the truck with delivery packages, while trucks can serve customers and/or operate the drone. Accordingly, we classify the HTDDS literature based on that. Table 2 summarizes the four classifications, namely, collaborative HTDDS operations with truck and drone delivery (type 1), collaborative HTDDS operations with drone delivery (type 2), HTDDS with independent delivery operations (type 3), and HTDDS operations with drone resupply (type 4).

This section presents the problems that fall under each category. To the best of the authors' knowledge, the literature is rich with 34 identified abbreviations. However, these differences in nomenclature do not necessarily provide the main difference in problem definition. Many of these problems have variants that add new features to the original problem, such as increasing the number of trucks and drones, incorporating new drone operational characteristics, changing the type of objective function, and altering constraints and/or parameters. For quick reference, we provide a brief description of the problems according to the roles of trucks and drones.

1) COLLABORATIVE HTDDS OPERATIONS WITH TRUCK AND DRONE DELIVERY

The collaborative HTDDS operation is referred to as both vehicles (trucks and drones) having the role of serving customers. In addition, the truck is responsible for operating the drone. Figure 4 illustrates this type of HTDDS design, where the truck is responsible for launching and collecting the drone at the customer nodes that the truck visits. This type of integrated operation between the two vehicles is widely considered in the literature such as the flying sidekick traveling salesman problem (FSTSP), traveling salesman problem with a drone (TSP-D), vehicle routing problem with drones (VRP-D), and other problems. A brief discussion of each problem and its variants is given in this part.

a: FSTSP AND ITS VARIANTS

Murray and Chu [53] were the first to introduce the assignment of a drone working collaboratively with a truck to provide delivery services to customers. The FSTSP considers a single truck-single drone system configuration to minimize the time required to serve all customers and return both vehicles to the depot. The truck can serve several customers at the same time as the drone makes a single delivery. Additionally, both vehicles can only reconnect at a customer location that has not been visited previously, and the drone may return to the depot separately. Furthermore, the drone is allowed to fly between customers, while the truck should travel along with the road network. The problem is also addressed by [54], [55], [56], [57], [58], [59], [60], [61], which employed different solution methods.

The FSTSP has been extended in different ways. Murray and Raj [62] consider a fleet of heterogeneous drones, each of which varies in terms of weight or volume capacity and endurance. The problem is known as the multiple-flying

TABLE 2. Characteristics of the vehicles' roles-based categories.

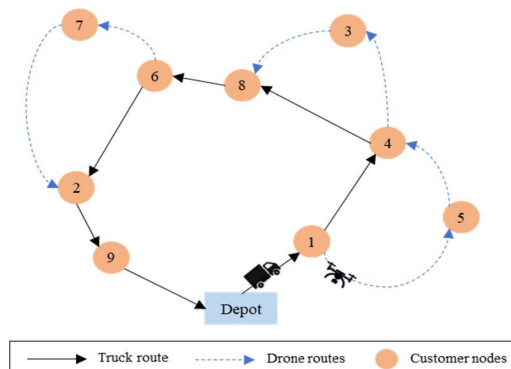| Category	Truck delivery	Drone delivery / delivery and pickup	Responsibility for operating drone	Drone resupply
Type 1	✓	✓	✓	-
Type 2	-	✓	✓	-
Type 3	✓	✓	-	-
Type 4	✓	-	-	✓

FIGURE 4. Illustration of type 1.

sidekick traveling salesman problem (mFSTSP). Despite the truck's ability to transport all the drones at once, only one drone is launched or retrieved at a time. As in FSTSP, the drone cannot be launched from the same location more than once. Jeong *et al.* [63] modify the FSTSP by proposing the flying sidekick traveling salesman problem with energy consumption and no-fly zone (FSTSP-ECNZ) problem. The FSTSP-ECNZ considers no flying zones for the drones, which are shaped like circles and do not overlap. No-fly zones are areas where drones are not permitted to operate at any given time. Taking this constraint into account presents a significant challenge when optimizing, but it does demonstrate the regulatory rules imposed on drones. To tackle this constraint, a time-dependent detour method was designed, which provides a detour decision. Also, FSTSP-ECNZ considers the parcel weight, which is used to establish an energy consumption model to calculate the drone's energy expenditure and approximate flight time in accordance. Raj and Murray [64] develop a new version of the mFSTSP known as the multiple-flying sidekick traveling salesman problem with variable drone speeds (mFSTSP-VDS), which incorporates the drone's speed as a variable. Each drone has a fixed battery capacity and can fly at any speed up to the maximum speed, with the drone's endurance determined by these two parameters (battery capacity and speed). The objective is to reduce the total time it takes to deliver to all customers and return to the depot, and a three-phased algorithm is proposed which dynamically changes the drone's speed to provide the minimum total time. In contrast to the results obtained by fixing the drone's speed to its highest permissible limit, the

results obtained by using variable drone speeds yield better solutions. Kitjacharoenchai *et al.* [65] suggest an extended version of the FSTSP referred to as a two-echelon vehicle routing problem with drone (2EVRPD) that involves delivering goods with several drones and trucks. Two-echelon routing levels are addressed in this model, with the first level considering the truck's delivery role and the second level dealing with the drone's delivery function. Each truck can only accommodate a certain number of drones at any given time, and multiple drones cannot be launched or retrieved at the same node. Gonzalez-R *et al.* [66] present the truck-drone team logistics (TDTL) problem, which is a generalization of the FSTSP. The system considers a truck and a drone working in conjunction to fulfill customer orders. The drone can only rendezvous at customers' nodes and can visit several customers per trip if its battery capacity is not exceeded. The earliest departure from the mission's end node is minimized, and an optimal solution is given. In some cases, the drone is responsible for delivering and picking up delivery packages. For instance, Gacal *et al.* [67] present a new technique for battery switching that maximizes the energy replenishment for an FSTSP while addressing the drone's restricted flying range. The hovering duration is incorporated as part of the battery optimization to accurately track the condition of the drone's charge. This is due to the drone's energy being spent while hovering. Schermer *et al.* [68] combine the notion of drone stations with the concept of the FSTSP to reduce delivery time by combining expensive high-speed aerial aircraft with less expensive ground-operated and slower-moving vehicles. They suggest the drone-assisted traveling salesman problem (TSP-D-RS), in which a single truck is outfitted with a single drone and prospective locations for stations that house robots for unattended deliveries. Luo *et al.* [69] extend the FSTSP by introducing the multi-visit TSP with multi-drones problem (MTDSP-MD). In contrast to the FSTSP description, this problem considers the combination of a single truck with multiple that are capable of serving multiple customers per trip. Gomez-Lagos *et al.* [70] also present a new variant of the FSTSP called the traveling salesman problem with drone and parking (TSPDS). This variant considers multiple drones in conjunction with a truck, which launches and collects the drones at parking lots.

b: TSP-D AND ITS VARIANTS

Many studies have been conducted on the TSP-D problem. Among them, Agatz *et al.* [12] were the first to propose TSP-D, which considers the combination of a single truck and a single drone to make deliveries to customers. The TSP-D's goal is to determine the shortest time to complete the route of serving all customers by either the truck or the drone. In this problem, the truck can only launch and retrieve the drone when it is stopped at the customer's location or the depot. Furthermore, the two vehicles' meeting points can be visited several times, and the truck's travel time between any two locations is proportional to the Euclidean distance.

Ha *et al.* [31] build on the work of Murray and Chu [53] and Agatz *et al.* [12] by focusing on the cost aspect of the objective function rather than the time aspect. To present the problem known as min-cost TSP-D, two heuristics are proposed: Greedy Randomized Adaptive Search Procedure (GRASP), and TSP with Local Search (TSP-LS) which is adapted from the heuristic proposed by Murray and Chu [53]. Tu *et al.* [71] propose the TSP with multiple drones (TSP-mD) problem which extends the TSP-D by taking into account multiple drones. A certain number of drones are permitted to fly at the same time and be retrieved by truck at the same or different location. Both vehicles cannot wait for each other for more than a specific period of time. GRASP, which was initially developed by Ha *et al.* [31], was used to solve the problem. Kitjacharoenchai *et al.* [72] enable several trucks and drones to serve customers as salesmen. The aim of the multiple traveling salesmen problem with drones (mTSPD), which uses a version of mTSP called min-max TSP, is to reduce each salesman's overall tour length (in terms of time). In this routing problem, the following solutions are permitted: drones can depart and return to the depot, drones can depart from the depot and fly back to the truck; or drones can be launched from the truck and retrieved by either the same truck; or a different truck from where they were launched.

c: VRP-D AND ITS VARIANTS

Wang *et al.* [73] introduce the VRP-D, which deals with multiple trucks and drones for serving customers. The analysis was performed on several worst-case scenarios, from which they propose bounds on the best possible savings in time when using both vehicles instead of trucks alone. In VRP-D, drones can be dispatched from and picked up only at customer locations and the depot.

Further development of this research was studied by Poikonen *et al.* [74], where they extended the worst-case bounds to more generic distance/cost metrics and explicitly considered the limitations of battery life and cost objectives. The vehicle-drone routing problem with time window (VDRPTW) is a variant of the VRP-D with time windows which is considered by Pugliese and Guerriero [75]. Another extension of the VRP-D is the vehicle routing problem with drones and enroute operations (VRPDERO) proposed by Schermer *et al.* [76], which allows the trucks to retrieve the drones not only at customers' locations or the depot but at discrete points along the truck's path. Puglia *et al.* [77] and [78] extend the VRP-D by imposing a service time window. Add to that, the energy consumption of the drone is considered a function of the drone's traveling distance.

d: OTHER PROBLEMS

The multi-trip traveling repairman problem with drones (MTRPD) presented by Moshref-Javadi *et al.* [29] considers the same system configuration as in the simultaneous traveling repairment problem with drones (STRPD), but the truck serves customers only. The drone is launched from the depot or from one of the truck's customers' locations,

with multiple dispatches from the same location to allow for the drone to serve multiple customers in sequence. Yun-qi *et al.* [79] present the multi-objective vehicle routing problem with time window and drone (MO-VRPTW-D), which takes into account a fleet of heterogenous trucks and heterogenous drones. Each truck is equipped with a single drone, in which the truck travels the horizontal distance to the customer's location before raising the drone to complete the delivery. Each truck in this model has a limited payload capacity and travel range. In addition, each customer has a time window, and if the truck arrives late, a penalty is imposed. Chiang *et al.* [80] propose a multi-VRP for drones that incorporates the sustainability aspect of the routing system. The goal of the green vehicle routing problem with unmanned aerial vehicles (GVRP-UAV) is to investigate the impact of drones on cost savings and fuel consumption. A multiple vehicles-multiple drones system configuration is considered, and each vehicle is equipped with a single drone. Both types of vehicles can transport a fixed number of requested packages, which are measured in weight units. Baniasadi *et al.* [81] suggest a transformation technique for the clustered generalized traveling salesman problem (CGTSP) of a drone-assisted parcel delivery service. In this problem, a single truck and multiple drones serve customers, where customer locations are divided into clusters and subclusters. The truck only visits one node in the subcluster, while the drones visit all of the remaining nodes. Salama and Srinivas [82] introduce the jointly optimized delivery locations clustering and truck-drone routing (JOCR) problem, where a delivery system consists of a single truck and a fleet of drones. A subset of customer locations can be served by either a truck or drones, while the remainder can only be visited by the truck. Customer locations are partitioned into clusters, each with a focal point that serves as a truck stop. Parallel shipping operations by drones are assigned if clusters have more than one customer location. Drones return to the focal point, where the truck is waiting, after serving customers. Wule *et al.* [83] present the heterogeneous vehicles on traveling salesman problem (HCVTSP), in which a single unmanned ground vehicle and a single drone collaborate to service customers. Both vehicles are synchronized at the launching and rendezvous nodes. In contrast to the FSTSP, the drone can return to the same node from whence it was launched.

2) COLLABORATIVE HTDDS OPERATIONS WITH DRONE DELIVERY

In some HTDDS, the truck acts as a moving depot only while the drone serves customers. The truck's role is to launch, collect, replenish, and maintain the drone. Figure 5 demonstrates this model type, where the truck has a set of potential sites for launching and collecting the drone. While the drone is in operation, the truck can either remain at the same stop or travel to another stop to collect the drone. A variety of problems reviewed in the literature consider the truck as a moving depot for the drone, and they are discussed below.

The traveling salesman problem with a moving depot (TSP-MD) presented in Madani and Ndiaye [84] considers the truck acting as a moving depot for launching and collecting the drone. The drone can deliver to multiple customers before returning to the truck, and the goal is to find the optimal locations for launching and retrieving the drone while minimizing the traveling costs of both vehicles. Moshref-Javadi *et al.* [85] introduce the STRPD problem, in which a truck acting as a moving depot and a fleet of drones are synchronized to serve customers. The truck can only launch the drone at a customer location and retrieve it back at one of the stops along its route. The truck and drones move in tandem, and multiple drones can be launched simultaneously. Liu *et al.* [86] extend the traditional two-echelon routing problem by incorporating a single truck and a single drone into the delivery system. In the two-echelon routing problem for parcel delivery by cooperated truck and drone (2E-RP-T&D), the truck serves customers and acts as a moving depot for the drone, which can deliver to multiple customers before returning to the truck. An energy consumption model has been proposed to investigate the impact of the payload on the drone's energy consumption and estimate the cost of the drone's sub-routes. The objective is to optimize the truck's main route and the drone's sub-routes while satisfying the drone's capacity constraints on battery and payload. The k-multi-visit drone routing problem (k-MVDRP) introduced by Poikonen and Golden [87], considers a truck and k drones to serve a set of customers. The truck only serves as a moving depot and recharging platform for the drones; it does not provide delivery services. The drones can carry multiple packages of varying weights and make multiple visits before returning to the truck to be recharged or pick up new packages. Karak and Abdelghany [88] introduce the hybrid vehicle-drone routing problem (HVDRP), which consists of a single vehicle acting as a moving depot, and multiple drones to pick up and/or deliver packages of different weights. In this model, drone stations are used, where both vehicles can wait for each other. This setting allows for multiple drone dispatches from different stations, resulting in a larger customer population covered. Each drone can return to any of the stations, which could be similar to the same or different from the dispatch station. Boysen *et al.* [89] consider the drone scheduling problem (DSP) for a single truck-multiple drone delivery system. The truck follows a fixed route and can dispatch and retrieve the drones at any of the predetermined stops along the route. A single drone is launched from the truck at a time, and after delivering, it can return to the same or a different stop. The objective is to schedule the launch of the drones so that the total delivery time is minimized.

Bai *et al.* [90] propose a single truck-single drone delivery system configuration. The truck is restricted to following a set of street-vertices while the drone serves customers. A precedence constraint is ensured to indicate which customer is to be visited before the other customer. The objective is to minimize the time when the last customer is served to increase
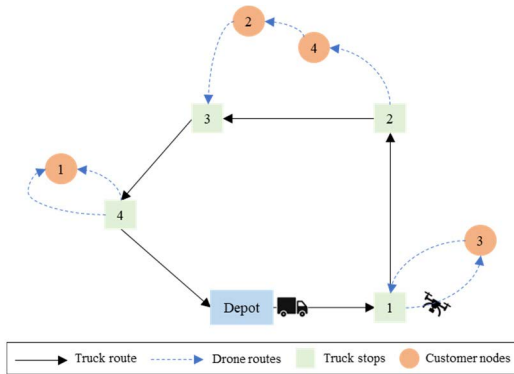
the customer satisfaction index. The precedence-constrained heterogenous delivery problem (PCHDP) is formulated as a constrained minimization problem, and several heuristic task assignment algorithms based on nearest insertion and minimum marginal cost are designed. Moeini *et al.* [91] propose a system comprised of a single truck, multiple drones, and autonomous transport vehicles (ATVs). In the truck-drone-ATV routing problem (TDA-RP), drones are in charge of delivering light parcels, whereas ATVs are in charge of both light and heavy parcels. The truck is serving as a moving depot, and the drones and ATVs may rendezvous with it at the same launching point. Wang and Lan [92] combine a vehicle, a truck, and a drone to form the vehicle truck UAV traveling salesman problem (VTUTSP). While the vehicle and drone make deliveries, the truck functions as a mobile warehouse and a landing platform for the drone. The UAV is launched from the truck and returned to it for replenishment for the next delivery service. The truck is thought to drive on the ring-expressway to act as a platform for UAV service, and the objective is to reduce delivery time. Mathew *et al.* [93] present the heterogeneous delivery problem (HDP) using a truck and a drone. The truck does not deliver, but rather transports the drone to a neighboring node within the drone's flying range. The goal is to find the best truck and drone routes that decrease overall delivery time. Jeong and Lee [94] introduce the drone routing problem with a truck (DRP-T), where the truck does not service customers but merely transports drones to a parking location. Following that, the drones will take-off to serve a single customer before returning to another parking place to be collected by the truck. The goal is to have the truck arrive at the depot as soon as possible so that all deliveries may be completed.

3) HTDDS WITH INDEPENDENT DELIVERY OPERATIONS
The HTDDS independent operation entails the individual functioning of trucks and drones. When the customer's location is within the drone's flying range, the need for a truck is eliminated. In this case, the drone will return to the depot for recharging, repair, or replenishment of packages. The truck, on the other hand, will serve customers and eventually return

to the depot independently of the drone. Figure 6 illustrates the parallel delivery operations of the truck and the drone. In the evaluated literature, a few problems with this operation are considered, and they are given below.

a: PDSTSP AND ITS VARIANTS
The parallel drone scheduling traveling salesman problem (PDSTSP) was first introduced by Murray and Chu [53], and the problem considers a single truck and a fleet of identical drones serving customers in parallel, implying that the two types of vehicles are not synchronized. The truck follows a TSP tour, while drones fulfill customer deliveries only within the distribution center's flight range. As in FSTSP, the objective of PDSTSP is to minimize the latest time to return to the depot for both the truck and drones. Different solution methods were used to solve the same problem in [95], [96], and [97]. Kim and Moon [98] extend the PDSTSP to overcome the large distance between the distribution center and the customer locations, allowing the drones to cover a larger number of customers. The proposed traveling salesman problem with drone station (TSP-DS) considers a drone station located at a distance greater than the drone's maximum flight distance, which was used for charging and refilling the drones with parcels. Schermer *et al.* [99] integrate the routing of the truck, location of the drone stations, and scheduling of the drones to provide a general case of the PDSTSP and TSP-DS. The integrated traveling salesman drone station location problem (TSDSLP) model incorporates drone deliveries into TSP tours as well as the use of multiple drone delivery stations. Each drone station can only handle a certain number of drones, and each drone must return to the same station from which it was launched.

4) HTDDS WITH DRONE RESUPPLY OPERATIONS
In some circumstances, the drone's conventional duty of serving customers is supplanted by a different role. The drone can serve as a replenishment source for the truck, which is the only mode of delivery. Figure 7 provides an example of the resupply operations. The drone resupplies the truck at certain customer nodes and returns to the depot independently. The literature that considers the resupply operation is given below.

Pina-Pardo *et al.* [100] propose the traveling salesman problem with release dates and drone resupply (TSPRD-DR). The objective is to find the shortest possible time route for a single truck that is resupplied by a drone while enroute to fulfill customer orders. The orders and their associated information are known at the beginning of the day, but they may not be ready to ship. While the truck is making other deliveries, the drone is loaded at the depot with ready-to-ship orders and only resupplies the truck at customers' locations.

Dayarian *et al.* [101] present the vehicle routing problem with drone resupply (VRPDR), which considers a fleet of vehicles and a fleet of drones assisting each other to perform home deliveries. Similar to Pina-Pardo *et al.* [100], drones are used to resupply the truck, but unknown orders arrive dynamically throughout the day. While the truck is stationary,
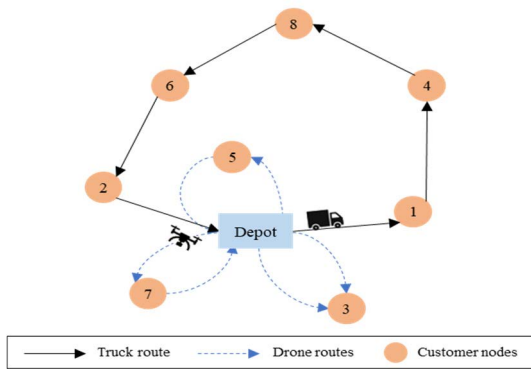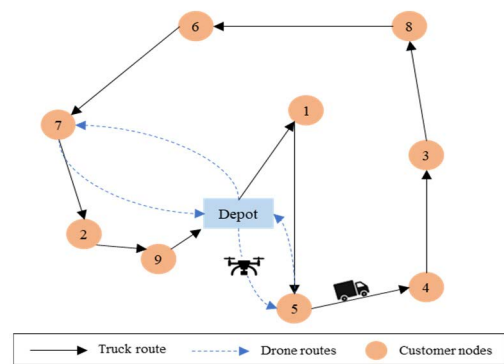
FIGURE 6. Illustration of type 3.

FIGURE 7. Illustration of type 4.

the resupply operation takes place, and two associated strategies are considered: restricted resupply and flexible resupply. The truck can only be resupplied by the drone at the end of its delivery route with a restricted resupply, whereas the flexible resupply allows it to happen at some locations. Unlike TSPRD-DR [100], the VRPDR problem is not supported by an exact solution, and algorithms based on nearest insertion, Large Neighborhood Search (LNS), and a greedy approach are incorporated.

B. SYSTEM CONFIGURATION

In this subsection, we classify the literature based on the HTDDS configuration, which refers to the number of trucks and drones utilized in the system as well as their synchronization. As a result, the surveyed papers are classified into three categories: single truck-single drone, single truck-multiple drones, and multiple trucks-multiple drones. In the operation of HTDDS, synchronization between the two vehicles is important. Synchronization is referred to as the waiting of either the truck or the drone at the rendezvous location for the other vehicle [64]. It is needed for charging, maintaining, and replenishing the drone with delivery packages.

1) SINGLE TRUCK - SINGLE DRONE

The difficulty of modeling and optimizing the problems of HTDDS is affected by the number of vehicles (trucks and drones) considered in the model. The FSTSP introduced by Murray and Chu [53] is the first to consider a single truck-single drone configuration, where both vehicles serve customers. The two vehicles are synchronized to arrive at the reconnection node simultaneously. The same configuration is addressed in [54], [55], [56], [57], [58], [60], [61], and [67]. Besides the FSTSP problem that requires synchronization, Murray and Chu [53] deal with another problem. The latter problem is known as the PDSTSP which considers the independent operation of the two vehicles.

The TSP-D considered in [12], [31], [102], [103], [104], [105], [106], [107], [108], and [109] allows for both vehicles to make deliveries. It also requires the synchronization between the vehicles to be at either the customer's

location or the depot. However, Marinelli *et al.* [110] allow for synchronization to occur en route. Other problems that cover the synchronization and the delivery role of both vehicles are FSTSP-ECNZ [63], TDTL [66], HCVTSP [83], TSP-D-RS [68], and 2E-RP-T&D [86]. The truck can also serve solely as a moving depot, used for launching and collecting drones such as TSP-MD [84], VTUTSP [92], PCHDP [90]. The drone role can be extended to include resupplying, in which the drone can resupply the truck with delivery packages as in the problems presented in [100] and [101]. The TSPRD-DR in Pina-Pardo *et al.* [100] requires synchronization between the truck and the drone, while the VRPDR in Dayarian *et al.* [101] does not require that. Similarly, the truck may be used for delivery only [111], [112], [113], as a moving depot only [114], or both [115]. Allowing the truck to act as a moving hub, in addition to fulfilling customers' orders, increases the service range of the drone [53], [85]. As a result, the drone's advantages are fully utilized.

2) SINGLE TRUCK - MULTIPLE DRONES

The use of multiple drones with a single truck increases the modeling challenge while improving the efficiency of the delivery system. This challenge results from the increased number of operational possibilities associated with multiple drones [116]. The PDSTSP introduced by [53] presents a single truck and multiple homogenous drone delivery systems. This system does not need to be synchronized, and both vehicles serve customers. Dell'Amico *et al.* [96] and [97] also present the PDSTSP, but with different solution methods. Similar problems to the PDSTSP are the TSP-DS [98] and the TSDSLP [99]. The trucks and drones must be synchronized [29], [62], [64], [71], [82], [117]. While in [71], the TSP-mD does not allow the two vehicles to wait for each other for more than a specific time, during which the drones can re-join with the truck at the same/different node along the truck's tour. The mFSTSP in Murray and Raj [62] extends the FSTSP by considering multiple heterogenous drones, and each drone can either be loaded onto the truck or be refilled with a new package. The mFSTSP-VDS is another extension

of the FSTSP that deals with heterogenous drones and a single truck [64]. In mFSTSP-VDS, both vehicles perform deliveries, whereby the truck can only serve customers between the launching and retrieval nodes of the drones. Also, the truck launches one drone at a time, which requires scheduling the drone launches and retrievals. Unlike mFSTSP-VDS, the MTRPD allows for multiple drones to be launched from the truck concurrently [29]. Similarly, the JOCR allows for the parallel shipping operation of drones [82]. In [81], [118], and [119], vehicle synchronization is not required.

As in the case of a single truck-single drone, the truck can act as a moving hub for multiple drones. The HVDRP [88] and the DSP [89] consider homogenous drones. Conversely, the k-MVDRP considers k drones with varying energy drain functions depending on the heterogeneous weights of delivery packages [87]. Other articles consider the truck as a moving depot [91], [120], [121]. Further, the dual role of the truck, serving as a moving depot and a delivery resource, is illustrated in STRPD [85].

3) MULTIPLE TRUCKS - MULTIPLE DRONES

Extending HTDDS to include multiple trucks and multiple drones adds further difficulty to the system. This configuration is attracting high attention from researchers and academicians due to the difficulty of optimizing it. The VRP-D problem is the first to introduce the case of multiple trucks and multiple drones, which requires synchronization and allows for the trucks to make deliveries. In this context, [73], [74], [77], [78], [122], [123], [124], [125], and [126] consider the ability of each truck to handle multiple drones, where each drone must return to the same truck from which it was launched. In a few cases, docking hubs are used as landing nodes for the drones, and the truck can only supply any of the drones that are in the docking hub [127]. Among the VRP-D variants, Sacramento et al. [28] consider the case where each truck is equipped with a single drone, which should be picked up by the same truck. Extended versions of the VRP-D are VDRPTW [75] and VRPDERO [76], where each truck is equipped with multiple drones, and each drone is restricted to combine with the same truck only.

Ham [95] extends the PDSTSP in Murray and Chu [53] by integrating multiple trucks and multiple drones into the delivery system. Unlike PDSTSP, the drone has a dual role of serving customers and picking up customer packages. Das et al. [128] consider a fleet of trucks and drones, each equipped with a single drone, and both vehicles serve customers within a predetermined time window. The truck serves as a mobile launching and retrieval station for the drone, in addition to its delivery function. The drone can serve only those customer nodes that follow the weather conditions identified at the time of routing. Kitjacharoenchai et al. [72] present a fleet of trucks, each equipped with multiple drones, serving multiple customers, and returning to any available truck. In [72], synchronization is required at customer nodes, from where the truck can only merge with the drones. At the same time, multiple drones are not allowed to be launched

or collected from the same node. Li et al. [129] propose a delivery system using multiple trucks and drones, where no synchronization is required, while Pugliese et al. [130] allow for the drone to wait for a specific time for the truck. Wang et al. [131] consider a HTDDS consisting of multiple trucks, multiple truck-carried drones, and independent drones. Each truck carries one drone, in which synchronization is needed between them. On the other hand, independent drones do not require synchronization with the trucks. They depart from the depot, serve customers according to their payload capacity and return to the depot. Ulmer and Thomas [132] propose a same-day delivery system, where a fleet of trucks and drones is used to fulfill the customers' changing demands. Like PDSTSP, no synchronization is needed between the vehicles. Table 3 summarizes the reviewed literature based on the proposed classification. The literature is first classified based on the four vehicles' role-based categories introduced earlier. Then, the literature is grouped based on the system configuration, which involves the number of vehicles and the synchronicity between them.

IV. REVIEW OF HTDDS BASED ON OPTIMIZATION MODELS

In this section, the reviewed literature is used to categorize the objective functions, followed by discussing the used constraints and parameters.

A. OBJECTIVE FUNCTION CLASSIFICATION

Truck-drone delivery systems are introduced to address the issues of LMD, which is the most costly, polluting, and inefficient element of the supply chain [5]. As a result, multiple objective functions addressing various concerns in the LMD, such as traveling costs, carbon emissions, delays, missing deliveries, and others, have been identified. In this subsection, we summarize these objective functions based on four elements: total traveling time, operational and transportation costs, environment, and service.

a: TOTAL DELIVERY TIME ELEMENT

Minimization of the total delivery time of trucks and drones. Considering the time element as the objective of delivery operation has been covered substantially in the literature. A total of 58 papers in the evaluated literature examine the time aspect. Compared to the conventional modes of transport, drones can make better and faster decisions. They can provide new opportunities to improve home delivery processes. They operate without a human pilot, avoid the congestion of traditional road networks by flying over them, and are faster than trucks. Add to that, Amazon emphasized fast delivery by deploying drones to provide deliveries within 30 minutes [24]. Hence, minimizing the total time would be a rational objective function.

b: TRANSPORTATION AND OPERATIONAL COSTS ELEMENT

Delivery performance is usually measured by the total cost. The transportation cost includes traveling costs, fixed costs,

and vehicle operating costs. The assessed literature reveals two main objective functions for this element, which are detailed below.

- Minimization of the total transportation costs of trucks and drones [12], [67], [71], [75], [77], [78], [84], [86], [93], [118], [128], [130], [133]. In addition to the transportation costs of both vehicles, Chiang *et al.* [80] considered the fixed cost of employing trucks, while Salama and Srinivas [82] accounted for the fixed cost of operating the drones. The objective function of [31] includes the total transportation costs of the truck and the drone, as well as the cost of waiting at the meeting point between the two vehicles.
- Minimization of the total operating costs of both vehicles [28], [31], [82], [88], [104], [110], [126], [129]. In Karak and Abdelghany [88], the operational cost comprises the vehicle's operational cost to dispatch and collect the drone and the operational cost of the routes constructed for the drones to visit all customers.

Other aspects that may be included in the total cost are drone ownership and battery inventory, as in Cokyasar *et al.* [144]. The cost element can also involve fixed daily vehicle fares, driver wages, and fuel and electricity consumption, as in Conidreau *et al.* [143].

c: ENVIRONMENTAL ELEMENT
Total carbon emissions and energy consumption have also been considered to manage the environmental challenges. In this element, three objective functions are found in the evaluated literature, and they are described below.

- Minimization of the total carbon emissions, including the emissions of vehicles and drones [80], [135].
- Minimization of the total energy consumption of trucks and drones [112], as well as the total number of utilized trucks [79].
- Minimization of the total energy cost of the truck-drone system [140].

d: SERVICE ELEMENT
The service's performance is addressed to increase customer satisfaction and address delays that occur during the delivery process. The literature identifies four objectives within the service element, which are outlined below.

- Maximization of the number of orders delivered by taking into consideration the service time [101].
- Maximization of the possible improvements in customers' waiting times by determining the optimal sequence of customers served by trucks and drones [29].
- Maximization of customer service level in same-day delivery in terms of timely deliveries [128].
- Minimization of the total customer waiting times by determining the optimal routes of the truck and drones [85], [137].

In Luo *et al.* [138], the objective function seeks to minimize the distribution cost while maximizing customer satisfaction.

B. MODEL CONSTRAINTS AND PARAMETERS
Researchers used various types of parameters and constraints to define the HTDDS problems on hand. Capturing the real structure of HTDDS is reflected in the nature of the constraints and parameters considered. A detailed description of the constraints and parameters is presented below.

1) MODEL ASSUMPTIONS AND PARAMETERS
The main assumptions and parameters considered in the reviewed literature deal with operational characteristics such as service time or drone technical characteristics such as speed, weight, and energy consumption, as well as other considerations such as customer demands, the fuel consumption of trucks, and distance metrics, as provided below.

- During delivery, the drones and trucks need some time to serve the customer. This is associated with the delivery mechanisms of each drone and truck. For instance, different mechanisms of drone delivery can occur, such as delivering goods via tether, landing, or parachute [62], which all require a duration to complete the service for customers.
- The drone's speed is considered to be constant in the surveyed literature except in Liu *et al.* [64] and [86], where the speed is not a fixed input but instead a function of other parameters. In Liu *et al.* [86], the speed is a function of the drone's weight, the drone's power, payload, the energy loss of the drone battery, conversion efficiency, and lift rotation. In Raj and Murray [64], speed is a decision variable that changes as the drone takes off, lands, delivers, and waits at the retrieval node. The speed of the drone affects its power consumption, which in turn affects its flying range and endurance. For instance, when considering a variable drone's speed, energy consumption is minimized when considering a lower speed than the maximum speed [87].
- The drone's energy consumption provides a realistic coverage of the drone's life. It may be proportional to the drone's flying distance [77], [78], [130] or as a function that depends on the drone's weight, parcels' weights, speeds, and other factors [63], [64], [67], [69], [79], [86], [87], [112], [131]. In such studies, balancing the payload, the drone's endurance, and battery capacity are significant contributors to minimizing the cost or time of the drone's delivery [145].
- The drone's weight contributes to energy consumption, battery life, and speed. In recent studies, the drone's weight is assumed to be a fixed input [63], [69], [80], [86], [112], [131], [135].
- The drones are assumed to be either homogeneous or heterogeneous [62], [64], [88], [132], [138], [139] with a difference based on speeds, service time, payload capacities, and endurance.
- Delivery trucks are generally assumed to be homogeneous or heterogeneous [132].
- Stochastic customer requests are considered as the orders occur dynamically. In [101] and [132], Trucks and

TABLE 3. Reviewed literature classification.

Reference	Vehicles roles	System configuration	Synchronization	
			Yes	No
[12, 31, 53-58, 60, 61, 63, 66, 68, 83, 86, 102-109, 111-113, 115, 133-135]	type 1	single truck – single drone	✓	
[136]				✓
[67]	type 1 with drone delivery and pickup		✓	
[84, 90, 92, 93, 110, 114]	type 2			✓
[53]	type 3			✓
[101]	type 4			✓
[100]				✓
[29, 62, 64, 69-71, 82, 85, 98, 117, 137-139]	type 1	single truck – multiple drones	✓	
[53, 81, 118, 119, 140]				✓
[87, 89, 91, 94, 120, 121, 141]	type 2		✓	
[88]	type 2 with drone delivery and pickup		✓	
[96, 97, 99]	type 3			✓
[28, 59, 65, 72-78, 80, 122, 124-126, 131, 142, 143]	type 1	multiple trucks – multiple drones	✓	
[127-130, 132]	type 1			✓
[144]	type 2			✓
[95]	type 3 with drone delivery and pickup			✓

drones are used to perform same-day deliveries, where customers place orders dynamically throughout the day. Conversely, customer demands are known before the start of operations in the remaining surveyed studies.

- The time required for the drone's launching and collection is taken into account. This assumption is considered in most of the reviewed literature.
- The type of customer demand can be considered as the followings:
  - The demand is assumed to be a single product, which is the most common type.
  - The demand is based on the weight of the product [63], [64], [65], [69], [77], [78], [80], [87], [88], [98], [112], [127], [131], [139].
  - Customers can order multiple products with different shipping priorities/different weights [79], [95], [130].
  - The demand follows a probability density function [115], [119].
  - The demand follows a Poisson distribution [144].
- The distance metrics followed by trucks and drones:
  - The truck follows the Manhattan metric while the drone follows the Euclidean distance [56], [58], [63], [68], [75], [80], [83], [96], [97], [100], [110], [111], [130], [143]. In such a case, drones are assumed to be unaffected by traffic and can fly in a straight line without following the street network because they are usually faster than trucks. Trucks, unlike drones, are required to obey traffic signs and adhere to the road network. Thus, for the two vehicles, it is feasible to consider a separate road network, where the truck has its own road network, representing the potential locations for launching and collecting the drone.

item Truck and drone distances are calculated using the Euclidean metric [60], [61], [67], [69], [76], [84], [85], [87], [90], [92], [99], [103], [115], [117], [118], [131], [137]. In this case, both vehicles are assumed to travel in a straight line, without following any road network.
- Fuel consumption and the weight of vehicles (trucks) are considered using a linear expression [80].

2) MODEL CONSTRAINTS
The main constraints include the payload capacity of the vehicles, the endurance of the drone, the locations of the drone's launching and collection, the penalty for vehicles waiting, and time windows as examined below.

- Most of the reviewed articles consider the single delivery of the drone, which states that the drone must visit only one customer before it returns to the truck/depot.
- The drone can do multiple deliveries before returning to the truck/depot. Although 86% of Amazon's delivered packages are less than 2.3kg, there are many potential commercial drones capable of carrying several multiples of that payload capacity. For instance, the Alta 8 from Freefly Systems is capable of carrying up to 18 kilograms [146]. Similarly, the Tarot T-18 and DJI drones can carry up to 8 and 8.2 kilograms, respectively [146], [147]. Thus, considering drones with the technical capability of carrying multiple packages is rational.
- The total delivery load must be less than the truck's capacity on each route/trip [28], [65], [67], [72], [73], [80], [91], [123], [124], [125], [126], [127], [128], [129], [130], [131].
- Not all customer nodes can be served by the drone. Limiting the drone's delivery operations to certain customers can be due to the parcel's size, customer's location, which could be unsafe for the drone to

land, whether a customer signature is needed, and whether the customer's delivery parcel contains hazardous materials.

- The drone must not exceed its operational time, endurance, or flying time. In such a case, the battery is recharged or replaced when the drone returns to the truck, docking hub, or depot.
- The drone must not exceed its limited traveling range: the drone's battery life can be expressed in terms of the traveling range.
- The majority of the reviewed studies assume that the battery life of the drone has a fixed amount of time or distance. Instead, the battery life can be a function of the weight of the package.
- After delivery, the drone must return to different locations, as summarized below.
  - The drone must return to the truck after delivery.
  - The drone must return to the depot after delivery. This constraint is applied to situations when the drone is used to resupply the truck with delivery packages. It is also more commonly used in problems involving parallel drone delivery scheduling.
  - The drone must return to the truck or depot after delivery.
  - The drone must return to a drone station after delivery. Having docking hubs or drone stations is considered preferable in the industry of drone delivery systems [148]. The drone stations/hubs are locations where drones are stored, maintained, and supported. For safety purposes, they are designed for the drone to land carefully, instead of landing at a customer node. According to [149], special conditions are required for the drone to land such as providing the drone with instructions to guide it to land accurately and securely.
  - In the case of multiple trucks with multiple drones, each drone must either return to the same truck from which it was launched or to any available truck.
- The drone must be launched and collected by the truck at different locations summarized below:
  - The drone must be launched and collected at the customer's location.
  - The drone must be launched and collected at the customer's location or depot.
  - The drone must be launched and collected at the drone station.
  - The drone must be launched and collected at parking lots.
  - The drone must be launched and collected at a fulfillment center.
  - The drones must be launched and collected at a point along the truck's route. In most of these studies, the truck has a set of predetermined stopping points that are potential stops for launching and collecting drones. This constraint is covered little in the reviewed studies, because stopping the truck at intermediate locations on its route may not always be feasible [103].
  - The drone must be launched and collected at the cluster's center. Clustering the delivery areas applies to situations where customer areas are divided based on zip codes [150] or drone flying zones following governmental regulations [151]. Additionally, allowing the return of drones to the depot or customer location provides better optimization of the delivery model, in which the truck's stop can be anywhere in the delivery area [82].
- A penalty cost is applied when trucks and drones wait for each other [31].
- The arrival time of the truck or the drone at the customer's location should be within the time window [75], [77], [78], [79], [95], [101], [128], [130], [138], [143]. Ordering multiple products with different shipping priorities requires considering the shipment of each package with different time windows [95]. Amazon took this limitation in its patent for Airborne Fulfilment Center Utilizing UAVs for Item Delivery [34]. For instance, the customer might specify the delivery time of two orders within the same day but at different times. Thus, the same customer has two time-windows on the same day. Table 4 summarizes the most common constraints in the evaluated literature.

V. REVIEW OF HTDDS BASED ON MODELING TECHNIQUES AND SOLUTION METHODS

Several solution methods are used in the context of HTDDS, which are classified as exact, heuristics, metaheuristics, and other solution methods.

A. EXACT SOLUTIONS

Different modeling techniques have been considered for approaching HTDDS. These techniques include Mixed Integer Linear Programming (MILP), Integer Linear Programming (ILP), and Constraint Programming (CP). They also cover Non-Linear Programming (NLP), Mixed Integer Non-Linear Programming (MINLP), Dynamic Programming (DP), and Multi-Objective (MO). Figure 8 depicts the distribution of these techniques, with MILP being the most commonly used technique in the reviewed literature (70.3%), followed by ILP (15.6%). Contrarily, CP (4.7%), MO (3.1%), MINLP (3.1%), DP (1.6%), and NLP (1.6%) are the least used techniques in the literature.

For the least common techniques, a brief description of each is given to understand their implementations in the context of the HTDDS. In terms of DP, Bouman *et al.* [103] used a three-pass approach based on Bellman-Held-Karp DP to solve TSP-D. The purpose of the use of DP is to overcome the limitations of the exact approaches used by Agatz *et al.* [12], which are only capable of solving small instances (up to 10 nodes). DP is known for its capability of solving larger instances. Due to the exponential number of variables and

constraints of the TSP-D, DP continuously outperforms the ILP when utilizing the instances of [12].

Ham [95] used CP to model the PDSTSP problem of integrated trucks and drones with single and multiple depots. Also, CP is considered by Bai *et al.* [90] to model a precedence-constrained task assignment problem. The model aims to minimize the time spent serving the last customer, thereby increasing the customer satisfaction index. The study compared MIP and artificial intelligence CP where MIP provided optimality for less than 12 nodes, while CP achieved that for less than 80 nodes. CP has been used to solve combinatorial optimization problems, primarily scheduling problems. It has proven to be a formidable competitor to mathematical programming-based methods, frequently outperforming cutting-edge MIP solvers. Given the nature of the PSDTSP in [95], with drop and pickup synchronization and multiple depots, MIP may not be a good choice. This is due to its inability to manage the problem description while also providing quality solutions. On the other hand, CP has a high level of expressiveness and an efficient algorithm for dealing with transition matrices generated by the PDSTSP.

Chang and Lee [120] presented a situation where the truck has a delivery path among the centers of clusters, representing delivery areas. In Chang and Lee [120], NLP is used to change the centers of clusters to further locations away from the depot. This is attained while achieving wider regions of drone delivery and minimizing the traveling distance of the truck. It is critical to find a delivery path that minimizes the total delivery time for a truck's path between cluster centers and drone paths within clusters. Drones outperform trucks in terms of cost and speed of operation. Therefore, increasing the flight distance of the drones while minimizing the traveling distance of the trucks is the most efficient. This is done most successfully by shifting cluster centers closer to or farther away from a depot. Shift weights, which are used to relocate the centers of clusters to shorten total delivery time, will make this situation achievable. The NLP approach is able to shorten the total delivery time when shifting the centers of clusters after implementing the k-means clustering method.

Das *et al.* [128] considered MO to minimize the traveling cost and maximize the customer service level, based on the delivery time window criterion. Incorporating the two objectives provides a more realistic configuration of the HTDDS and addresses the challenges of LMD. Other exact solution methods involve the Benders decomposition approach [78], [139], the branch-and-cut algorithm [59], [60], [141], and the branch-and-price algorithm [108].

Cokyasar *et al.* [144] proposed the notion of locating automated battery swapping machines to tackle the drone's limited flight range. Given a set of trucks and drones operating independently, the objective is to optimally select the locations of the machines and the delivery-mode choice (truck-only, drone-only, or mixed vehicles) such that the total cost is minimized. To model the problem, a MINLP is developed to locate the battery swapping machines and drone routes while
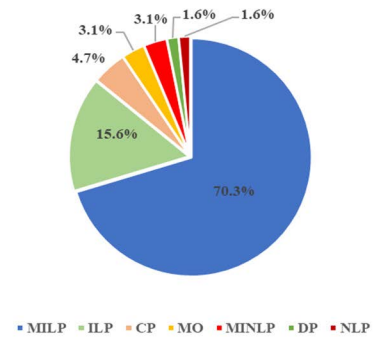

FIGURE 8. HTDDS literature by modeling techniques.

accounting for any congestion at battery swapping operations using queueing theory.

As for the exact solvers, the most commonly used solvers are CPLEX, GAMS with CPLEX, and Gurobi. As shown in Figure 9, the majority of the reviewed literature (61.8%) considered exact solutions, with 27% of the articles using only exact methods. The remainder (34.8%) accounts for heuristics and/or metaheuristics along with exact methods. HTDDS routing problems are extended versions of classical VRPs with various sources of modeling challenges. This may include the number of trucks and drones, the number of depots, and drone and truck operational limitations. When the HTDDS considers a single truck stop, a single drone, and a single delivery route, the problem is reduced to a TSP. TSPs are known to be NP-hard, and consequently, HTDDS problems are NP-hard, which makes them computationally difficult to reach optimality. Due to this NP-hard nature, developing efficient heuristics and metaheuristics is required for large-size problems [152].

B. HEURISTICS AND METAHEURISTICS SOLUTIONS
A variety of heuristics and metaheuristics are implemented to solve HTDDS problems. For solving the FSTSP, Murray and Chu [53] used a route and re-assign heuristic, which is based on savings, nearest neighbor, and sweep, to solve problems with up to 20 customer nodes. The solution methods proposed by Murray and Chu [53] were able to solve small-size instances. Other studies were able to solve larger instances by improving the performance of solution methods. For example, in Kundu and Matis [58], the effect of wind and battery-power consumption are considered. As a result, the authors have modified the same heuristic to solve up to 100 customer locations. To overcome the traditional heuristic methods proposed by Murray and Chu [53], de Freitas and Penna [54] used the Randomized Variable Neighborhood Descent (RVND) as a local search method. The RVND was able to solve instances with up to 100 nodes. de Freitas and Penna [56] have further improved the solution method for solving the FSTSP to handle instances with 200 nodes using a hybrid method. The work uses an exact model to

TABLE 4. Model constraints.

References	Drone payload capacity		Drone serviceable customers	Drone limited flying time/range	The drone must return after delivery to			The drone must be launched and must be collected by the truck at					
	Single	Multiple			Truck only or truck and depot	Depot only	Drone station	Customer only or customer and depot	Drone station	along the truck's route	cluster's center	Parking lots	Fulfillment center
[29, 55, 58-64, 72, 74, 82, 83, 100, 102, 104-108, 111, 113, 115, 124, 125, 128, 129, 137-139, 142, 143]	✓			✓	✓			✓					
[12, 28, 31, 53, 54, 56, 57, 68, 71, 75, 77, 78, 85, 109, 118, 122, 126, 130, 133, 135]	✓		✓	✓	✓			✓					
[67, 92, 93, 112, 119]	✓				✓			✓					
[65, 66, 69, 80, 86, 117]		✓		✓	✓			✓					
[76, 90, 110]	✓			✓	✓						✓		
[96, 97]	✓		✓	✓		✓		✓					
[103, 140]	✓		✓		✓			✓					
[89, 114]	✓				✓						✓		
[95, 132]	✓			✓			✓	✓					
[101]		✓					✓	✓					
[84]		✓			✓						✓		
[136]	✓						✓	✓					
[81]	✓				✓							✓	
[120]	✓			✓	✓							✓	
[121]		✓		✓	✓						✓		
[88]		✓		✓			✓		✓				
[98]	✓		✓	✓			✓		✓				
[91]	✓		✓	✓	✓						✓		
[87]		✓			✓						✓		
[99, 134, 141]	✓			✓			✓		✓				
[127]		✓	✓	✓			✓		✓				
[73]	✓				✓				✓				
[131]		✓		✓		✓					✓		
[70, 94]	✓			✓	✓							✓	
[144]	✓			✓	✓								✓

obtain the initial solution and then a hybrid General Variable Neighborhood Search (GVNS) metaheuristic composed of three steps as an improvement heuristic. The first step finds a TSP solution where the truck fulfills all customers, while the second step uses the same heuristic as in Murray and Chu [53] to shift some truck customers to drone customers. The third step implements the GVNS for improving the solution. Crişan and Nechita [55] used a new greedy heuristic for solving the Romanian TSP instances of 2950 nodes, and Bulgarian TSP instances of 1954 nodes.
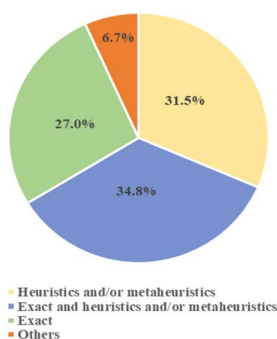

FIGURE 9. HTDDS literature by solution methods.

Murray and Raj [62] extended the FSTSP to mFSTSP and developed a three-phased iterative heuristic. The first phase considers initial customer assignments, while the second creates the drones' paths. Finally, the starting times for the truck and drone operations, and the queuing of launching and collecting, are determined. A variant of the FSTSP is the mFSTSP-ECNZ, where a two-phase constructive and search heuristic is used to solve it [63]. Another variant is mFSTSP-VDS where a three-phased iterative heuristic is proposed. The heuristic includes partitioning customers and creating TSP tours; creating the drone's path; and scheduling the operations and timing [64].

The TSP-D was solved using different methods, such as the route first-cluster second heuristic approach based on local search and dynamic programming [12], GRASP [31], [110]. These two methods were capable of solving instances with up to 100 nodes. Other methods used included a hybrid Genetic Algorithm (GA) [104] and CP-based heuristic [106]. The hybrid GA is a mix of a GA and 16 local search operators. It also involves a population management, diversity control, and penalization mechanism that balances the search between feasible and infeasible search areas. It is proven to provide better solution quality for instances of size 100 compared to the GRASP method [31]. Nevertheless, Nguyen *et al.* [111] applied the Monte Carlo tree search algorithm that is capable of solving instances of 200 nodes. In the TSP-mD, GRASP and Large Neighborhood Search (LNS) metaheuristics are used [71]. It is worth mentioning that the GRASP method was repeatedly used in the TSP-D problem and its variant.

The VRP-D problem, which is a generalization of the TSP-D has used several solution methods. Firstly, a metaheuristic based on the parallel Clarke and Wright (CW) savings is used as an initialization and local search for improvements [122]. The method solves instances of the size of 100 nodes. To cover larger instances, Sacramento *et al.* [28] used an adaptive LNS, which solves large-size instances (200 nodes). Further, single-phase and two-phase heuristics by Schermer *et al.* [123] were able to solve instances of 1000 nodes.

Other heuristics and metaheuristics covered in the reviewed literature are the improved artificial bee colony metaheuristic [79], [126], Lin-Kernighan (LK) heuristic, and Cross-Entropy (CE) metaheuristic [81], Simulated Annealing (SA) metaheuristic [66]. Add to that, Tabu Search metaheuristic [86], Adaptive Tabu Search-Simulated Annealing (ATSA) [29], Evolutionary Algorithm (EA) [117], and k-means clustering [119] are considered, to mention a few.

C. OTHER SOLUTIONS

In addition to exact and heuristics/metaheuristics solution methods, a few studies have considered solutions like continuous approximation (CA) [115], [129] and policies [132]. In Carlsson and Song [115], CA is applied to the Horsefly problem, which is difficult to optimize as it is considered a generalization of the TSP. Accordingly, CA is used to reduce the problem to a small set of parameters. The objective is to minimize the completion time of visiting all customers with the demand of a known probability density in a Euclidean plane. In a similar work, Li *et al.* [129] used the CA method to study the economic impact of HTDDS by developing transportation distances and cost functions.

To tackle the same-day delivery challenge with heterogeneous fleets of drones and vehicles, an approximate DP known as the parametric policy function approximation (PFA) is utilized [132]. Approximate DP seeks to tackle the challenges of the exponential state and action spaces by proposing high-quality solutions. To satisfy unknown future requirements for same-day delivery using HTDDS, a decision on which vehicle to employ should be properly made. In general, trucks may be appropriate in dense areas near the depot, but drones may be suitable in more distant regions with dispersed consumers. The PFA determines the optimal threshold parameter values. As a result, the PFA method will divide the service regions into two zones, improving decision-making.

D. DISCUSSION

It is worth mentioning that the evaluated literature can be classified into three main problems: routing of a set of locations; scheduling; and task assignment. The majority of the literature is related to the first class of problems, while a limited number of studies focus on the other two classes.

In the context of HTDDS problems, scheduling problems are more concerned with the scheduling of drone operations that are in simultaneous operation with the truck [53], [96], [97], [98], [99]. These scheduling problems are analogous to the parallel machine scheduling problem, in which each customer is assigned to a drone based on the flight time required to complete the operation. For problem formulation, the MILP approach is employed as a modeling technique. Ham [95], on the other hand, addressed the parallel scheduling of multiple vehicles, drones, and depots. The PDSTSP problem here is distinguished as an unrelated parallel machine scheduling problem with a sequence-dependent structure (traveling distances), a precedence relationship (parcel delivery and pickup), and reentrant behavior (multiple visits and time window). This clearly demonstrates the problem's difficulty, validating the adoption of CP as a modeling technique.

Task assignment problems are very much less commonly considered in the HTDDS literature. They emerge with multiple vehicle operations that need coordinated planning. For instance, the PCHDP in Bai *et al.* [90] is presented as a task assignment with precedence constraints. These constraints specify which customers should be served before others. As a result, the PCHDP is formulated as a constrained minimization problem.

The vast majority of the modeling techniques are of the same type. MILP models are extensively employed due to the structure of the problems introduced, which takes into account fixed drone characteristics. On the other hand, heuristic and metaheuristic solutions are more popular when the drone's characteristics such as speed and energy consumption are changing. When considering the drone's speed as a variable, Raj and Murray [64] and Liu *et al.* [86] relied on solutions other than the exact approaches. Three-phased iterative heuristic, SA, and Tabu Search are applied, respectively. Similarly, Yun-qi *et al.* [79], Baek *et al.* [112], and Wang *et al.* [131] evaluated the drone's energy consumption as a function of characteristics such as drone weight, package weights, speeds, and others. The authors used an enhanced artificial bee colony method, a greedy heuristic, and a hybrid heuristic, respectively. Exact solutions are implemented in only a few circumstances. Pugliese *et al.* [130], for example, took the drone's power consumption to be proportionate to its flying distance and found an ILP solution. In Poikonen and Golden [87], the problem is formulated as an ILP. However, it can only be solved via a heuristic approach. In addition, the energy consumption function of the drone is linearized using linear regression and a MILP solver is used in [63].

Furthermore, the performance of MILP solvers is limited to small instances (about 10-15 customers), and only a few studies focused on enhancing the performance of exact solutions. For instance, Dell'Amico *et al.* [57] improved the original FSTSP mathematical formulation by proposing three and two-indexed formulations. In the improved formulations, a novel objective function is proposed that could significantly

increase the lower bounds. A set of inequalities are also introduced, to be separated in a branch-and-cut fashion that provides an important contribution to obtaining better solutions in a faster way. The two-indexed formulation outperforms the other one, in which 59 of the 72 benchmark instances of Murray and Chu [53] could be solved to optimality. Boysen *et al.* [89] developed two MIP models for the DSP, where the second model reduces the number of variables by decoupling the route information of each drone from the customer assignment. MIP-2 demonstrates effectiveness in dealing with instances involving up to 100 consumers, while a few instances of size 100 are solved by MIP-1. Schermer *et al.* [105] proposed two compact MILP formulations that can handle instances with up to ten customers in a matter of seconds. Then a third formulation for the TSP-D based on an exponential number of constraints is presented. This version is amenable to being solved by the branch-and-cut algorithm This technique was utilized to identify optimal solutions within one hour for instances involving up to 20 customers. Boccia *et al.* [60], Boccia *et al.* [141], and Tamke and Buscher [59] implemented the branch-and-cut algorithm to solve larger size problems. For instance, Boccia *et al.* [60] used the column generation procedure along with the branch-and-cut algorithm for solving the FSTSP. The method resulted in solving instances of size 20 to optimality. In a similar manner, Tamke and Buscher [59] developed a branch-and-cut algorithm capable of solving problems of the size of 30 customer nodes. Roberti and Ruthmair [108] proposed a compact MILP for TSP-D variants based on timely synchronizing truck and drone flows, which can compete with state-of-the-art MILPs. In order to do this, dynamic programming recursions are developed and used in an exact branch-and-price technique based on set partitioning formulations and three-level hierarchical branching. The suggested technique effectively optimized instances with up to 39 customers.

Recent work in heuristics and metaheuristic solutions does not adhere to a certain solution technique while addressing specific problems. This shows that research on HTDDS has not matured sufficiently to draw firm conclusions on which solution methods should be used. This is due to the fact that modeling HTDDS is challenging and affected by obstacles like regulations, traffic management, and drone operational characteristics.

Table 5 summarizes the reviewed literature based on heuristic solution methods. Other heuristics include the Monte Carlo tree search algorithm, LK, CE, task assignment algorithm, variable-ordering, Pareto ant colony, artificial bee colony, and other novel heuristics.

VI. RESEARCH KEY FINDINGS AND RECOMMENDATIONS

In this section, we provide several observations regarding HTDDS problems and identify research gaps along with future research directions. We also discuss the roadblocks to HTDDS implementation.

A. RESEARCH GAPS AND FUTURE RECOMMENDATIONS

Despite the strong interest in the research of HTDDS, it is still in its early infancy and requires improvements in various dimensions. Most of the reviewed literature has considered drones with limited payload capacity (single delivery per dispatch) and fixed speed, range, and energy consumption. Adding the variability of the drone characteristics will provide a more accurate routing solution. Research gaps related to drone technical characteristics are discussed below.

- Almost 86% of the surveyed literature limits the drone's ability to carry only a single package per dispatch. With the current advancements made in the drone's capabilities, drones can now carry multiple packages as presented in [146] and [147]. The consideration of multiple packages will certainly reduce the completion time of delivery operations in the HTDDS while increasing the complexity of finding the best delivery routes.

- Many of the reviewed literature ignored the variability of the drone's range. Thus, models should reflect the actual drone range affected by the flight profile of the drone, which may include the vertical traveling distance and hovering. In cases where drones need to reach customers in buildings, the vertical distance should be taken into account in the drone's range calculations [79]. Further, the range of the drone is affected by the drone's battery capacity limit, which is influenced by the payload weight during operations [63].

- The drone's speed is a critical aspect that has an impact on the drone's energy consumption, range, and endurance. The consideration of varying drone speed is scarcely limited in the literature to [64], [86] who have addressed it. Treating the drone's speed as a variable also affects the operational cost, service time, and completion time of total delivery, all of which are critical to the LMD challenges. In addition, the consideration of variable speeds is essential when allowing the launching/retrieval of the drone to occur while the truck is in motion. The truck when merging with the drone needs to increase its speed while the drone should reduce its speed. This type of operation is demonstrated by Amazon patents such as the train-mounted mobile hubs for drone delivery that allows the handover of delivery parcels to occur while the train is in motion [48]. In a similar patent, the Amazon Airborne Fulfillment Center permits the mobile replenishment of drones by small airships [48].

- Realistic drone energy or power consumption is a critical aspect when modeling the HTDDS. The energy consumption model is mainly a function of the payload weight, the speed of the drone, and the drone's self-weight. It determines the battery life of the drone and thus reflects the actual performance of the UAV. It also reflects the drone's environmental impact and the associated cost savings [80]. Therefore, it will be interesting to see more studies focusing on considering the drone's technical characteristics in novel ways.

Most of the studies allow the drone's retrieval at certain locations only (customer nodes or depot). On the other hand, few studies consider the rendezvous between the two vehicles at intermediate locations long the truck route [76], [84], [87], [89], [90], [91], [110], [114], [121], [131]. Allowing the retrieval to be]at non-customer nodes (drone station, enroute, parking lots, etc.) provides possible benefits for the operation of the HTDDS. It increases the utilization of the drone by extending its battery life, which allows the drone to service wider ranges of customer nodes, leading to a reduction in the traveling cost [76], [110]. Considering the retrieval at any location in the space will certainly increase the modeling challenges of the problem, introducing a continuous retrieval location space. Thus, developing new solution methods other than the current network-based approaches is essential.

While most studies assume customer demands to be known before the start of the delivery operations, customers may order additional packages before the initially scheduled deliveries take place. Companies such as Amazon, Walmart, FedEx, and UPS offer same-day delivery to satisfy their customers' needs for providing on-time services. However, delivery delays are increased in same-day delivery services due to the tight service times [1]. Drones are found to be useful in providing fast deliveries on demand, which makes them beneficial in the case of dynamic ordering [132]. Therefore, future research should be directed toward dynamic HTDDS routing problems. This also necessitates developing solution methods capable of addressing the dynamic nature of LMD.

Aside from the issue of missing deliveries, the LMD is the most polluting part of the supply chain, and environmental concerns are growing. Drones are environmentally friendly, generating fewer carbon emissions than traditional delivery vehicles. Precisely, they are more energy-efficient than trucks when traveling short distances or serving a small number of customers [153], [154]. However, for longer traveling distances or a higher number of customers, they become less energy-efficient than trucks [154]. Reviewed literature has focused mainly on the financial and some of the operational elements of the HTDDS problems, except [79], [80], [112], [135], [140] in which the total carbon emission and energy consumption of HTDDS are minimized. Thus, understanding the environmental impact of the drone in the context of HTDDS is still not clear, requiring further research and understanding.

Due to the large number of drone applications (e.g., parcel delivery, precision agriculture, land surveying, environmental assessment, etc.), the coverage of the airspace by drones is expanding, emphasizing the need for Unmanned Aircraft.

System Traffic Management (UTM). There has been very little research on drone routing related to UTM and the limitations that UTMs may impose. Incorporating regulatory rules enforced by aviation authorities into models used for constructing drone-based delivery systems is critical for real-world implementation. For example, operating the drone within the visual line of sight of the truck is overlooked in the literature. In addition, most countries permit only low-altitude

TABLE 5. Reviewed literature by heuristic/metaheuristic solutions.

Heuristic/metaheuristic	References
LNS	[28, 65, 71, 85, 101, 143]
GA	[80, 91, 104, 125, 133, 138, 140]
Iterative	[62, 64, 97, 102]
SA	[29, 66, 86]
GRASP	[31, 70, 71, 110]
TS	[29, 69, 76, 86, 111]
Greedy	[55, 101, 107, 121]
K-means clustering	[119, 120]
VNS	[54, 56, 76]
EA	[113, 117]
Route and re-assign	[53, 58]
Savings	[88, 122]
Others	[12, 63, 65, 72, 77, 79, 81-83, 87, 90, 92, 95, 96, 106, 114, 121, 123, 126, 128, 131, 132, 137, 141]

aircraft with maximum flying heights ranging from 300 ft to 500 ft above ground level, while ensuring the elimination of collisions between many aircraft [155]. Hence, modeling HTDDS might involve calculating drone operating heights and vertical and horizontal separation distances between drones, which is currently neglected in the literature. Additionally, the FAA has announced that drones should operate within its guidelines including prohibiting drones from flying in certain areas [156]. These zones cover airports, critical facilities, and other areas where the inoperability of drones during certain times is required, such as areas with severe weather conditions (e.g., wind, high temperatures, humidity). Thus, creating HTDDS models that incorporate safety and regulatory constraints such as no-fly zones is essential for modeling realistic applications of HTDDS problems.

Drone technology is rapidly evolving. It is important to develop the infrastructure and tools required to ensure proper handling in the delivery of different product types. The type of product being delivered dictates the requirements needed to maintain the quality of the goods. For example, assessing the stresses that may be encountered during drone delivery such as vibration, humidity, and temperature excursions, should be included as all of these can affect the critical properties of shipped products. Add to that, docking hubs or drone stations used for storing and facilitating the coordination between trucks and drones are attracting market for drone delivery [148]. This is because drones may need special conditions for a safe and secure landing [149]. However, a limited number of studies have introduced this concept and have predefined the locations of the hubs. One remarkable consideration is to determine the location, size, configuration of the hubs, and the allocation of drones to achieve an effective HTDDS.

As most of the literature focuses on the use of a single truck with a single drone, attention should be given to extending these systems to multiple trucks and multiple drones as well

as addressing the associated challenges. These challenges may include synchronization and coordination of multiple launches/collections at the same location (e.g., scheduling a sequence of drone launches/collections).

The majority of HTDDS problems are modeled as MILP, which are known to be NP-hard. Small-scale instances of HTDDS problems (10-15 customer nodes) may be solved to optimality using exact solution methods. The increased modeling and computational complexity of HTDDS optimization problems necessitate the development of better solution methods. Heuristic algorithms such as GRASP, LNS, SA, GA, EA, and others were employed in solving instances with an average size of 100 customer nodes. Given that the commercial application of HTDDS is near [47], [48], [157] which will cover high-density regions, further research should focus on developing effective heuristic methods capable of solving large-scale problems in a reasonable amount of time.

The development of standardized datasets based on real applications could be very useful for both researchers and practitioners in testing potential HTDDS routing models and solutions. It would also make comparing potential models easier and advance research.

B. KEY ROADBLOCKS TO THE USE OF HTDDS MODELS IN PRACTICE-MANAGERIAL IMPLICATIONS

The LMD is a very complex process that needs proper planning and managerial decisions to achieve optimal outcomes. It suffers from a lack of visibility in the delivery operations, high delivery costs, inadequate route planning, and high unpredictability. Implementing effective LMD procedures provides logistics companies with an invaluable chance to react to changing customer expectations and differentiate their services from the competition. Those who want to thrive with an online business must tackle LMD issues front-on. That necessitates the use of appropriate technology to support operations, a high level of transparency and visibility across the supply chain, and effective communication between the logistics providers and customers. The application of drone technology for delivery purposes is a recent but very active field of research interest. Current and future efforts are planned to broaden the models to cover new drone constraints and offer more efficient heuristics with better solutions, a larger size of instances, and/or shorter computing time. The current HTDDS models in the literature may be incapable of meeting the needs of the industry yet. Next, we discuss the implications of current HTDDS in tackling LMD challenges.

1) INCREASING THE EFFICIENCY OF DRONE OPERATIONS

To build efficient HTDDS capable of satisfying the industry's requirements, the current characteristics of drones considered in the literature should be modified to maximize the potential impact of drones on delivery operations. The role of a drone's speed is overlooked in the literature. Speed has a major impact on drone traveling range and energy consumption level, as well as affecting both cost and service performance.

Another aspect is the energy consumption of the drone, which provides a better understanding of the cost and environmental impact of the drone. The modeling of the drone's energy consumption is affected by the design of the drone, weather conditions, and limited drone battery capacity. Current battery-powered drones have significant range and endurance limitations. Future research should concentrate on alternate energy sources such as fuel cells and solar panels. This will alleviate the battery limitation that presently restricts the use of UAVs efficiently and result in significant cost savings when combined with traditional delivery vehicles for LMD.

The usability of drones is limited by the need for frequent recharging. In HTDDS literature, battery recharging is assumed to occur instantaneously and has a fixed amount of time rather than optimizing the required charging of the drone in a cost-optimal way. The optimization of dynamic battery recharging will result in more accurate routing. To do so, locating charging stations with a peer-to-peer network can be a highly promising solution [158]. The peer-to-peer network can assist drones in reserving a recharging slot at the nearest charging station on their route at the lowest possible cost. Thus, allowing drones to fly for extended periods of time.

2) UNPREDICTABILITY CONCERNS

Delivery processes are disrupted by unpredictable situations that may occur such as congestion, severe weather conditions, service time, and the dynamic restrictions of the UTM imposed on the drones. Adequate route planning is necessary for avoiding delivery delays, customer dissatisfaction, and high costs. Incorporating spatial and temporal constraints is critical for creating more realistic models. Specific regions will almost stay off-limits to drone fly-over, therefore ideal routes must account for these constraints. In addition, such uncertainty sources have a significant influence on drone safety and security. However, these critical uncertainty issues are not adequately addressed in the literature. To deal with uncertainty, data mining, machine learning, AI technologies, and blockchain technology could be considered [159], [160], [161], [162], [163], [164], [165]. Add to that, stochastic optimization methods such as robust optimization, stochastic programming, and dynamic programming should be utilized to model the uncertainty sources in HTDDS.

3) ADDRESSING SECURITY, TRANSPARENCY, AND SAFETY CONCERNS OF DRONE OPERATIONS

The most crucial requirement for ensuring customer loyalty is visibility into the delivery operations. Customers want to know exactly where their package is and when it will arrive. Drones have distinct advantages in addressing the LMD obstacles. However, their use raises a number of security concerns. These security concerns pervade the whole delivery business process, from package pickup to final payment by the consumer upon successful parcel receipt. Traditionally, each company's business data is stored independently in logistics systems. When disagreements arise, third-party

arbitration is frequently required. In practice, however, few reliable third parties can guarantee the impartiality of the arbitration. Currently, the majority of existing UAV delivery systems are based on cloud computing, which cannot match the requirements of many real-time services in UAV delivery systems efficiently [162]. Security difficulties in UAV delivery systems have also been raised due to the presence of numerous parties who may not have a mutual trust relationship. In the UAV delivery system, drones will not be able to reach their full potential until they can demonstrate their safety and security for human lives. It is necessary to measure the level of safety brought by drone operations, as the publicized catastrophe employing emerging technologies may result in a disproportionate societal backlash. Drones require immediate control, management, communication, data storage, and intelligent decision-making. Technologies such as machine learning algorithms and blockchain should be used in conjunction with other delivery systems to maintain privacy [159], [160], [162], [161].

VII. CONCLUSION

The continuous rise of e-commerce has increased logisticians' obligation to resolve the LMD problem, which is known to be the most costly, polluting, and inefficient component of the supply chain. To improve delivery operations, innovative technologies such as drones are being integrated with traditional delivery systems. When drones are paired with a truck, they form a more flexible truck-drone delivery system that allows customers to be reached using the truck and/or the drone. Scholars and practitioners are paying close attention to the HTDDS. As a result, this paper addressed the current state-of-the-art of HTDDS in the LMD, as well as research gaps and prospective research directions. The review can cover other applications of hybrid truck-drone systems such as healthcare [166], precision agriculture [167], disaster management [168], [169], and others to explore the different modeling aspects that could affect the optimization problems. In addition, a study like this could have considered other databases such as the Web of Science.

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