İSTANBUL UNIVERSITY PRESS

Journal of Transportation and Logistics,
JTL 2025, 10 (1): 1–17

https://doi.org/10.26650/JTL.2025.1609155

Submitted 29.12.2024
Revision Requested 10.01.2025
Last Revision Received 08.02.2025
Accepted 11.02.2025
Published Online 06.03.2025

Journal of Transportation and Logistics

Research Article

Open Access

Two-Echelon Location Selection and Unmanned Aerial Vehicle-Assisted Vehicle Routing Problem

Tolga Gedikli [1] & İsmail Karaoğlan [1]

[1] Konya Technical University, Department of Industrial Engineering, Konya, Türkiye,

Abstract In recent years, the potential use of Unmanned Aerial Vehicle (UAV) technology in logistics processes and the rapid developments in this field have made UAV-assisted routing problems an important research topic. In this paper, we consider a two-echelon location selection and UAV-assisted vehicle routing problem. In this problem, trucks leave from the main depot with their packages and UAVs, move through potential service points (mobile depot), and return to the main depot. At each mobile depot, UAVs are launched from the truck to service the customers, and the trucks wait for the UAVs to complete their service and return. The UAVs are capable of making multiple trips between the mobile depot and customers, carrying only one package at a time. The objective is to minimize the maximum tour time. In this paper, a new problem, which involves a multi-truck structure and multiple launches of UAVs from a mobile depot, is investigated for the first time to the best of our knowledge in the literature. A mixed integer linear programming model is proposed to solve the problem. In order to evaluate the performance of the proposed mathematical model, the number of trucks is determined as one and two, experimental analyses are performed and the results are reported in detail.

Keywords UAV Routing · vehicle routing · location · mathematical modeling

Author Note It is the expanded version of the paper selected at the YAEM 2024 Congress.

Citation: Gedikli, T. & Karaoğlan, İ. (2025). Two-Echelon location selection and unmanned aerial vehicle-assisted vehicle routing problem. *Journal of Transportation and Logistics*, *10*(1), 1-17. https://doi.org/10.26650/JTL.2025.1609155

Corresponding author: Tolga Gedikli tolgagedikli@gmail.com

Two-Echelon Location Selection and Unmanned Aerial Vehicle-Assisted Vehicle Routing Problem

The exponential growth in technology over the past decade has led to a notable increase in the utilization of Unmanned Aerial Vehicles (UAVs) or "drones", across a diverse range of sectors, including logistics, military operations, public security, and surveillance. It is noteworthy that several leading online retailers, including Amazon, Google, UPS, 7-Eleven, DHL and Walmart, have already started to integrate drones into their parcel delivery services. This reflects a growing interest in UAVs for "last-mile" delivery solutions (Macrina et al., 2020; Rojas Viloria et al., 2021).

The use of UAVs as a mode of transportation is becoming increasingly prevalent, with a variety of applications in the logistics industry (Moshref-Javadi & Winkenbach, 2021). The advantages of drones over conventional vehicles are numerous, including a constant and high travel speed, the absence of the need for physical road infrastructure, the directness of travel, and the avoidance of exposure to traffic and congestion (Macrina et al., 2020; Moshref-Javadi & Winkenbach, 2021; Rojas Viloria et al., 2021). These advantages are expected to result in reduced delivery times and increased responsiveness of logistics systems (Moshref-Javadi & Winkenbach, 2021). In light of ongoing urbanization, rapid growth in direct e-commerce deliveries, and increasing density and congestion levels, the benefits of UAV-based delivery are particularly pronounced in urban environments (Moshref-Javadi & Winkenbach, 2021). The resulting savings in time and cost could benefit both companies and customers in commercial logistics systems. Many prominent industry players, such as Amazon, Google Wing, United Parcel Service (UPS), and Rakuten, are actively working on developing and testing drone delivery models (Moshref-Javadi & Winkenbach, 2021). Given the anticipated growing importance of drones as a means of delivery in the near future, it is crucial to ensure a close and focused alignment between academic research and industrial practice in this field (Macrina et al., 2020; Moshref-Javadi & Winkenbach, 2021).

The use of UAVs for the delivery of last-mile packages is set to transform the structure of the logistics industry. However, before UAVs can be widely deployed in the commercial sector, several significant regulatory and technological challenges must be overcome. These include the capacity of the battery, the payload capacity, the maximum height at which they can fly, the inability to fly in restricted areas, the safety of the UAV and the parcel being transported, and the ability to detect and avoid obstacles. Despite these limitations, numerous researchers are currently engaged in efforts to mitigate the technical shortcomings of UAVs. While a substantial body of research has been conducted to address these technical issues, operational challenges have not been as extensively explored (Murray & Chu, 2015). For example, given the operations proposed by Amazon using UAVs with a direct depots-to-customer range of 16 km, UAV deliveries need to be made from distribution centers located close to customers. In this instance, it would be necessary for the existing distribution centers to be relocated or for new ones to be constructed. To benefit from economies of scale, these distribution centers would likely be located in proximity to densely populated urban areas with high-rise housing.

This paper addresses distribution network design problems where UAV-assisted distribution processes are planned through mobile depots instead of establishing distribution centers close to customers. Although UAV transportation offers great benefits in terms of both time and cost, UAVs have to move from distribution centers located close to customers due to constraints such as battery capacity for last-mile package deliveries. This may require relocating existing distribution centers near densely populated urban areas or building new ones. In this case, firms must incur high installation and operating costs. Moreover, the customers to be delivered in last-mile delivery vary from day to day. Locating the distribution center at a fixed-point leads to higher delivery times and costs. To overcome the aforementioned disadvantages, this study will focus on a UAV-assisted last-mile delivery network structure over mobile depots.

To overcome the aforementioned disadvantages, this study will focus on a UAV-assisted last-mile delivery network structure over mobile depots. In this structure, high-capacity trucks move from the depot (main depot) where the products to be delivered to the customers are located to the temporary stopping points (mobile depots) to be determined within the city with the products loaded to them and UAVs. Mobile depots can be parking lots of shopping malls, vacant lots, truck garages, etc. where trucks can wait temporarily. Upon reaching the mobile depot, the products loaded onto the UAVs in the trucks are delivered to the customers and the UAVs return to the trucks. After the deliveries to be made from the relevant mobile depot are completed, the trucks move to the next potential mobile depot, perform the same operations there, and return to the main depot at the end of the day. Thanks to this network structure, significant savings are achieved in distribution center installation and operating costs, and problems arising from variability in customer locations will be prevented. For example, when there is a delivery density in a certain region the next day, the mobile depot area that was not used the previous day can be rented with low costs such as daily rent, etc., and can be used as a mobile depot and deliveries can be made. In this proposed approach, it is necessary to determine which of the alternative regions should be selected as mobile depots, how to move between these mobile depots, which customer will be served from which mobile depot, by which vehicle, and on which route.

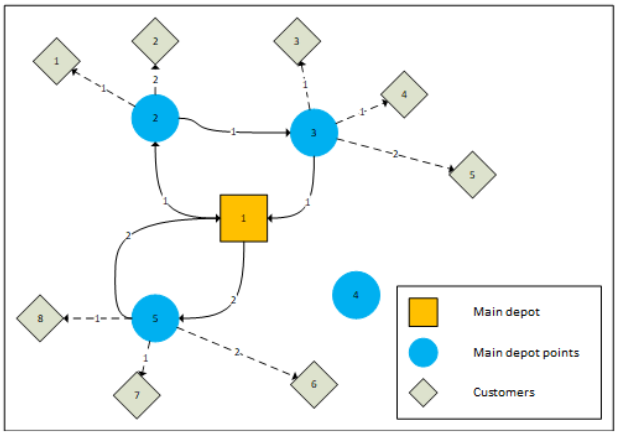
In this paper, we consider the UAV-assisted vehicle routing problem, where customers are served by drones, while trucks carry only UAVs and packages. This raises new routing variants that use a combination of trucks and drones for delivery. We call these problems two-echelon routing problems with trucks and drones (2ER-TD) and define them as prototypical problems. The main difference between the 2ER-TD and the classical two-echelon vehicle routing problem (2E-VRP) is that drones are used in the second echelon instead of trucks. In addition, because the drones are transported by truck to intermediate depots, the truck after launching the drones must stay at an intermediate depot to wait for the drones to come back. A single-truck version of the problem was previously considered by Vu, Vu, Ha, and Nguyen (2022). In this paper, we extend the work of Vu et al. (2022) by defining a new problem, which is an improved version of this problem with multiple trucks. Thus, the problem is transformed from a two-stage location and UAV-assisted vehicle routing problem to a two-stage location and UAV-assisted vehicle routing problem.

In this paper, a new problem, called “Two-Echelon Location Selection and Unmanned Aerial Vehicle Assisted Vehicle Routing Problem” (2E-UVRP), which involves a multi-truck structure and the ability to launch a UAV more than once from a mobile depot, is investigated for the first time to the best of our knowledge in the literature. The 2E-UVRP problem is shown in Figure 1. The dotted lines represent the back-and-forth transportation by drone and the solid lines represent the transportation by truck. The numbers in the dotted lines represent the drone identities, and the numbers in the solid lines represent the truck identities. For example, while the first truck was waiting at mobile depot 3, drone 1 performed two transportation tasks from this mobile depot to customers 3 and 4, while drone 2 performed only one transportation task to customer 5. In this scenario, no truck was directed to mobile depot point 4 and the depot was not activated. Allowing drones to perform more than one transportation task within the scope of the problem and using more than one truck can reduce the service time. In addition, the simultaneous movement of trucks makes it possible to serve customers in a shorter time compared to the single-truck problem.

The contributions of this study can be summarized as follows: First, a new problem type with a multi-truck structure is introduced to the literature on drone-assisted routing problems. Second, a mixed-integer linear programming model was developed that allows solving small- and medium-sized problem instances efficiently. The proposed model can be reduced to the 2ER-TD problem when the number of vehicles is one and can also solve single-truck problems efficiently. Third, in the experimental analysis performed using the test data presented by Vu et al. (2022), the number of vehicles was set as one and two, and detailed tests were applied under different configurations. All problems are solved optimally under a time constraint of 10 minutes. Finally, a more commercially viable structure is presented by providing faster delivery to customers within the scope of 2E-UVRP.

Figure 1

Figural representation of the 2E-UVRP



This study is structured as follows: Literature review section provides the main works in the literature on 2E-UVRP. Problem definition and mathematical models part presents the problem definition and the developed mixed integer linear mathematical models in detail. Experimental results chapter is devoted to the experimental studies and their comprehensive analysis. Conclusion and future research directions summarizes the conclusions of the study and makes recommendations for future research.

Literature review

The topic of UAV-assisted routing problems is a relatively new and current area of research within the literature. In one of the earliest works on this topic, Murray and Chu (2015) defined two new problems: the flying sidekick traveling salesman problem (FSTSP) and the parallel drone scheduling traveling salesman problem (PDSTSP). FSTSP is a deployment problem where a UAV and a truck move synchronously together. The problem is considered as a single truck with infinite capacity and multiple stops per route, and a single UAV with infinite capacity and one stop per route, where the truck and UAV move in unison, with the joining and departure points situated at customer locations. In this problem, the objective is to minimize the total tour length. A mathematical model and a heuristic method were developed for solving the problem (Murray & Chu, 2015). Carlsson and Song (2017) demonstrated that the improvement in efficiency resulting from the use of a single truck and a UAV is proportional to the square root of the ratio of the speeds of the trucks and the UAV. In a recent contribution to the field, Ha et al. (2018) proposed a novel variant of the UAV-assisted traveling salesman problem (UAV-GSP) to minimize operating costs. These costs include the total transportation cost and the cost associated with the loss of time incurred when one vehicle must wait for another. Phan et al. (2018) introduced a novel variant of the UAV-GSP, incorporating the use of multiple UAVs. Salama and Srinivas (2020) presented mathematical models for the joint optimization of route completion times for trucks and UAV routes with customer clustering, as part of their study, which considered a truck and a UAV fleet. The objective of this study is to identify the optimal truck route through the application of a standard traveling salesman problem (GSP) model. This model incorporates customer clustering and the determination of the central points through the k-means method. Subsequently, a truck visits these points. To minimize customer waiting times, Moshref-Javadi, Hemmati, et al. (2020) proposed a model in which multiple UAVs can be launched from a single location but are not expected to return. Conversely, Moshref-Javadi, Lee, et al. (2020) introduced a variation in which the trucks must wait for the return of all UAVs it has launched to continue their route. Morim, Campuzano, Amorim, Mes, and Lalla-Ruiz (2024) studied the drone-assisted vehicle routing problem with robot stations. They proposed a mixed integer linear programming mathematical model and a general variable neighborhood search metaheuristic algorithm for the objective functions of delivery time and operational costs. Jiang, Dai, Yang, and Ma (2024) investigated a multi-visit flexible docking vehicle routing problem that uses a fleet of trucks and drones to fulfill pickup and delivery requests in rural areas. They developed this problem as a mixed-integer linear programming model and solved it with a large neighborhood search metaheuristic. Savuran and Karakaya (2024) addressed the Multi-Capacity Mobile Depot Vehicle Routing Problem, a variant of VRP in which multiple drones with limited flight range operate from a mobile depot. The goal is to maximize the goal coverage while considering flight endurance, depot mobility, and drone multiplicity. They developed a new evolutionary algorithm that generates synchronized routes for the drones, taking into account all constraints.

The 2ER-TD considered in this study has some similarities with the FSTSP, where trucks act as mobile depots and UAVs make deliveries. However, since all locations (customers and depots) in the FSTSP have to be visited, there is no decision regarding the selection of the locations to be visited by trucks. In the 2ER-TD, location decisions, which determine which mobile depot to open based on customer locations, and decisions for assigning customers to these mobile depots are handled together. Another similar problem, PDSTSP, proposed by Murray & Chu (2015), is a distribution problem where a fleet of trucks and a fleet of UAVs move asynchronously from a depot to customers. This model is based on the following assumptions: *i*) the trucks and UAVs move asynchronously; ii) customers can visit by which vehicle is known in advance; *iii*) stops can be made at more than one per route; *iv*) the capacity of the UAV is infinite; *v*) with a single supporting vehicle, stops can be made at one per route; *vi*) the capacity of the supporting vehicle is limited; *vii*) there is a limited number of UAVs; and *viii*) there is a single depot. In this problem, the minimum tour length is taken as the objective function, and a mathematical model is developed to represent the problem. In this problem, customers who are situated outside the UAV's operational range or whose packages exceed the UAV's maximum payload are served by trucks, while other customers are served by either trucks or UAVs. In their study, Nguyen, Dang, Hà, and Pham (2022) extended the PDSTSP problem by incorporating a homogeneous fleet of trucks in addition to the UAV fleet. This problem, which they refer to as the Parallel Drone Scheduling Vehicle Routing Problem (PDSVRP), allows for the servicing of customers from an existing depot by both the truck fleet and the UAV fleet.

A review of the literature reveals that no studies have considered the impact of customer time windows and add-distribute operations on UAV-GSP problems. Furthermore, all studies have assumed that the capacity of trucks is unlimited. With the exception of the study by Gonzalez-R et al. (2020), all studies assume that a UAV is capable of making a single delivery. With the exception of some studies, the capacity of UAVs is not considered. Instead, it is assumed that UAVs can serve all customers (Dayarian et al., 2020; Ha et al., 2018; Murray & Raj, 2020; Song et al., 2018). Moreover, only a limited number of studies have employed energy consumption models (Ferrandez et al., 2016; Gonzalez-R et al., 2020; Jeong et al., 2019; Murray & Raj, 2020).

The second stage of the 2ER-TD considered in this study and the PDSTSP and PDSVRP models have similarities in that deliveries are made from a depot by UAVs and trucks. However, the network structure we propose differs in terms of the use of more than one mobile depot (the PDSVTSP and PDSVRP problems use a single depot), the location decision for the mobile depot in the first stage, and the determination of which customers will be served from these mobile depots. While the FSTSP offers considerable benefits when customer locations are distant, the PDSTSP provides advantages when customer locations are proximate (Murray & Chu, 2015). The two-stage structure, in which the location of mobile depots is selected in the first stage according to customer locations, and the distribution to customers is carried out in the second stage, allows for the simultaneous utilization of the advantages of FSTSP and PDSTSP. Consequently, the 2ER-TD distribution structure has the potential to mitigate the adverse effects of distance on the solution.

The closest problem to the one considered in this paper is considered by Vu et al. (2022). Vu et al. (2022) considered a new version of the two-stage routing problem in which parcels are delivered from depots to intermediate satellites, which in turn deliver them to customers. They first proposed mixed integer linear programming models to mathematically describe the problem and solve small instances optimally, and a metaheuristic based on the idea of a greedy random adaptive search procedure to handle larger instances. This paper describes the single-truck problem. Because it is a single-vehicle problem, it is closer to the traveling salesman problem. In this paper, we consider the multi-vehicle two-stage UAV-assisted vehicle routing problem, which is closer to the vehicle routing problem.

Problem definition and mathematical models

Problem Definition

In this study, a new problem is proposed to allow deliveries to be made in less time using more than one truck and to make the problem more realistic. In the proposed problem, there is a main depot, multiple high-capacity trucks, and multiple fleets of UAVs traveling with each vehicle. While the trucks serve as mobile depots, the distribution of parcels from the mobile depots to customers is carried out by UAVs. The assumptions of the model developed for this problem are detailed below.

- Each customer has a positive demand and is known.
- The distances between all nodes (main depots, mobile depots, and customers) are known.
- Multiple trucks act as mobile depots and their capacities are sufficient to meet all customer demands.
- Trucks have a certain number of homogeneous UAVs that provide services to customers.
- The set of customers that can be served by the UAVs from each mobile depot is known.
- The truck route starts from the main depot and ends at the main depot after visiting some or all the potential mobile depot points.
- At each mobile depot, the trucks wait for the UAVs' service time.
- UAVs can only serve one customer on the same route.
- UAVs can serve multiple customers from a mobile depot.

Under these assumptions, the aim is to minimize the time it takes for all trucks to leave and return to the main depot after serving all customers. It also aims to determine which mobile depot points are selected, which truck stops at which mobile depot point, and which customer is served by which mobile depot point.

This study addresses a problem that involves the use of both multiple trucks and multiple UAVs, where each UAV operates multiple times from a single mobile depot, integrating both transportation and aerial routing systems.

Mixed-integer linear programming formulations

In developing the MILP model for 2E-UVRP, the MILP model for 2ER-TD presented in Vu et al. (2022) was utilized and defined as follows: Let $G(V, D, A_1, A_2)$ be a connected network. In this network, V represents mobile depot nodes that can be visited by trucks and D represents customer nodes that must be visited by UAVs. A_1 and A_2 are the set of edges between nodes in cluster $(A_1 = \{(i,j) : i, j \in V \; ve \; i \neq j\})$ and $A_2 = \{(i,j) : i \in V, j \in D\}$ respectively. For each arc $(i,j) \in A_1$ positive movement time for trucks is defined by t_{ij} and for each arc $(i,d) \in A_2$ positive flight time for UAVs is defined by t'_{id}. The set V consists of main depot (0) and mobile depot nodes $(V_D = 1, 2, ..., n-1)$. Each customer has a positive demand $(d \in D)$, which is delivered by a single visit of the UAV to the customer. UAVs have a limited range due to their battery capacity, and within this capacity, the set of customers $(D_i : i \in V_D)$ that can be served by the UAVs from mobile depot i is known. In the problem, there is a set U of u identical UAVs and a set K of k high-capacity trucks. Each UAV is capable of autonomous flight and has a flight range of *r* units, measured in time. The decision variables for the developed MILP model are explained below.

X_{ijk} : binary variable equals 1 if truck k moves from point i to point j and 0 otherwise.

Y_{ik} : binary variable equals 1 if truck k visits node i, and 0 otherwise.

Z_{uid} : binary variable equals 1 if UAV u visits customer d from mobile depot i and 0 otherwise.

b_i : positive variable representing the visiting sequence of node i by a truck.

S_{ik} : positive variable representing the time truck k waits for UAVs at mobile depot i.

L_k : positive variable representing the time for the k^{th} truck to complete the route.

Objective Function

$$Minimize \; MaksTour \tag{1}$$

Subject to

$$\Sigma_{i \in V} X_{0ik} \leq 1 \quad \forall k \in K \tag{2}$$

$$\Sigma_{i \in V} X_{i0k} \leq 1 \quad \forall k \in K \tag{3}$$

$$\Sigma_{i \in V} X_{ijk} = Y_{jk} \quad \forall j \in V_D \forall k \in K \tag{4}$$

$$\Sigma_{j \in V} X_{jik} = \Sigma_{j \in V} X_{ijk} \quad \forall i \in V_D \forall k \in K \tag{5}$$

$$b_i - b_j + |Nc| \Sigma_{k \in K} X_{ijk} + (|Nc| - 2) \Sigma_{k \in K} X_{jik} \leq (|Nc| - 1) \Sigma_{k \in K} Y_{ik} \quad \forall i \in V_D, \forall j \in V_D, i \neq j \tag{6}$$

$$b_i \leq |Nc| \Sigma_{k \in K} Y_{ik} \quad \forall i \in V_D \tag{7}$$

$$b_i \geq \Sigma_{k \in K} Y_{ik} \quad \forall i \in V_D \tag{8}$$

$$b_i \leq |Nc| - (|Nc| - 1) \Sigma_{k \in K} X_{0ik} \quad \forall i \in V_D \tag{9}$$

$$Z_{uid} \leq \Sigma_{k \in K} Y_{ik} \quad \forall u \in U, \forall i \in V_D, \forall d \in D \tag{10}$$

$$\Sigma_{u \in U} \sum_{d \in D} Z_{uid} \geq \Sigma_{k \in K} Y_{ik} \quad \forall i \in V_D \tag{11}$$

$$\Sigma_{u \in U} \Sigma_{i \in V_D} Z_{uid} = 1 \quad \forall d \in D \tag{12}$$

$$S_{ik} \geq \Sigma_{d \in D} 2t'_{id} Z_{uid} - M(1 - Y_{ik}) \forall u \in U, \quad \forall i \in V_D, \forall k \in K \tag{13}$$

$$L_k = \Sigma_{i \in V} \Sigma_{j \in V_D} t_{ij} X_{ijk} + \Sigma_{i \in V_D} S_{ik} \quad \forall k \in K \tag{14}$$

$$MaksTour \geq L_k \quad \forall k \in K \tag{15}$$

$$X_{ijk} \in \{0,1\} \quad \forall i, j \in V_D, \forall k \in K \tag{16}$$

$$Y_{ik} \in \{0,1\} \quad \forall i \in V_D, \forall k \in K \tag{17}$$

$$Z_{uid} \in \{0,1\} \quad \forall u \in U, \forall i \in V_D, \forall k \in K \tag{18}$$

$$b_i \geq 0 \quad \forall i \in V_D \tag{19}$$

$$S_{ik} \geq 0 \quad \forall i \in V_D, \forall k \in K \tag{20}$$

$$L_k \geq 0 \quad \forall k \in K \tag{21}$$

The objective function (1) is to minimize the maximum tour time. Constraint set (2) ensures that a truck must move from the main depot before it can be used, while constraint set (3) ensures that each truck leaving the main depot returns to the main depot after completing its tour. Constraint set (4) guarantees that if a truck stops at any mobile depot, this depot is opened. Constraint set (5) guarantees that trucks leave each mobile depot they visit. Constraint sets (6)-(9) are Miller-Tucker-Zemlin (MTZ) sub-tour elimination constraints adapted for the multi-truck problem. Constraint set (10) ensures that no customer is served by a mobile depot that is not opened. Constraint set (11) ensures that if a mobile depot is opened, at least one customer is served from this mobile depot. Constraint set (12) ensures that each customer is served by only one UAV. Constraint set (13) calculates the waiting time of the truck for the UAVs. Constraint set (14) calculates the time it takes for each truck to leave the main depot and return to the main depot. The constraint set (15) ensures that the *MaxTour* parameter is equal to or greater than the tour time of the truck with the longest route. Finally, constraint sets (16)-(21) are known as integrality constraints.

Experimental results

In this section, the test cases generated by Vu et al. (2022) are used to test the effectiveness of the proposed mathematical model for the 2E-UVRP problem. The test cases are generated by first randomizing the mobile depot locations and then randomizing the customer coordinates such that each customer can be served by at least one mobile depot node. Depending on the size of the surface, four different layout combinations were created with different combinations of the number of mobile depots and the number of customers. For $d = 20$ problems, the number of mobile depots and number of customer combinations were 8-14 and 11-11, and for $d = 30$ problems these values were 11-22 and 17-16. When reporting the results, each example is presented in $d - n - m$ format. Where d is the side length of the square, n is the number of mobile depots and m is the number of customers.

The test cases also considered the speed of the UAV and the truck. For each problem, the truck speed is 40 km/h, while the UAV speeds are 40, 50, 60, 70, and 80 km/h, respectively. Since the UAVs can fly directly between the start and end points, the flight time of the UAVs is measured by the (t'_{ij}) Euclidean distance, while the movement time of the trucks between the nodes is calculated by the (t_{ij}) Manhattan distance. The UAV flight time is limited to 30 minutes. In other words, to serve a customer from a mobile depot, the sum of the travel time from the mobile depot to the customer and the arrival time at the customer must be less than or equal to 30 minutes.

In the study, the UAV speeds are different for each problem and the number of UAVs is determined as the minimum required number of UAVs ($u_{\min}$), one, two, and three more than $u_{\min}$. $u_{\min}$value represents the minimum number of UAVs required to be in trucks.

In this test set, 4 different mobile depot-client number combinations (20-8-14, 20-11-11, 30-11-22, and 30-17-16), 5 different UAV speeds (40, 50, 60, 70 and 80 km/h), 4 different UAV numbers$(u_{\min}, u_{\min} + 1, u_{\min} + 2, u_{\min} + 3)$ There are 80 test samples in total.

The mathematical model presented in the section titled “Mixed-integer linear programming formulations” was solved using the GAMS/CPLEX solver on a PC with a 2.30 GHz processor and 16 GB RAM with a run-time limit of 10 min. If the number of trucks is taken as one, the problem is transformed into the study of Vu et al. (2022). In the developed integer complex mathematical model, the problem proposed by Vu et al. (2022) can be solved faster and more efficiently if the number of trucks is set to one. The same optimal results were obtained for these problems.

Numerical Results

Within the scope of the experimental studies, the number of trucks for 2E-UVRP was determined as one and two, and experiments were carried out on these different configurations. In these problems, the UAVs can only visit a single customer on each route, while they provide service to more than one customer by traveling back and forth from the same mobile depot. A total of 160 problems were solved, 80 for the one-truck problem and 80 for the two-truck problem. In the mathematical model developed by Vu et al. (2022), they obtained optimal results in all problems under the constraint of one hour in the problems with $d = 20$. However, in the problem with $d = 30$, they could not reach optimal results in 20 problems. With the mathematical model proposed in this study, optimal results were obtained for all problems with a constraint of 10 min.

Table 1 shows the results for $d = 20$ problems. Optimum results were found for all test instances in an average of 0.237 s for one-truck problems. In the two-truck problems, optimum results were found for all test instances in an average of 1.42 s. While the objective function value is 1.52 on average in one-truck problems, it decreases to 0.99 on average in two-truck problems. This shows that the use of more than one truck will result in faster deliveries than in the case of a single truck. While the average number of depots opened was 1.73 in one-truck problems, it increased to 2.18 in two-truck problems. In this case, since two trucks are used simultaneously, more mobile depots are visited, and deliveries are made in a shorter time.

The analysis shows that problems with 11 mobile depots and 11 customers require longer solution times than problems with 8 mobile depots and 14 customers. It was found that the increase in the number of mobile depots was more effective on the difficulty level of the problem than the increase in the number of customers. However, the effect of the increase in the number of UAVs on the difficulty level was not found for these problems.

Table 1

Results of one-truck and two-truck problems for d = 20

Problem Name	v_d	u	One- Truck			Two-Truck		
			Number of depots opened	Objective function value	Solution time	Number of depots opened	Objective function value	Solution time
$u = u_{\min}$								
20-8-14	40	2	***3***	2.448	***0.12***	***3***	1.432	***0.45***
20-8-14	50	2	***3***	2.189	***0.16***	***3***	1.300	***0.39***
20-8-14	60	2	***3***	2.015	***0.17***	***3***	1.223	***1.88***
20-8-14	70	2	***3***	1.892	***0.19***	***2***	1.120	***0.50***
20-8-14	80	2	***2***	1.757	***0.17***	***2***	1.036	***0.44***
20-11-11	40	2	***4***	2.162	***0.20***	***4***	1.288	***2.72***
20-11-11	50	2	***2***	1.909	***0.11***	***2***	1.198	***5.99***
20-11-11	60	2	***2***	1.707	***0.12***	***2***	1.039	***4.16***
20-11-11	70	2	2	1.563	***0.20***	2	0.975	***3.48***
20-11-11	80	2	***1***	1.442	***0.25***	***2***	0.934	***1.20***
Mean			*2.5*	*1.908*	*0.17*	*2.5*	*1.155*	*2.12*

Problem Name	v_d	u	One- Truck			Two-Truck		
			Number of depots opened	Objective function value	Solution time	Number of depots opened	Objective function value	Solution time
$u = u_{\min} + 1$								
20-8-14	40	3	***3***	2.028	***0.14***	***3***	1.254	***0.33***
20-8-14	50	3	***3***	1.852	***0.17***	***2***	1.116	***0.30***
20-8-14	60	3	***1***	1.621	***0.38***	***2***	1.009	***0.50***
20-8-14	70	3	***1***	1.454	***0.23***	***2***	0.929	***0.36***
20-8-14	80	3	***1***	1.328	***0.23***	***2***	0.869	***0.39***
20-11-11	40	3	***3***	1.963	***0.33***	***3***	1.211	***2.97***
20-11-11	50	3	***2***	1.563	***0.31***	***2***	1.063	***3.98***
20-11-11	60	3	***1***	1.335	***0.28***	***2***	0.905	***2.02***
20-11-11	70	3	1	1.208	***0.27***	2	0.840	***1.20***
20-11-11	80	3	***1***	1.114	***0.19***	***2***	0.791	***1.12***
Mean			*1.7*	*1.547*	*0.25*	*2.2*	*0.999*	*1.32*
$u = u_{\min} + 2$								
20-8-14	40	4	***3***	1.961	***0.20***	***2***	1.111	***0.25***
20-8-14	50	4	***2***	1.775	***0.22***	***2***	1.019	***0.34***
20-8-14	60	4	***1***	1.330	***0.22***	***2***	0.888	***0.47***
20-8-14	70	4	***1***	1.205	***0.59***	***2***	0.835	***0.52***
20-8-14	80	4	***1***	1.110	***0.19***	***2***	0.791	***0.53***
20-11-11	40	4	***2***	1.864	***0.47***	***2***	1.053	***0.70***
20-11-11	50	4	***1***	1.335	***0.23***	***2***	0.973	***2.72***
20-11-11	60	4	***1***	1.125	***0.27***	***2***	0.888	***2.02***
20-11-11	70	4	1	1.029	***0.17***	2	0.826	***1.95***
20-11-11	80	4	***1***	0.956	***0.24***	***2***	0.779	***1.30***
Mean			*1.4*	*1.369*	*0.28*	*2*	*0.916*	*1.08*
$u = u_{\min} + 3$								
20-8-14	40	5	***2***	1.953	***0.22***	***2***	1.053	***0.16***
20-8-14	50	5	***2***	1.684	***0.23***	***2***	0.972	***0.23***
20-8-14	60	5	***1***	1.158	***0.27***	***2***	0.888	***0.67***
20-8-14	70	5	***1***	1.057	***0.23***	***2***	0.826	***0.41***
20-8-14	80	5	***1***	0.981	***0.19***	***2***	0.779	***0.39***
20-11-11	40	5	***2***	1.800	***0.25***	***2***	1.053	***0.41***
20-11-11	50	5	***1***	1.217	***0.30***	***2***	0.972	***1.02***
20-11-11	60	5	***1***	1.009	***0.36***	***2***	0.888	***5.44***
20-11-11	70	5	1	0.929	***0.19***	2	0.826	***1.66***
20-11-11	80	5	***1***	0.869	***0.22***	***2***	0.779	***1.39***
Mean			*1.3*	*1.266*	*0.25*	*2.0*	*0.904*	*1.18*
Overall mean			***1.7***	***1.522***	***0.24***	***2.2***	***0.993***	***1.42***

Table 2 shows the results for $d = 30$ problems. Optimum results were found for all test instances in an average of 1.95 s for one-truck problems. In the two-truck problems, optimum results were reached for all test instances in an average of 68 s. While the average value of the objective function is 2.71 in the one-truck problems, it decreases to 1.71 in the two-truck problems. While the average number of depots opened in one-truck problems is 3, it increases to an average of 3.35 in two-truck problems. In this case, because two trucks are used simultaneously, more mobile depots are visited, and deliveries are made in a shorter time.

Table 2

Results of one-truck and two-truck problems for d = 30

Problem Name	v_d	u	One- Truck			Two-Truck		
			Number of depots opened	Objective function value	Solution time	Number of depots opened	Objective function value	Solution time
$u = u_{\min}$								
30-11-22	40	3	***4***	4.243	***1.14***	***4***	2.507	***3.22***
30-11-22	50	3	***3***	3.217	***1.02***	***3***	2.020	***9.38***
30-11-22	60	3	***3***	2.914	***1.09***	***3***	1.861	***8.47***
30-11-22	70	3	***3***	2.698	***0.53***	***3***	1.738	***5.81***
30-11-22	80	3	***2***	2.388	***2.02***	***3***	1.452	***1.17***
30-17-16	40	2	***5***	4.115	***2.30***	***5***	2.398	***65.27***
30-17-16	50	2	***4***	3.235	***2.22***	***4***	1.962	***65.77***
30-17-16	60	2	***4***	2.954	***2.09***	***4***	1.815	***173.84***
30-17-16	70	2	3	2.665	***0.77***	3	1.607	***26.16***
30-17-16	80	2	***2***	2.420	***0.86***	***3***	1.493	***29.94***
Mean			*3.3*	*3.085*	*1.40*	*3.5*	*1.885*	*38.90*
$u = u_{\min} + 1$								
30-11-22	40	4	***4***	3.810	***0.33***	***4***	2.307	***2.72***
30-11-22	50	4	***3***	2.791	***1.30***	***3***	1.817	***4.34***
30-11-22	60	4	***3***	2.559	***0.47***	***3***	1.700	***4.56***
30-11-22	70	4	***3***	2.394	***0.61***	***4***	1.621	***6.53***
30-11-22	80	4	***2***	2.043	***3.06***	***3***	1.290	***1.27***
30-17-16	40	3	***4***	3.734	***2.89***	***4***	2.175	***68.19***
30-17-16	50	3	***3***	2.860	***6.41***	***4***	1.779	***88.47***
30-17-16	60	3	***4***	2.632	***3.88***	***3***	1.670	***180.75***
30-17-16	70	3	3	2.287	***0.81***	3	1.443	***91.39***
30-17-16	80	3	***2***	1.929	***0.92***	***3***	1.242	***21.84***
Mean			*3.1*	*2.704*	*2.07*	*3.4*	*1.704*	*47.01*
$u = u_{\min} + 2$								
30-11-22	40	5	***4***	3.678	***0.31***	***4***	2.253	***2.98***
30-11-22	50	5	***3***	2.641	***0.45***	***3***	1.761	***3.59***
30-11-22	60	5	***3***	2.434	***0.44***	***3***	1.634	***4.69***
30-11-22	70	5	***3***	2.286	***0.50***	***3***	1.543	***4.66***
30-11-22	80	5	***2***	1.841	***0.67***	***3***	1.285	***2.44***
30-17-16	40	4	***4***	3.695	***2.67***	***4***	2.150	***272.92***
30-17-16	50	4	***3***	2.708	***6.62***	***4***	1.735	***246.08***
30-17-16	60	4	***3***	2.492	***4.91***	***3***	1.613	***129.66***

Problem Name	v_d	u	One- Truck			Two-Truck		
			Number of depots opened	Objective function value	Solution time	Number of depots opened	Objective function value	Solution time
30-17-16	70	4	2	2.049	***1.20***	2	1.299	***42.42***
30-17-16	80	4	***1***	1.639	***3.73***	***2***	1.051	***18.22***
Mean			*2.8*	*2.546*	*2.15*	*3.1*	*1.632*	*72.77*
$u = u_{\min} + 3$								
30-11-22	40	6	***4***	3.678	***0.30***	***5***	2.253	***3.69***
30-11-22	50	6	***3***	2.641	***0.48***	***3***	1.761	***5.03***
30-11-22	60	6	***3***	2.434	***0.58***	***3***	1.634	***6.22***
30-11-22	70	6	***3***	2.286	***0.73***	***3***	1.543	***5.95***
30-11-22	80	6	***2***	1.746	***0.78***	***3***	1.285	***2.28***
30-17-16	40	5	***4***	3.695	***3.12***	***4***	2.150	***363.92***
30-17-16	50	5	***3***	2.703	***5.51***	***4***	1.735	***161.86***
30-17-16	60	5	***3***	2.480	***7.58***	***4***	1.613	***322.50***
30-17-16	70	5	2	1.888	***1.69***	2	1.299	***239.58***
30-17-16	80	5	***1***	1.435	***1.00***	***3***	1.051	***25.28***
Mean			*2.8*	*2.499*	*2.18*	*3.4*	*1.632*	*113.63*
Overall mean			***3.0***	***2.708***	***1.95***	***3.4***	***1.714***	***68.08***

Figure 2 shows the objective function value and solution times according to the size of the problem (number of mobile depots and number of customers), UAV speeds, and number of UAVs. Figure 2. a shows the average objective function values of all the problems. While the average value of the objective function is 2.12 for the problems with one truck, the average value of the objective function is 1.35 for the problems with two trucks. When the number of trucks is two, the service time to customers is reduced by approximately 36%. The use of multiple trucks brings the problem closer to real-life scenarios while enabling shorter service delivery times in last-mile delivery processes. This situation improves customer satisfaction and provides a more sustainable and effective solution, especially for real-world applications. Figure 2. b shows the average solution time for all the problems. Problems with one truck were solved in 1.09 seconds on average, while problems with two trucks were solved in 34.75 seconds on average. This result shows that the increase in the number of trucks has a serious impact on the solution time and significantly increases the complexity of the problem. Problems with two trucks require more coordination and synchronization, which dramatically increases the solution time due to the enlargement of the search space and the increase of constraints. This demonstrates the significant impact of increasing the number of resources on the computational load and algorithmic performance in transport and route optimization.

The analysis shows that problems with 17 mobile depots and 16 customers require a longer solution time than problems with 11 mobile depots and 22 customers. It was found that the increase in the number of mobile depots was more effective on the difficulty level of the problem than the increase in the number of customers. Problems with 11 mobile depots and 22 customers were solved in an average of 4.45 s, while problems with the same number of mobile depots but 11 customers were solved in an average of 2.37 s. Although the number of customers doubled, the increase in the solution time was less than double, indicating that the increase in the number of customers has a limited effect on the difficulty of the problem. On the other hand, problems with 17 mobile depots and 16 customers were solved by an average of 131.70 s, while this time reduced to 0.48 s for problems with 8 mobile depots and 14 customers. These results clearly show that for 2E UVRP problems, increasing the number of mobile depots makes the problem much more complex than increasing the number of customers.

Figure 2

Objective function value and solution times according to the name of the problem, UAV speed, and number of UAVs

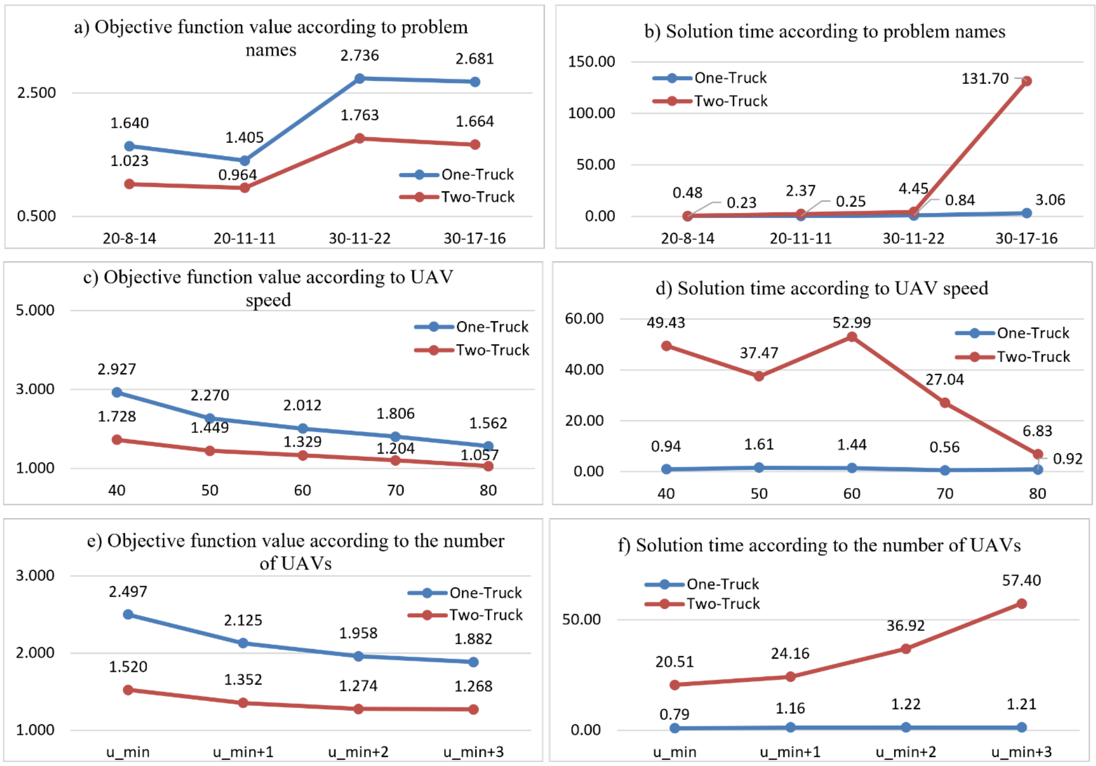


Figure 2c shows that the objective function values for the one-truck and two-truck problems gradually converge as the UAV speeds increase. Similarly, Figure 2e shows that as the number of UAVs used increases, the objective function values become relatively closer to each other. These findings reveal that in scenarios where the number and speed of UAVs are low, two-truck solution approaches are more advantageous than one-truck solutions in terms of the efficiency of logistics operations.

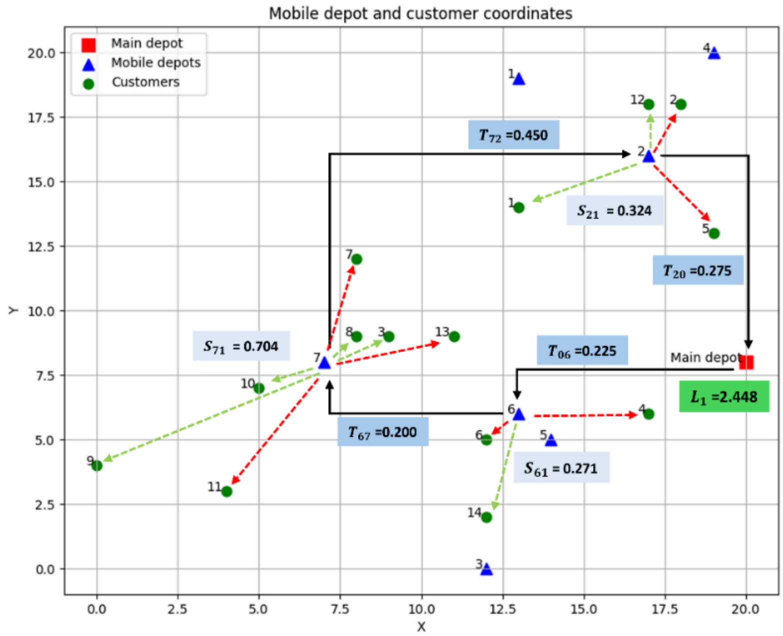
Figure 2d shows the solution time with increasing UAV speeds. In particular, it was found that the solution time was shorter when the UAV speed was 70 km/h or higher than when the speed was 60 km/h or lower. However, it is clearly seen in Figure 2f that the increase in the number of UAVs increases the solution times for the problems.

Graphical representation of the results

In this section, the results for the one-truck and two-truck scenarios for the problem “20-8-14”, where the UAV speed is set to 40 km/h and the number of UAVs is set to 2, are analyzed graphically. In Figure 3 and Figure 4, the black solid arrows and blue solid arrows represent the routes of the trucks; the green dashed arrows represent the movements of the first UAV; and the red dashed arrows represent the movements of the second UAV. The term $Truck_{ik}$ refers to the movement time of the truck between the mobile depots; S_{ik} refers to the waiting time of the trucks for the UAVs at the mobile depots; and L_k refers to the return time of each truck to the main depot.

Figure 3

Graphical representation of the problem with one-truck (problem name = 20-8-14, v_d=40, u =2)

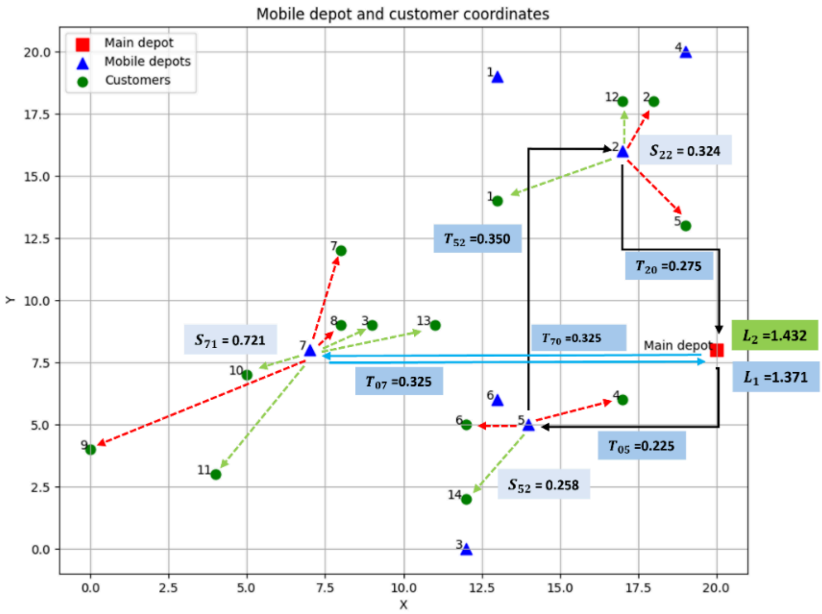


The solution results for the one-truck problem are presented in Figure 3. In this problem, the truck departs from the main depot and visits points 6, 7, and 2, respectively, and returns to the main depot, completing a route with a total length of 1.150 units. The waiting times of the truck at mobile depots 6, 7, and 2 were measured as 0.271; 0.704 and 0.324 units, respectively, and the total waiting time was calculated as 1.298 units. The total route length includes the sum of the waiting times of the truck's route and the UAVs at the mobile depots and was calculated as 2.448 units.

The solution results of the two-truck problem are presented in Figure 4. The first truck, shown with the blue solid arrows, departed from the main depot and reached mobile depot 7, and returned to the main depot, following a route with a total length of 0.65 units. The first truck completed the route in a total time of 1.371 units with a waiting time of 0.72131 units at mobile depot 7. The second truck, indicated by the black solid arrows, visited mobile depots 5 and 2, respectively, after departing from the main depot and returned to the main depot and followed a route of 0.85 units. The waiting times at mobile depot 5 and mobile depot 2 were measured as 0.258 and 0.324 units, respectively, and the total waiting time was calculated as 0.582 units. The total route length of the second truck, including the routes followed by the trucks and the waiting time for the UAVs in the mobile depots, was calculated as 1.432 units in total. In the two-truck problem, the total tour length is the time for both trucks to return to the main depot. This time is calculated as 1.432 units, which is the route length of the second truck and reflects the time to serve all customers.

Figure 4

Graphical representation of the problem with two-trucks (problem name = 20-8-14, v_d=40, u =2)



Conclusion and future research directions

This study examines a logistics model that is expected to provide future benefits in the logistics sector. The model involves the integration of a fleet of high-capacity trucks that depart from a main depot and act as mobile depots and a fleet of UAVs that fly from these trucks. The model integrates the UAV routing problem with the location selection problem by enabling UAVs to depart from mobile depots to serve customers and then return to the same mobile depot for battery replacement and/or package loading. In this context, high-capacity trucks act as mobile depots and depart from the main depot, are positioned at designated alternative mobile depot locations and wait there during the delivery period. UAVs moving from the trucks deliver the packages to customers and return to the trucks after completing the distribution task. When all delivery operations are completed, the trucks and UAVs return to the main depot and end the operation.

The basic structure of the two-echelon location selection and UAV-assisted routing problem was investigated by Vu et al. (2022), and both a complex integer mathematical model and a heuristic approach were developed as solution methods. In their study, Vu et al. (2022) considered two different problems where a truck is involved and UAVs can be used once or multiple times from a mobile depot. In this paper, a mathematical model is proposed for the 2E-UVRP, which is considered for the first time in this paper, where multiple trucks are involved and UAVs can be used more than once from a mobile depot. The proposed model is applied to the test cases created by Vu et al. (2022) and obtains optimal solutions in a very short time.

In the 2E-UVRP problem, if the number of trucks is taken as one, the problem becomes a 2ER-TD problem. In this context, the developed model can solve both the 2E-UVRP problem and the 2ER-TD problem. From a commercial point of view, 2E-UVRP stands out as a more feasible problem. In this study, single-truck and multi-truck problems are compared and the effects of changes in the number of mobile depots, number of customers, number of UAVs, and number of trucks on the solution times of the 2E-UVRP problem and the efficiency of the model are examined. The results show that increasing the number of mobile depots significantly increases the solution time. In particular, it is found that if the number of mobile depots is doubled, the solution time increases by 277 times. On the other hand, the effect of increasing the number of customers on the resolution time was found to be relatively limited. Increasing the number of UAVs relatively reduces the difficulty of the problem. Increasing the number of trucks makes the problem more complex and requires more coordination and synchronization. However, multi-truck solutions offer a more advantageous option for real-world applications. It can increase customer satisfaction by shortening service times, especially for last-mile deliveries. In conclusion, this study shows that increasing the number of mobile depots and trucks significantly increases the difficulty of the 2E-UVRP problem; however, multi-truck systems offer more efficient and feasible solutions in real-world scenarios.

Future research may focus on addressing UAV routing problems in more complex and dynamic environments. In particular, the integration of factors such as air traffic, weather conditions, energy consumption, and real-time decision-making processes into the model will significantly increase the applicability and practical value of the problem in terms of real-world applications. Additionally, developing new algorithms to enhance the cooperation and coordination of multiple UAV systems could significantly contribute to safety and flexibility while improving routing efficiency. Furthermore, the integration of artificial intelligence and machine learning techniques can enhance the autonomous capabilities of UAVs, enabling more flexible and efficient solutions.

Peer Review: Externally peer-reviewed.
Author Contributions: Conception/Design of Study- T.G., İ.K.; Data Acquisition- T.G.; Data Analysis/Interpretation- T.G., İ.K.; Drafting Manuscript- T.G., İ.K.; Critical Revision of Manuscript- İ.K.; Final Approval and Accountability- T.G., İ.K.
Conflict of Interest: Authors declared no conflict of interest.
Grant Support: Authors declared no financial support

Author Details

Tolga Gedikli
[1] Konya Technical University, Department of Industrial Engineering, Konya, Türkiye,
0000-0002-0558-2439 tolgagedikli@gmail.com

İsmail Karaoğlan (Prof. Dr.)
[1] Konya Technical University, Department of Industrial Engineering, Konya, Türkiye,
0000-0002-6023-6918 ikaraoglan@ktun.edu.tr

References

Carlsson, J. G., & Song, S. (2017). Coordinated Logistics with a Truck and a Drone. *Management Science*, *64*(9), 4052–4069. https://doi.org/10.1287/MNSC.2017.2824

Dayarian, I., Savelsbergh, M., & Clarke, J.-P. P. (2020). Same-day delivery with drone resupply. *Transportation Science*, *54*(1), 229–249. https://doi.org/10.1287/trsc.2019.0944

Ferrandez, S. M., Harbison, T., Weber, T., Sturges, R., & Rich, R. (2016). Optimization of a truck-drone in tandem delivery network using k-means and genetic algorithm. *Journal of Industrial Engineering and Management (JIEM)*, *9*(2), 374–388. https://doi.org/10.3926/JIEM.1929

Gonzalez-R, P. L., Canca, D., Andrade-Pineda, J. L., Calle, M., & Leon-Blanco, J. M. (2020). Truck-drone team logistics: A heuristic approach to multi-drop route planning. *Transportation Research Part C: Emerging Technologies*, *114*, 657–680. https://doi.org/10.1016/J.TRC.2020.02.030

Ha, Q. M., Deville, Y., Pham, Q. D., & Hà, M. H. (2018). On the min-cost Traveling Salesman Problem with Drone. *Transportation Research Part C: Emerging Technologies*, *86*, 597–621. https://doi.org/10.1016/J.TRC.2017.11.015

Jeong, H. Y., Song, B. D., & Lee, S. (2019). Truck-drone hybrid delivery routing: Payload-energy dependency and No-Fly zones. *International Journal of Production Economics*, *214*, 220–233. https://doi.org/10.1016/j.ijpe.2019.01.010

Jiang, J., Dai, Y., Yang, F., & Ma, Z. (2024). A multi-visit flexible-docking vehicle routing problem with drones for simultaneous pickup and delivery services. *European Journal of Operational Research*, *312*(1), 125–137. https://doi.org/10.1016/J.EJOR.2023.06.021

Macrina, G., Di Puglia Pugliese, L., Guerriero, F., & Laporte, G. (2020). Drone-aided routing: A literature review. *Transportation Research Part C: Emerging Technologies*, *120*, 102762. https://doi.org/10.1016/j.trc.2020.102762

Morim, A., Campuzano, G., Amorim, P., Mes, M., & Lalla-Ruiz, E. (2024). The drone-assisted vehicle routing problem with robot stations. *Expert Systems with Applications*, *238*, 121741. https://doi.org/10.1016/J.ESWA.2023.121741

Moshref-Javadi, M., & Winkenbach, M. (2021). Applications and Research avenues for drone-based models in logistics: A classification and review. *Expert Systems with Applications*, *177*, 114854. https://doi.org/10.1016/j.eswa.2021.114854

Moshref-Javadi, M., Hemmati, A., & Winkenbach, M. (2020). A truck and drones model for last-mile delivery: A mathematical model and heuristic approach. *Applied Mathematical Modelling*, *80*, 290–318. https://doi.org/10.1016/j.apm.2019.11.020

Moshref-Javadi, M., Lee, S., & Winkenbach, M. (2020). Design and evaluation of a multi-trip delivery model with truck and drones. *Transportation Research Part E: Logistics and Transportation Review*, *136*, 101887. https://doi.org/10.1016/J.TRE.2020.101887

Murray, C. C., & Chu, A. G. (2015). The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery. *Transportation Research Part C: Emerging Technologies*, *54*, 86–109. https://doi.org/10.1016/j.trc.2015.03.005

Murray, C. C., & Raj, R. (2020). The multiple flying sidekicks traveling salesman problem: Parcel delivery with multiple drones. *Transportation Research Part C: Emerging Technologies*, *110*, 368–398. https://doi.org/10.1016/j.trc.2019.11.003

Nguyen, M. A., Dang, G. T.-H., Hà, M. H., & Pham, M.-T. (2022). The min-cost parallel drone scheduling vehicle routing problem. *European Journal of Operational Research*, *299*(3), 910–930. https://doi.org/10.1016/j.ejor.2021.07.008

Phan, A. T., Nguyen, T. D., & Pham, Q. D. (2018). Traveling salesman problem with multiple drones. *ACM International Conference Proceeding Series*, 46–53. https://doi.org/10.1145/3287921.3287932

Rojas Viloria, D., Solano-Charris, E. L., Muñoz-Villamizar, A., Montoya-Torres, J. R., Solano-Charris, E. L., Muñoz, A., Muñoz-Villamizar, M., & Montoya-Torres, J. R. (2021). Unmanned aerial vehicles/drones in vehicle routing problems: a literature review. *International Transactions in Operational Research*, *28*(4), 1626–1657. https://doi.org/10.1111/itor.12783

Salama, M., & Srinivas, S. (2020). Joint optimization of customer location clustering and drone-based routing for last-mile deliveries. *Transportation Research Part C: Emerging Technologies*, *114*, 620–642. https://doi.org/10.1016/j.trc.2020.01.019

Savuran, H., & Karakaya, M. (2024). A novel solution for routing a swarm of drones operated on a mobile host. *Engineering Applications of Artificial Intelligence*, *138*, 109337. https://doi.org/10.1016/J.ENGAPPAI.2024.109337

Song, B. D., Park, K., & Kim, J. (2018). Persistent UAV delivery logistics: MILP formulation and efficient heuristic. *Computers & Industrial Engineering*, *120*, 418–428. https://doi.org/10.1016/J.CIE.2018.05.013

Vu, L., Vu, D. M., Minh Hoàng, H., & Nguyen, V. P. (2022). The two-echelon routing problem with truck and drones. *International Transactions in Operational Research*, *29*(5), 2968–2994. https://doi.org/10.1111/ITOR.13052