Bitlis Eren Üniversitesi Fen Bilimleri Dergisi
BİTLİS EREN UNIVERSITY JOURNAL OF SCIENCE
ISSN: 2147-3129/e-ISSN: 2147-3188
VOLUME: 12 NO: 3 PAGE: 853-862 YEAR: 2023
DOI:10.17798/bitlisfen.1323976

A constructive heuristic for the heterogeneous drone delivery problem that considers packages' setups and battery capacity with the aim of minimizing weighted total waiting times of customers

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Keywords: Drone delivery problem, drone routing problem, energy consumption, unmanned aerial vehicles, route planning.

Abstract
This article considers the heterogeneous drone routing problem, which takes into account the setup times of customers' packages and aims to minimize the weighted total waiting times of customers. Cases where drones differ from each other in terms of battery capacity, carrying capacity, speed and load capacity have been handled. The battery capacity has been associated with the payload carried by the drone as long as it stays in the air. A constructive heuristic has been suggested and many test instances have been used to show how the efficiency of the algorithm changes when different priority values are used. As a result, it has been seen that good solutions can be obtained by assigning the light customer packages to the fast drones for the given test instances by using the suggested constructive heuristic.

1. Introduction

Along with technological improvements, there have been significant developments and applications in the field of unmanned aerial vehicles (UAVs) in recent years. The integration of online shopping into daily life has also increased the need for innovative solutions in logistics operations. In this context, businesses have started to prefer drone transportation for satisfying customer demands uninterruptedly and quickly. With drone transportation, it has become possible to make carriage to locations where access is difficult, traffic congestion is intense and infrastructure requirements have not been completed yet [1].

UAVs like as drones have the potential to significantly reduce the transportation cost and time required to deliver materials since they are less expensive than traditional delivery vehicles such as trucks and needs much lower energy requirements. In parallel with recent advancements in UAVs technology and the stated advantages, large companies like Amazon, DHL, Federal Express have start to package delivery with UAVs for their commercial services. Thanks to these developments a new delivery system has been emerged and, a new problem category arises, drone routing problem. Despite the increasing focus on UAVs and the field's status as an emerging technology, there is no comprehensive literature about the transportation characteristics and the methods used to solve drone routing problem in the current state [2]. The drone routing problem has very similar structures with vehicle routing problem in general. However, in many aspects drone routing problem can differ from the simple routing problem such as; the battery capacity; the ability to visit different charging stations; the ability to make only one tour from the depot as well as the ability to tour more than once; delivering the packages both drones and trucks and etc. Drone routing problem contains too much stochastic information in contrast to vehicle routing problem, as drones should be able to adapt, modify, and optimize their routes in delivering packages. In addition to the objectives used in general routing problems, many individual objectives may be used in drone routing problem such as minimizing the

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Received: 07.07.2023, Accepted: 07.09.2023

customers' waiting times, reducing drone transportation costs, enhancing profitability, increasing safety in operations, minimizing the total delivery times and etc. Drone routing problems are affected many parameters in contrast to traditional vehicle routing problems. For instance drone routing should be in 3D environment and changing weather conditions (wind direction, air condition, loaded package weight, wind speed and etc.) should be considered in solutions [2].

Considering the given information, it is obvious that drone routing will have an important place in real life applications. When this routing problem is examined, it is possible to divide it into many different classes. Considering the literature review proposed by Macrina et al., [3] it is seen that drone routing can be divided into two different basic groups. In the first problem group drones and trucks perform the delivery, in the second one, only drones perform the delivery. It is possible to detail the first group of problems depending on the number of drones and trucks used and their synchronization with each other. It is possible to divide the type of problem in which the delivery is made only through drones, into two classes depending on whether trucks are used or not. In addition, it is possible to diversify all these types of problems according to the types of objective functions, the drone features used, the number of depots used, the number of tours that can be performed and etc..

It is known that the transportation costs are generally low in drone distribution, so customer satisfaction can come to the fore as the aim function. In this study, heterogeneous drone routing problem has been tried to be solved by using drones with different characteristics in terms of speed, transport and battery capacities in order to minimize the weighted total waiting times of the customers. In the problem, each customer has a weight in the objective function and it is desired that the customer with a high weight has no or low delay. Beside that a setup time is required for customer packages to be loaded into drones.

The problem addressed in this study is directly related to vehicle routing and drone routing problems. It is known that the vehicle routing problem has a large literature and it is seen that the studies on drone routing have intensified in recent years. Studies on drone routing are given in detail in the literature survey proposed by Macrina et al., [3].

Coelho et al. [4] suggested a multi-objective drone delivery problem for overcoming difficulties related to limited driving range, they addressed charging stations. For evaluating energy consumption, the authors presented a consumption rate only related to the speed of the drone. The handled problem was tried to solve by using a mathematical formulation and a metaheuristic. An important study was proposed by Dorling et al. [5] that solves drone delivery problems in which drones may perform multi-trips and serve more than one customer per route. They modelled energy consumption of the drones as a function of a battery and payload weight, considering a constant speed value. They tried to solve the problem by presenting a mixed integer linear programming formulation and a simulated annealing heuristic. Yadav and Narasimhamurthy [6] improved a heuristic for optimizing delivery schedule of drones that could serve one or several customers depending on the capacity constraints. In the problem handled by Troudi et al. [7], drones could perform multiple visits and multiple deliveries per day. An approximation model similar to that of Dorling et al. [5] has been proposed to calculate the energy consumption during a mission. Liu [8] considered an on-demand meal delivery process and suggested a dynamic drone's delivery model to optimize this process.

As in this problem, considering the drone routing problems which aim to minimize the total waiting times of customers; Moshref et al. [9] present a mathematical formulation and a heuristic solution approach for the optimal planning of delivery routes in a multi-modal system which combines truck and drone operations. The presented optimization model minimizes the waiting time of customers in the system. Moshref et al. [10] extend the traveling repairman problem by supposing a single truck that can stop at customer locations and launch drones multiple times to serve customers. The stated problem has been mathematically modelled, several bound analyses are developed to determine the maximum possible improvements in customer waiting times with an efficient hybrid tabu search-simulated annealing algorithm.

Cheng et al. [11] tried to solve a multi-trip drone routing problem, where drones' energy consumption was modelled as a nonlinear function of payload and travel distance. Logical cuts and sub gradient cuts were added in the solution process to tackle the more complex nonlinear (convex) energy function, instead of using the linear approximation method. A uniform framework to facilitate understanding different drone energy consumption models and the inter-relationships between key factors for drone delivery operations is presented by Zhang et al. [12]. Recently a literature review which considers advances in drone technologies and their popularity has been suggested by Viloria et al. [13]. In the stated study academic contributions on drone routing problems have been analysed between 2005 and 2019 to state the research trends and recent improvements. Phalapanyakoon and Siripongwutikorn [14] considered route planning for rechargeable UAVs under the mission time constraint in cases where more than one trip can be done by drones due to limited battery capacities. Phalapanyakoon and Siripongwutikorn [15] handled with the route planning of multiple rechargeable heterogeneous UAVs with multiple trips under mission time and payload carrying constraints. They tried to detect the types and number of drones to be used and their flying paths that minimizes the monetary cost.

Literature review shows that there are many studies which take into account the waiting times of customers and heterogeneous drone routing problem separately. However, no study has been conducted on the heterogeneous drone routing problem, which tries to minimize the weighted total waiting times of customers yet. This article suggests a constructive heuristic for the heterogeneous drone routing problem to minimize the weighted total waiting times of customers. It is shown on many test instances how the efficiency of the algorithm changes when different priority values are used. The rest of the article as follows. In section 2 problem definition in detail is given while the solution method is presented in section 3. Computational experiments are given in section 4. Lastly, the conclusions and future research directions are presented in section 5.

2. Problem Definition

This article considers drone routing problem for minimizing the weighted total waiting times of customers. What needs to be decided in the problem is the order in which the customer packages will be delivered with which drone, based on the customers' and drones' information given. Customers' packages are requested to be delivered by a certain time which is named as *due time* (dt_i). If customer packages are delivered later than this time, a penalty, which is equal to multiplied by the customer's weight and the delay time (l_i), is added to the objective value. Delay time is depend on the difference between the service time (st_i) and due time (dt_i), and calculated as $l_i = \max(0, st_i - dt_i)$. The delivery of each customer's package has different degrees of importance and this value is defined as *customer weight* (cw_i). The objective value is computed as $z = \sum_{i \in N} cw_i \cdot l_i$ where N represents the set of customers.

In the studied problem, cases where drones differ from each other in terms of battery capacity, carrying capacity, speed and load capacity are considered. It has been stated by Dorling et al., (2016) that there is an almost linear relationship between the capacity of battery of a drone and the airtime depending on the load it carries. Therefore, in this study the battery capacity is associated with the payload carried by the drone as long as it stays in the air. In addition to all these, a setup time is required for customer packages to be loaded into drones. The main purpose is delivering the packages to the customers without exceeding the specified due times. If that is not possible, the weighted total delay time is tried to be minimized. The rest of the assumptions is given below:

1. There is only one of each type of drone.
2. Each customer has a weight in the objective function and the aim is minimizing the weighted total delay time.
3. Each drone has different carrying capacities in terms of load and quantity. Again, each drone has different battery capacity and speed.
4. The distances between customer locations are calculated in Euclidean.
5. It takes a certain time (setup time) for customer packages to be loaded on drones, and this time does not change depending on the drone to which the customer package is assigned.
6. Setup times do not cause a decrease in the battery capacity of the drone.
7. There is a linear relationship between the battery life of drones and the load carried by the drone itself and the time it stays in the air.
8. Each drone is initially in the depot and can only take 1 tour.
9. When assigning customer packages to drones, the drone carrying capacity, battery life and the load capacity of the drone should not be ignored.

Information about the example with 3 drones and 6 customers (there are 7 locations with depot) is given in Table 1.

Table 1. Information about the test instance.

(a) Information about the drones

Drone ID	Unit Capacity	Weight Capacity	Velocity	Battery Capacity	Energy Consumption	Drone Weight
1	3	6	300	5000	3*γ	2.0
2	4	8	275	5500	4*γ	2.5
3	5	10	250	6000	5*γ	3.0

(b) Information about the customers

Customer ID	$X_{Coordinate}$	$Y_{Coordinate}$	Package Weight (pw_i)	Due Time	Objective Weight	Package Setup Times
1 (Depot)	1500	1500	-	-	-	-
2	1813	2545	0.87	5	0.15	0.15
3	1934	4443	2.16	8	0.53	0.22
4	366	3316	1.62	10	0.44	0.20
5	692	2563	3.6	14	0.7	0.16
6	4148	348	0.63	12	0.2	0.33
7	555	28	0.25	8	0.08	0.14

From the Table 1 the Euclidian distances between the customer locations can be computed easily. In the stated table γ is a constant value used to determine the battery capacity that the drone consumes depending on the load and the time it stays in the air. A solution for this example is given in Figure 1.

As is seen in Figure 1 package 2 and 3 are assigned to the drone 1 and route for this drone must be 1-2-3-1. It shouldn't be ignored that the weight and unit capacities of drone 1 are sufficient for package 2 and 3. Euclidean distances from location 1 to 2, 2 to 3 and 3 to 1 are respectively equal to nearly 1091, 1902 and 2975. Total setup time for this drone is computed as (0.15 + 0.22) 0.37 and travel time is calculated as (3.63 + 6.34 + 9.91) 19.88. In this example drone 1 firstly flies from depot to location 2 in 3.63 time unit with 3.03 (0.87 + 2.16) package weight. Notice that package 2 and package 3 are uploaded to drone 1 at depot. The required battery capacity of drone 1 for flying from depot to location 2 is equal to multiplied total weight (the weight of drone and the weights of packages) with the flying duration and constant $\left((2 + 3.03)\cdot(3.63)\cdot 3\cdot\gamma = 54.77\gamma\right)$. γ is accepted as 10 for this example. Similarly required capacity from location 2 to location 3 and from location 3 to depot are respectively computed as 79.12γ and 59.46γ. Total required battery capacity for route 1-2-3-1 is equal to 193.35γ. If the value of γ was greater than 25.86 the battery capacity of drone 1 would be insufficient for the given assignments. Arrival times of location 2 and 3 are detected by considering flying and setup times as 0.37+3.63=4 and 0.37+3.63+ 6.34 = 10.34 respectively. Route of drone 2 is 1-4-5-1 and the flying time from location 1 to 4, location 4 to 5 and location 5 to 1 are respectively 7.78, 2.98 and 4.85. Similarly route of drone 3 is 1-6-7-1 and the flying time from location 1 to 6, location 6 to 7 and location 7 to 1 are respectively 11.55, 14.42 and 7. Consequently, arrival times of the drones to the customer locations are (4 – 10.34 – 8.14 – 11.12 – 12.02 – 26.44). Waiting time of each customer is computed considering due time and arrival time. These are (0 – 2.34 – 0 – 0 – 0.02 – 18.44) and weighted waiting times for each customer is (0 – 1.240 – 0 – 0 – 0.004 – 1.475). The value of the objective for this solution is computed as 2.719.

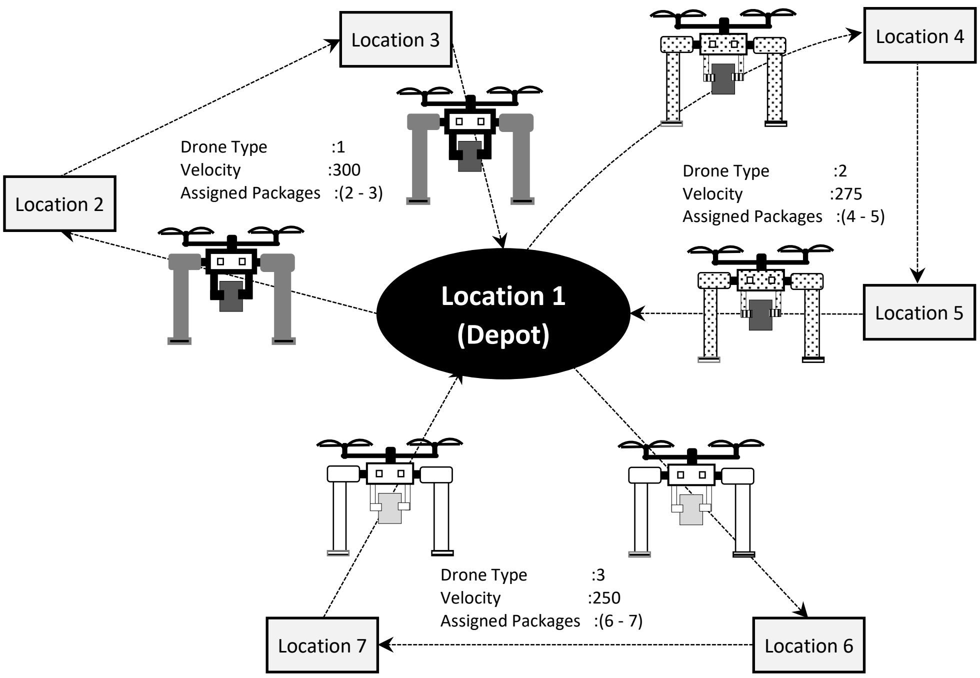

Figure 1. An illustrative example for heterogeneous drone routing problem with setup times.

To the author best knowledge the drone routing problem described above and illustrated on an example is not considered in the literature for the stated purpose. Therefore, in the following section, a new constructive heuristic method has been suggested for the solution of the problem is presented.

3. Solution Method

An effective constructive solution method has been suggested for solving the heterogeneous drone routing problem with setup times by using an array with (n + m) elements where n represents the number of customer and m shows the number of drones. In the similar studies from literature, permutation coding is generally used since it is more suitable for the structure of the problem. However, in this study, it is preferred to convert the continuous values to permutation representation later in order to use different priority values. For the example given in Figure 1 a continuous array and its conversion to permutation representation is given Figure 2. Note that location 1 is depot. As is seen in Figure 2 the customer or drone which has the highest value is assigned smallest position in the permutation encoding.

Location 2	Location 3	Location 4	Location 5	Location 6	Location 7	Drone 1	Drone 2	Drone 3
0,30	0,25	0,61	0,88	0,58	0,12	0,90	0,26	0,50
Customer Sequence *n*=6						Drone Sequence *m*=3		

(a) Array with continues numbers.

Position 1	Position 2	Position 3	Position 4	Position 5	Position 6	Position 1	Position 2	Position 3
5	4	6	2	3	7	1	3	2
Customer Sequence *n*=6						Drone Sequence *m*=3		

(b) Permutation encoding.

Figure 2. An illustrative example of an array with continuous numbers and its permutation encoding.

The steps of the constructive heuristic are given in Figure 3. The assignments of the customers' packages to the drone have been satisfied by using this algorithm. As is seen in this figure all routes of drone start from depot since drones are ready at depot.

Algorithm **:** Generating a solution from an array which shows assignment priorities for the drone and customers
Input **:** An array which shows assignment priorities, information about the drones and locations
Output **:** Objective function value and the routes for drones

Step 1. Set $\mathbf{DR} = \{dr_k = 0 \mid k \in \mathbf{K}\}$; $\mathbf{DW} = \{dw_k = 0 \mid k \in \mathbf{K}\}$; $\mathbf{DU} = \{du_k = 0 \mid k \in \mathbf{K}\}$; $Route_k = \{1\},\ k \in \mathbf{K}$.
Step 2. Generate the permutation encoding from the given array.

while (*all customers are not assigned to a drone*)
{
Step 3. Take current customer (i) from permutation encoding**,** and find the most appropriate drone which can take the customer package.

Step 3.1. Find the elements of **AD** set which shows the appropriate drones by controlling the drone unit capacity, drone weight capacity and drone battery capacity
$$\mathbf{AD} = \{k \mid (du_k + 1) \le uc_{\boldsymbol{k}},\ \ (dw_k + q_i) \le wc_{\boldsymbol{k}},\ RB_{\boldsymbol{k}}(Route_{\boldsymbol{k}} + i) \le bc_{\boldsymbol{k}}\}$$

Step 3.2. ***If*** **(AD** = {}**)** Add penalty value to the objective function value and Go to **Step 6**;
Else Find the selected drone (k) $k = \min_{\boldsymbol{k} \in \mathbf{AD}} (dr_k)$ and k is the first drone element in the permutation encoding

Step 4. Update the $dr_k = dr_k + (d_{ji}/v_k)$ where j is the last location in $Route_k$
$dw_k = dw_k + q_i$;
$du_k = du_k + 1$; $Route_k = Route_k + i$
}
Step 5. Compute the objective function value considering setup times of drones.
Step 6. Output the objective function value and the routes for drones.

DR: set of ready times of drones; **DW**: set of the total weights of packages which are assigned to each drones; **DU**: set of the number of the packages which are assigned to each drones; $Route_k$: route of drone k; q_i: package weight of location i; d_{ji}: the distance between location j and i, v_k: velocity of drone k; $RB_{\boldsymbol{k}}(Route_{\boldsymbol{k}} + i)$: the required battery capacity for the new route which is formed by inserting the location i to the route of drone k ($Route_k$)

Figure 3. The main steps of the constructive heuristic.

In the first step of the algorithm, required sets are generated then in the second step continuous numbers are converted to permutation representation. It is requested that the package of the customer with the highest priority be assigned to the earliest available drone. If more than one drone is available at the earliest, the customer package is requested to be assigned to the drone with the highest priority value. When calculating the value of RB_k, it should not be ignored that the battery capacity required for the return of the drone to the depot is also calculated on the given route. Some permutations may form such that the capacity of the drones is not sufficient to carry customer packages. In such cases, the algorithm is stopped by giving a very high value (penalty) to the objective function. It shouldn't be ignored that the setup times of customer packages to the drones are added to the service times after the routes are obtained. An illustrative example for constructive heuristic with given array is presented in Figure 4.

Remaining Customers	*Selected Location*	*Appropriate Drones*	*Most Suitable Drones*	*Selected Drone*	*Drone Suitable Times (dr_k)*	*Drone Route Assignments*
5-4-6-2-3-7	5	1-2-3	1-2-3	1	{4.45} {0} {0}	{1-5} {1} {1}
4-6-2-3-7	4	1-2-3	2-3	3	{4.45} {0} {8.56}	{1-5} {1} {1-4}
6-2-3-7	6	1-2-3	2	2	{4.45} {18.68} {8.56}	{1-5} {1-6} {1-4}
2-3-7	2	1-2-3	1	1	{8.19} {18.68} {8.56}	{1-5-2} {1-6} {1-4}
3-7	3	1-2-3	1	1	{14.53} {18.68} {8.56}	{1-5-2-3} {1-6} {1-4}

7	7	2-3	3	3	{14.53}{18.68} {16.29}	{1-5-2-3} {1-6} {1-4-7}

Generated routes for drones	:{1-5-2-3-1} {1-6-1} {1-4-3-1}
Service time	: {0 – 9.12 – 15.06 – 8.09 – 4.98 – 20.68 – 16.63}
Lateness for customers	: {0 – 4.12 – 7.06 – 0 – 0 – 8.68 – 8.63}
Weighted Total Lateness	: $(4.12 \cdot 0.15) + (7.06 \cdot 0.53) + (8.68 \cdot 0.2) + (8.63 \cdot 0.08) = 6.79$

Figure 4. An illustrative example for the suggested constructive heuristic.

In the suggested constructive heuristic, nine different priority approaches for customers and three different priority approaches for drones are used to measure the effectiveness of the algorithm. Explanations of the priorities for customers are given in Table 2.

Table 2. Explanations of priority approaches for customers.

Priority ID for customer	Explanation
1	Random number between 0 and 1 [0-1]
2	$(1/dt_i)$
3	(cw_i)
4	$1/(setup_i)$
5	$1/(pw_i)$
6	(cw_i/dt_i)
7	(pw_i / dt_i)
8	(cw_i / pw_i)
9	$cw_i / (dt_i \cdot pw_i)$

dt_i: due time of customer i, cw_i: the objective weight of customer i, $setup_i$: setup time of package i, pw_i: package weight of customer i.

As is seen in Table 2 the first priority is generated randomly, and second one is related to the customers' due times. Logically, if a customer's due time is late, that customer's package can be delivered later. Therefore second priority is arranged as $1/dt_i$. Third priority is the customer objective function weight. While the fourth one gives the highest priority to the customer whose package has the smallest setup time, the fifth priority gives the highest priority to the customer whose package is the lightest. While sixth priority is obtained by dividing customer's objective function weight by the due time, seventh priority is obtained by dividing customer's package weight by the due time. Eighth priority value gives the highest priority to the customer who has the highest objective function weight for per package weight unit. The last priority is computed considering customer's objective function value weight, due time and package's weight. Explanations of priorities for drones are given in Table 3.

Table 3. Explanations of priority approaches for drones.

Priority ID for drone	Explanation
1	Random number between 0 and 1 [0-1]
2	Velocity of drone
3	Unit capacity of drone

As is seen in Table 3, first priority is generated randomly, and the second one gives the highest priority to the fastest drone. According to the last one, highest priority is given to the drone with the highest unit carrying capacity. 27 $(9 \cdot 3)$ different priority sequences have been created by crossing these drone and customer priority values. In the experimental study, these 27 different priority values are used as inputs in the constructive algorithm mentioned above. In the next section, computational experiments are given.

4. Computational Experiments

In order to measure the effectiveness of the suggested priority values on the proposed constructive heuristic, 34 different test problems, consisting of the smallest 5 customer 3 drones and the largest 20 customer 7 drones, were used. These test instances have been generated for this study randomly. The constructive heuristic is coded in the C# programming language and the calculations took less than 1 second for each test instance. In order to compute the efficiency, the best solution obtained from 27 different priority values for these 34 samples was taken into account. Deviations from the best solution found were calculated for each priority as in equation (1).

$$\%\ gap = 100 \cdot {(sol_i - sol_{Best})}/{sol_i} \qquad (1)$$

In equation (1) sol_i represents the objective function value of the solution obtained by using priority *i* and sol_{Best} shows the best objective function value obtained by using all priority approaches. The summary of the calculation results on the basis of the priorities of drones and customers is presented in Table 4.

Table 4. Summary of the computational study according to priorities of the customers and drones.

Priority for customer	Priority for drone	# of instances	Average *% gap*	#of best solution	# of no solution
1	1	34	53.742	0	5
1	2	34	30.969	2	6
1	3	34	58.343	0	5
2	1	34	43.022	0	5
2	2	34	35.612	2	6
2	3	34	46.678	0	**1**
3	1	34	50.136	1	2
3	2	34	24.447	**8**	6
3	3	34	48.645	0	2
4	1	34	45.502	2	3
4	2	34	25.892	5	2
4	3	34	51.292	0	3
5	1	34	40.572	0	8
5	2	34	**20.045**	3	**7**
5	3	34	47.812	1	9
6	1	34	45.622	0	3
6	2	34	37.839	0	2
6	3	34	47.741	0	2
7	1	34	51.222	0	3
7	2	34	49.889	1	2
7	3	34	50.154	0	**1**
8	1	34	49.129	1	4
8	2	34	22.261	6	4
8	3	34	49.492	0	6
9	1	34	43.556	1	3
9	2	34	32.578	1	7
9	3	34	46.654	2	3

Note: Bold values shows the best value among the column.

In Table 4, while the first and second column shows the priority IDs for customers and drones, third column states the number of instances. Forth column gives the average *% gap* of 34 test instances for the given priorities. Fifth column gives the number of best solution obtained by this priorities. For example any best solution could not obtain among the 34 test instances by using priority 1 approach in the suggested constructive heuristic. The last column shows the number of infeasible solution obtained by suggested priority values. When Table 4 is examined, it is seen that the best approach in terms of *% gap* value is the 5th priority approach for the customer and the 2nd priority approach for the drone. In other words, good solutions were obtained in parallel with the loading of the light ones from the customer packages to the fast drones. Similarly, it has been seen that good results can be obtained by loading customer packages with high objective function weight and lightest package weight priority into fast drones.

Considering the number of reaching the best solution, it is seen that the most effective method is the 3rd priority approach for customers and the 2nd priority approach for drones. In other words, it is seen that the probability of reaching the best solutions is higher by assigning the customer packages with a high objective function weight to the fast drones. The summary of the computational study only according to the customer priority values is presented in Table 5.

Table 5. Summary of the computational study based on priorities for only customers.

Priority For Customer	# of instances	Average % gap	# of best solution	# of no solution
1	102	47.879	2	16
2	102	42.057	2	12
3	102	41.799	**9**	10
4	102	40.735	7	8
5	102	**35.787**	4	24
6	102	43.714	0	7
7	102	50.411	1	**6**
8	102	40.085	7	14
9	102	41.305	4	13

Note: Bold values shows the best value among the column.

As is seen in Table 5 the best priority approach for the customer is the 5th priority approach when only average *% gap* value is considered. However, the probability of obtaining an infeasible solution with the constructive heuristic is also quite high with this priority approach, since this approach obtained infeasible solutions in 24 of the 102 examples. Considering the number of best solution 3rd priority approach is quite effective. The summary of the computational study according to the drone priority values is presented in Table 6.

Table 6. Summary of the computational study based on priorities for only drones.

Priority For Drone	# of instances	Average % gap	# of best solution	# of no solution
1	306	47.045	5	36
2	306	**31.338**	**28**	42
3	306	49.596	3	**32**

Note: Bold values shows the best value among the column.

Not many priority approaches have been used in terms of drone priorities, but it is seen that the best method is to give the highest priority to the fastest drone. In order to increase the probability of obtaining a suitable solution, it seems logical to give the highest priority to the drone with a high carrying capacity.

5. Conclusions and Future Research Direction

In parallel with technological developments on UAVs, the use of these vehicles in package delivery systems has been increased. And the integration of online shopping into daily life has also increased the need for innovative solutions in logistics operations. Along with all these developments, innovative research on drone routing was needed. This article considers the heterogeneous drone routing problem, which takes into account the setup times of customers' packages to the drones and aims to minimize the weighted total waiting times of customers. A constructive heuristic has been suggested to solve the stated problem. 27 different priority approaches and 34 different test instances, consisting of the smallest 5 customers with 3 drones and the largest 20 customers with 7 drones have been used for evaluating the suggested constructive heuristic. Through the computational experiments it has been seen that good solutions can be obtained by assigning the light customer packages to the fast drones for the given test instances by using the suggested constructive heuristic.

As a result, in this study, a new variation of drone routing has been discussed and a constructive heuristic has been developed. Considering the drone routing area, it is seen that it is a new and open research area and different solution methods are needed. Therefore, it is necessary to investigate the effectiveness of metaheuristic such as simulated annealing, tabu search, genetic algorithm and exact solution methods such as branch & bound, branch & cut, benders decomposition on the solution of the stated problem. In this study, it is assumed that all data are deterministic, but in many real-life applications, data are known may be stochastic. Considering this situation, new solution approaches can be developed for stochastic drone routing problems.

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