An Algorithm Based on Priority Rules for Solving a Multi-drone Routing Problem in Hazardous Waste Collection

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***Abstract*—This research investigates the problem of assigning pre-scheduled trips to multiple drones to collect hazardous waste from different sites in the minimum time. Each drone is subject to essential restrictions: maximum flying capacity and recharge operation. The goal is to assign the trips to the drones so that the waste is collected in the minimum time. This is done if the total flying time is equally distributed among the drones. An algorithm was developed to solve the problem. The algorithm is based on two main ideas: sort the trips according to a given priority rule and assign the current trip to the first available drone. Three different priority rules have been tested: Shortest Flying Time, Longest Flying Time, and Median Flying Time. Two recharging conditions are maintained: recharging needed time and recharging full duration. By applying each priority rule and each recharging condition, we generate a six versions of the algorithm. The six versions of the proposed algorithm were implemented in Java programming language.The results were analyzed and compared proving that the Longest Flying Time priority rule surpasses the other two rules. Moreover, recharging a drone just enough for taking the next trip proved to be better than fully recharging it.**

***Keywords*—Drones; trip assignment; priority rules; flying capacity; load balance**

I. Introduction

The Vehicle Routing Problem (VRP) is an important problem discussing the process of finding the optimal routes for a single or multiple vehicles, to perform a certain task or service. VRPs have been extended for numerous of problems. Most recently, VRPs using a single or multiple drones also called Unmanned Aerial Vehicles (UAVs) have spread widely. Those varied to truck-drone, truck-multi-drone, and multi-truck-multi-drone problems to achieve precise goals and maintaining a set of constraints. The author in [1] presented the vehicle routing problem with drones (VRPD) as a design of the combination of truck-drone routes and timetables to serve a group of customers with specific requirements and time limitations. The applications of VRPD or as called, Drone Routing Problems (DRPs) received a massive amount of attention from different fields and concerned parties. Media has shown interest in drones equipped with cameras to cover stories in different areas [2], commerce companies have been intrigued with last-Mile delivery using UAVs for speeding the process and lowering shipping costs [3], scientists for great discoveries [4], medical staff for urgent transportation of equipment [5], program developers and even the entertainment sector for mesmerizing drones shows. Environmentalists have utilized drones for addressing great problems threatening our earth, affecting humans and all living creatures [6]. Specialized VRPs regarding critical environmental issues such as CO2e emission, air pollution and global warming are called Green Vehicle Routing Problems (G-VRPs). Hazardous waste is another serious problem that puts us in danger by the minute. Taking advantage of the VRPD and G-VRP, our study highlights the formation of a hazardous waste collection plan, where waste is collected in the minimum time possible using multiple drones (MTMD). The authors in [7] proved the strongly NP-hardness of the problem and proposed a 2-phase approach and a linear program to solve it using a single Unmanned Aerial Vehicle. In their research, a set of efficient trips have been produced for each solved instance. Each trip is a path that starts from a depot site, visits some other sites to collect the maximum waste in the minimum time, respecting the drone flying and waste capacities before returning back to the depot for charging and some minor maintenance. In the current research, we adopt those datasets of generated trips and extend the study using multiple drones. The motivation behind this research was mainly to propose efficient algorithms that will allow an optimal or near-optimal use of the flying and weight capacities of a fleet of drones in order to collect hazardous waste in a shortest time from many sites. This research studies a new Drone Routing Problem (DRP) using m drones. Constraints related to the flying capacity and recharge duration of each drone are set. The aim of the study is to assign pre-generated tours in [7] so that completion time of the last drone is minimum. To solve this problem, the authors proposed priority rules-based algorithm. These rules have the purpose of sorting the trips prior distribution among the drones. The algorithm allows a maximum use of each drone's charge without exceeding the flying capacity. An experimental study using benchmarks was conducted to compare the efficiency of the proposed algorithm for each priority rule.

The remaining of the paper is structured as follows. In Section II, the literature review highlights the related and relevant areas of the research. The methodology used for conducting the research is detailed in Section III. Next, the experimental results and discussion are explained in Section IV followed by the conclusion and future work.

II. Literature Review

New Vehicle Routing Problems (VRPs) studies have been intensively emerging in the last few decades, especially those using Unmanned Aerial Vehicles (UAVs). The author in [8] acknowledged that the interest in the use of drones in various applications has grown significantly in recent years. Accompanied with specific constraints, limitations and several goals, VRPs are becoming progressively challenging. Most commonly, Different approaches to solve Drone Routing Problems (DRPs) have been proposed for last-Mile delivery. Moreover, transportation of medical equipment as in [9], collection of waste, surveillance, search and rescue missions and even forest monitoring to detect fire as presented in [10]. The author in [11] stated that similar to the traditional vehicle routing problem, the vehicle routing problem with drones (VRPD) involves the use of drones in addition to trucks for delivery. When trucks and drones are routed together, the challenge is substantially more complex and distinct from traditional vehicle routing problems.

Most DRPs were organized to truck-drone routing problems, as [12] demonstrated how incorporating truck-drone tandems into transportation systems can enhance delivery speed while also allowing the fleet size to be reduced without impacting delivery times or adding to truck drivers' workload. The author in [13] presented and solved a truck-drone hybrid routing problem with time-dependent road travel time (TDHRP-TDRTT) to resolve the truck-drone cooperative issue. TDHRP-TDRTT was solved using an iterative local search heuristic method. Whereas, in [14], they thought of several drones, each with a different set of capabilities, such as speed and battery life, are transported by and sent out from the truck, working together to satisfy customers. The truck must wait until each drone returns and numerous drones can all be dispatched at once. The proposed model was given the name heterogeneous drone-truck routing problem (HDTRP), and a formulation of the problem using mixed-integer programming was provided.

Likewise, A parallel Drone Scheduling Traveling Salesman Problem was solved in [15]. In this approach, deliveries are divided between a truck and one or more drones. The truck goes on a tour from the depot, but the drones can only go back and forth. The goal is to finish as soon as possible. The problem was expanded by taking into account many vehicles. A hybrid metaheuristic, as well as a Mixed Integer Linear Programming formulation and a simple branch-and-cut algorithm, were also presented as solutions. In addition, A mixed-integer linear programming (MILP) model for the multi-trip Capacitated Arc Routing Problem was proposed in [16] to reduce the overall cost of waste collection (CARP).

Logically, the algorithms developed in solving the problems varied. A widely known algorithm is the neighborhood search. In [17], an Adaptive Large Neighborhood Search metaheuristic for the vehicle routing problem with drones (VRPD) was proposed, following minimum time and cost constraints, using multiple trucks. They developed a mathematical model to create a problem close to the Flying Sidekick Traveling Salesman Problem to optimize huge instances. Nevertheless, a tabu search heuristic algorithm in [18] proposed a new neighborhood generation process for a distribution company, to transport commodities from a single depot to multiple dealers. And a hybrid genetic algorithm was studied in [19] combining sweep and genetic algorithms in an enhanced approach. Both are recognized algorithms to solve the VRPD in the literature.

Other important algorithms are those whose called nature based. An ant colony optimization (ACO) technique was developed to solve the NP-hard VRPs with drones in [20]. The studies showed that the suggested ACO algorithm can solve the VRDP efficiently for diverse size instances and area distributions. Similarly, a novel dynamical artificial bee colony (DABC) was used in [21] to reduce operating costs. To identify employed bee swarm and onlooker bee swarm, two bee swarms were formed. Also, variable neighborhood descent was used in employed bee phase and onlooker bee phase in varying methods. An artificial bee colony-based hybrid approach was developed to solve the waste collecting problem while taking the halfway disposal pattern into account in [22]. Moreover, [23] suggested a Particle Swarm Optimization (PSO) algorithm to solve uncertain VRP, alongside a decoding scheme to improve its efficiency. According to [24], a simulated annealing heuristic algorithm was proposed to solve one of the Green Vehicle Routing Problems (G-VRPs), which is the Hybrid Vehicle Routing Problem (HVRP).

The clustering algorithms are majorly common. The author in [25] proposed two different hybrid metaheuristic algorithms in regards of the Clustered Vehicle Routing Problem (Clu-VRP). The first algorithm relies on an Iterated Local Search algorithm, in which only possible solutions are searched. The second one is a hybrid genetic search where the shortest Hamiltonian path between every set of vertices inside each cluster is precomputed.

The Location-Routing Problem for delivering orders to a group of clients was discussed in [26]. They attempted to reduce the overall CO_2 emissions using trucks and drones for last-mile deliveries. The problem was resolved using a mathematical model. Their findings focused on how adopting greener transportation technology can be a start to the substantial contribution that UAVs make to problems with parcel delivery routing. Hence, it is considered one of the G-VRPs, which highlight serious environmental issues like high CO_{2e} emission, pollution, global warming, low sustainability lifestyle and many others, as clearly stated in [27]. Waste collection problem is another example of the G-VRPs. Conveniently, [28] introduced a particle swarm optimization (PSO) approach in a capacitated vehicle-routing problem (CVRP) model to establish the optimal waste collection and route optimization solutions. The PSO-based CVRP model included threshold waste level (TWL) and scheduling approaches. Solomon's insertion algorithm was developed to solve a real-world waste collection vehicle routing problem with time windows (VRPTW) in [29].

This research investigates the process of collecting hazardous waste from different sites using constrained drones (UAVs), proposing priority rules-based algorithm to help efficiently collect the waste in the minimum time using multiple drones (MTMD). Using the outcomes of [7] as the base of the study, extending it by assigning the trips to multiple drones instead of a single drone.

Despite the magnitude of research conducted on VRPs following versatile approaches and proposing applicable solutions, shedding lights on such problem with this significance and effect on the daily life and unknown future of livings on the face of earth is crucial and deserving. Also, employing the latest modern technology like drones to accomplish the desired goal efficiently makes a distinctive difference. On that account, presenting an algorithm maintaining sensitive constraints and imposing priority rules as a solution would narrow the gap and expedite the plan to a safer, healthier and waste free planet.

To the best of our knowledge, there is no existing literature that addresses the specific challenges associated with using drones in hazardous waste collection. Therefore, we are unable to compare the proposed algorithm with existing solutions in this context.

III. RESEARCH METHODOLOGY

To assign the trips to the drones in an efficient way so that the total waste will be collected from all sites in the minimum time, we developed an algorithm that is mainly based on three principles:

- Order the trips to be traveled according to their flying times. The trips are then executed according to either an increasing order of their flying times: Shortest Flying Time (SFT), a decreasing order of their flying times: Longest Flying Time (LFT), or alternatively from the median time: Median Flying Time (MFT).
- Assign the current trip to the first available drone. This principle will guarantee an efficient use of the drones, balance distributing the flying times between the drones, and collect the waste in a minimum time.
- When the current charge of a given drone is less than the flying duration of the next trip, then charge it according to two principles. The first is fully recharge the drone before taking the next trip. The second is to recharge the drone just enough for it to take the next trip.

The suggested algorithm enables multiple drones to access the list of trips at the same time, where each drone has a maximum flying and weight capacity, as well as a recharging duration. The flying capacity and drone's recharge are the two key constraints defined. The algorithm's two primary tasks are: parallel assignment of trips to multiple drones and recharging of drones. The trips are assigned to the drones as long as the list of trips is not empty, employing one of three proposed priority rules and following one of the charging principles. As a result, six versions of the main algorithm are proposed. The details of these algorithms are illustrated in Algorithms 1 to 4. Note that Algorithms 1 and 2 each has two versions. A version uses the SFT rule and another version uses the LFT rule. The notations used to develop the algorithm are summarized in Table I.

TABLE I. PROBLEM NOTATIONS

n	Number of trips in an instance
m	Number of drones
T	Maximum flying time of a drone if fully charged
r	Time needed to fully recharge a drone
c_j	Completion time of the last trip assigned to drone $j, 1 \leq j \leq m$
t_i	Flying duration of trip $i, 1 \leq i \leq n$
q_j	Remaining flying capacity of drone j

Algorithm 1 Assignment of trips to drones using SFT/LFT rule and charging drones when needed

1: *input:* m, n, T, r, t_i
output: C_{max}: The completion time of the last trip.
2: Sort t_i in increasing/decreasing order
3: **for** $j \leftarrow 0$ to $m-1$ **do**
4: $\quad c_j \leftarrow 0$
5: $\quad q_j \leftarrow T$
6: **end for**
7: $i \leftarrow 0$
8: **while** $(i < n)$ **do**
9: $\quad a \leftarrow\ index\ of \min c_j$
10: $\quad$ **if** $(q_a < t_i)$ **then**
11: $\quad\quad c_a \leftarrow \frac{t_i - q_a}{T} \times r + t_i$
12: $\quad\quad q_a \leftarrow 0$
13: $\quad$ **else**
14: $\quad\quad c_a \leftarrow c_a + t_i$
15: $\quad\quad q_a \leftarrow q_a - t_i$
16: $\quad$ **end if**
17: $\quad i \leftarrow i + 1$
18: **end while**
19: **return** $\max c_j$

Algorithm 2 Assignment of trips to drones using SFT/LFT rule and charging drones fully

1: *input:* m, n, T, r, t_i
output: C_{max}: The completion time of the last trip.
2: Sort t_i in increasing/decreasing order
3: **for** $j \leftarrow 0$ to $m-1$ **do**
4: $\quad c_j \leftarrow 0$
5: $\quad q_j \leftarrow T$
6: **end for**
7: $i \leftarrow 0$
8: **while** $(i < n)$ **do**
9: $\quad a \leftarrow index\ of\ \min c_j$
10: $\quad$ **if** $(q_a < t_i)$ **then**
11: $\quad\quad c_a \leftarrow \frac{T - q_a}{T} \times r + t_i$
12: $\quad$ **else**
13: $\quad\quad c_a \leftarrow c_a + t_i$
14: $\quad$ **end if**
15: $\quad q_a \leftarrow q_a - t_i$
16: $\quad i \leftarrow i + 1$
17: **end while**
18: **return** $\max c_j$

Note that steps 3 to 5 in all algorithms have the purpose of initializing the completion times of the drones to zeros and set their initial charge to full so that they can fly for T unites of time. Step 9 assigns the next trip to the first free drone. Step 10 in Algorithms 1 and 2 and 17 in Algorithms 3 and 4 means that the drone does not have enough charge to fly the next trip. For that reason, the drone needs either to be partially enough charged to fly the next trip (as in algorithms 1 and 3) or fully charged up to its maximum flying capacity T (as in algorithms 2 and 4). The last statement in all algorithms returns the maximum completion flying time of the last trip for all drones. The six proposed algorithms ensure an early completion time of the waste collection by assigning the next trip to the first available drone. This method maintains also an equilibrium between the total flying time between the drones.

Algorithm 3 Assignment of trips to drones using MFT rule and charging drones when needed

input: m, n, T, r, t_i
output: C_{max}: The completion time of the last trip.
Sort t_i in increasing order
for $j \leftarrow 0$ to $m-1$ **do**
  $c_j \leftarrow 0$
  $q_j \leftarrow T$
end for
$left \leftarrow \lfloor \frac{n}{2} \rfloor,\ right \leftarrow \lfloor \frac{n}{2} \rfloor + 1,\ k \leftarrow 0$
while $(k < n)$ **do**
  $a \leftarrow index\ of\ \min c_j$
  if $(k \mod 2 = 0)$ **then**
    $i \leftarrow left$
    $left \leftarrow left - 1$
  else
    $i \leftarrow right$
    $right \leftarrow right + 1$
  end if
  if $(q_a < t_i)$ **then**
    $c_a \leftarrow \frac{t_i - q_a}{T} \times r + t_i$
    $q_a \leftarrow 0$
  else
    $c_a \leftarrow c_a + t_i$
    $q_a \leftarrow q_a - t_i$
  end if
  $k \leftarrow k + 1$
end while
return $\max c_j$

Algorithm 4 Assignment of trips to drones using MFT rule and and charging drones fully

input: m, n, T, r, t_i
output: C_{max}: The completion time of the last trip.
Sort t_i in increasing order
for $j \leftarrow 0$ to $m-1$ **do**
  $c_j \leftarrow 0$
  $q_j \leftarrow T$
end for
$left \leftarrow \lfloor \frac{n}{2} \rfloor,\ right \leftarrow \lfloor \frac{n}{2} \rfloor + 1,\ k \leftarrow 0$
while $(k < n)$ **do**
  $a \leftarrow index\ of\ \min c_j$
  if $(k \mod 2 = 0)$ **then**
    $i \leftarrow left$
    $left \leftarrow left - 1$
  else
    $i \leftarrow right$
    $right \leftarrow right + 1$
  end if
  if $(q_a < t_i)$ **then**
    $c_a \leftarrow \frac{T - q_a}{T} \times r + t_i$
  else
    $c_a \leftarrow c_a + t_i$
  end if
  $q_a \leftarrow q_a - t_i$
  $k \leftarrow k + 1$
end while
return $\max c_j$

IV. Experimental Study

The six versions of the proposed algorithms were implemented in Java. Distributing the number of trips among multiple drones grants completing all the trips in a sooner time than assigning all the trips to a single drone, because all the drones are flying simultaneously; whenever a drone completes a trip and it is available in the depot, the program assigns another trip to it, not taking into account the status of the other drones.

Testing the program using the three priority rules: SFT, LFT and MFT while recharging only for the time needed once, and again recharging the drones till they are full, generated six distinctive cases. Twenty instances varying from 101 to 941 sites, with a number of trips in the range $[23, 249]$, have been used for validation of the proposed algorithms. A summary of results is shown in Tables II, III, IV, and V. For the six algorithms, the time each drone takes to complete the trips assigned to it was compared; the longest time means that it is the last drone to finish. As observed, the last drone finishing time of the cases that follow the LFT rule and recharge only for the time needed, is mostly the shortest, which means the LFT rule frequently guarantees a faster execution of the routing process. However, in some cases, multiple drones finish on the same time.

TABLE II. Values of C_{max} for Different Instances when $m = 2$

		Needed charge			Full charge		
Instance	n	SFT	LFT	MFT	SFT	LFT	MFT
I_{101}	23	294	289	**284**	296	293	**284**
I_{121}	28	392	**384**	392	393	388	393
I_{141}	32	416	**409**	416	416	411	416
I_{161}	34	353	**345**	353	353	349	353
I_{181}	52	606	**598**	606	607	600	607
I_{341}	69	725	**719**	720	725	720	720
I_{301}	75	708	702	**699**	708	703	703
I_{381}	82	960	**952**	960	960	957	957
I_{321}	87	1107	**1101**	1097	1076	1089	1098
I_{361}	100	866	**862**	866	866	**862**	866
I_{461}	118	1365	**1357**	1365	1365	**1357**	1365
I_{481}	127	**960**	1128	1133	1365	1357	1133
I_{641}	121	1494	**1470**	1488	1494	1471	1488
I_{661}	143	1847	**1840**	**1840**	1847	1841	1841
I_{701}	156	1519	**1511**	1519	1519	1512	1519
I_{721}	162	1662	**1652**	1662	1662	1658	1662
I_{741}	183	1493	**1487**	1489	1493	1488	1489
I_{861}	194	2188	**2182**	2188	2188	2184	2188
I_{901}	207	2158	**2151**	2153	2158	2152	2153
I_{941}	249	2159	**2151**	2154	2159	2152	2154

Moreover, the three cases where the drones are fully recharged every time the battery ran out, took a slightly longer total time to complete all the trips, regardless of the number of drones used, than those three cases which the drones are recharged for only the time needed to be assigned the next suitable trip. Table VI confirms this result for instance I_{101}.

Although, the recharge count could be the same for both recharging conditions, the remaining charge in the cases that recharge only the needed duration is always zero. Whereas the cases that recharge fully, have useless remaining charge; that adds extra period of time, which increases the completion time of all the trips. Therefore, it is better to consider the cases that will reduce the total time by charging the drones only for the time needed.

TABLE III. VALUES OF C_{max} FOR DIFFERENT INSTANCES WHEN $m = 3$

		Needed charge			Full charge		
Instance	n	SFT	LFT	MFT	SFT	LFT	MFT
I_{101}	23	196	**191**	195	198	195	197
I_{121}	28	272	266	**264**	273	270	**264**
I_{141}	32	284	**277**	283	284	279	284
I_{161}	34	246	**234**	242	246	237	242
I_{181}	52	419	**403**	408	420	408	410
I_{341}	69	483	**474**	484	483	476	485
I_{301}	75	467	**462**	471	470	465	469
I_{381}	82	651	**640**	647	651	642	646
I_{321}	87	729	**726**	735	730	729	736
I_{361}	100	591	**581**	584	591	582	584
I_{461}	118	923	**911**	921	923	**911**	918
I_{481}	127	767	**752**	761	767	754	762
I_{641}	121	1004	**995**	1000	1004	**995**	1000
I_{661}	143	1227	**1226**	1230	1233	1229	1232
I_{701}	156	1015	**1007**	1018	1015	**1007**	1020
I_{721}	162	1112	**1098**	1114	1112	1102	1113
I_{741}	183	997	**987**	1000	997	988	1000
I_{861}	194	1465	**1457**	1466	1464	1458	1465
I_{901}	207	1437	**1430**	1443	1438	1431	1442
I_{941}	249	1444	**1431**	1445	1444	1431	1444

TABLE IV. VALUES OF C_{max} FOR DIFFERENT INSTANCES WHEN $m = 4$

		Needed charge			Full charge		
Instance	n	SFT	LFT	MFT	SFT	LFT	MFT
I_{101}	23	148	**142**	150	150	143	151
I_{121}	28	200	**190**	201	200	193	201
I_{141}	32	212	**203**	215	212	205	215
I_{161}	34	191	**173**	186	191	181	185
I_{181}	52	309	**301**	312	309	305	313
I_{341}	69	373	**363**	368	373	366	368
I_{301}	75	352	**346**	352	356	349	361
I_{381}	82	488	**480**	486	488	482	487
I_{321}	87	554	**548**	554	555	551	555
I_{361}	100	440	**431**	444	441	432	444
I_{461}	118	692	**681**	691	692	682	692
I_{481}	127	578	**562**	577	578	564	577
I_{641}	121	761	**749**	755	761	**749**	755
I_{661}	143	925	**919**	928	927	920	928
I_{701}	156	765	**754**	767	766	756	768
I_{721}	162	838	**827**	841	838	832	842
I_{741}	183	748	**742**	755	748	744	754
I_{861}	194	1103	**1095**	1102	1104	1098	1102
I_{901}	207	1085	**1075**	1085	1085	**1075**	1085
I_{941}	249	1091	**1079**	1087	1091	1083	1088

TABLE V. VALUES OF C_{max} FOR DIFFERENT INSTANCES WHEN $m = 5$

		Needed charge			Full charge		
Instance	n	SFT	LFT	MFT	SFT	LFT	MFT
I_{101}	23	125	**114**	125	126	118	126
I_{121}	28	169	**159**	167	169	162	167
I_{141}	32	181	**170**	176	181	172	176
I_{161}	34	155	**135**	155	155	136	154
I_{181}	52	261	**242**	257	262	247	258
I_{341}	69	294	**286**	299	294	287	299
I_{301}	75	281	**274**	287	284	278	292
I_{381}	82	398	**384**	394	398	390	399
I_{321}	87	451	**444**	450	452	447	452
I_{361}	100	355	**345**	360	355	**345**	360
I_{461}	118	556	**543**	556	557	546	557
I_{481}	127	471	**453**	468	471	455	467
I_{641}	121	613	**602**	609	613	**602**	609
I_{661}	143	750	**738**	750	750	739	749
I_{701}	156	620	**610**	619	620	613	619
I_{721}	162	676	**662**	673	676	663	671
I_{741}	183	603	**595**	605	603	596	604
I_{861}	194	883	**872**	885	883	876	883
I_{901}	207	876	**865**	872	876	866	872
I_{941}	249	876	**860**	877	874	**860**	876

TABLE VI. TOTAL TIME COMPARISON FOR INSTANCE I_{101}

	Needed charge			Full charge		
m	SFT	LFT	MFT	SFT	LFT	MFT
2	562	563	562	566	569	568
3	556	557	556	561	566	559
4	549	550	550	557	557	556
5	544	543	544	553	558	553

In addition, the average of the time each drone took to complete the assigned trips was calculated. The difference between the time each drone took, and the average was also calculated, to illustrate how balanced the assigning of trips among the drones was. The total difference of those differences was then summed up to accentuate the exact gap between the time all the drones took to complete the trips and the average of it. It is noticeable that the total difference generated by SFT rule is always the biggest compared to the LFT and MFT rules. Whilst, the MFT cases often have smaller total difference than the SFT cases and a few of them have the same total difference as the LFT or SFT cases. In numerous instances, the MFT cases have the smallest total difference out of all three rules. Furthermore, a decreasing pattern in the number of those instances was noticeable, where the number of instances and the number of drones used have an inverse relationship; whenever the number of drones used increases, the number of the instances having the smallest total difference in the MFT cases decreases. However, the LFT cases mostly have the smallest total difference amongst all three. Additionally, in some LFT cases the total time of all the drones is the same as the average time, which means the total difference is zero. This comparison truly demonstrated how the LFT rule performs best in regards of the assignment of trips among the drones, despite their number, which ensures that all the drones take up nearly the same time to complete the trips. Moreover, it is an indication that the drones visit approximately the same number of trips. As a resultant, sorting the trips from the longest flying time to the shortest flying time (LFT) almost equally assigns the trips to the drones, which executes a more efficient program, effectively fulfilling the objective of the proposed algorithm MTMD.

"Fig. 1, "Fig. 2", "Fig. 3" and "Fig. 4" below, clarify the contrast between the total differences in each rule (SFT, LFT and MFT) for all 20 instances using 2, 3, 4 and 5 drones.

V. CONCLUSION AND FUTURE WORK

A. Conclusion

In conclusion, studying the Vehicle Routing Problem using Drones (VRPD) and how it can be applied to help finding a solution to the accumulated hazardous waste problem was the first step. The diversified literature of VRPs gave the proper background and knowledge to investigate this major problem and propose an algorithm to resolve it.

Adopting the outcomes of an existent research as a dataset, six versions of a proposed algorithm were brought forward that allow multiple drones to access the list of trips at the same time, where the drones have maximum flying and weight capacities and a recharge duration. Concentrating on the flying capacity and the recharging of drones as constraints, the

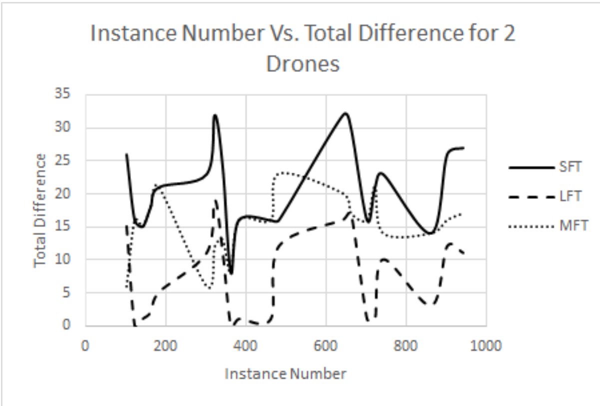

Fig. 1. Total differences for each rule using 2 drones.

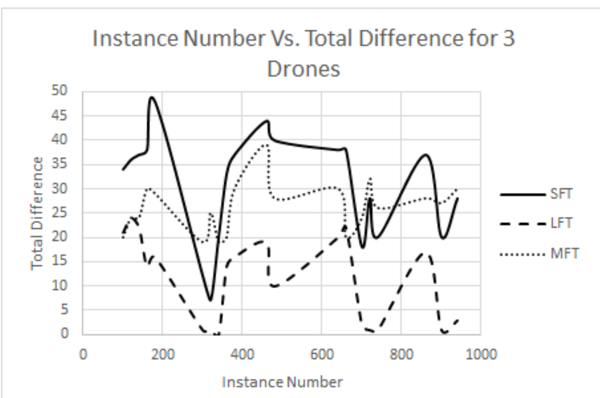

Fig. 2. Total differences for each rule using 3 drones.

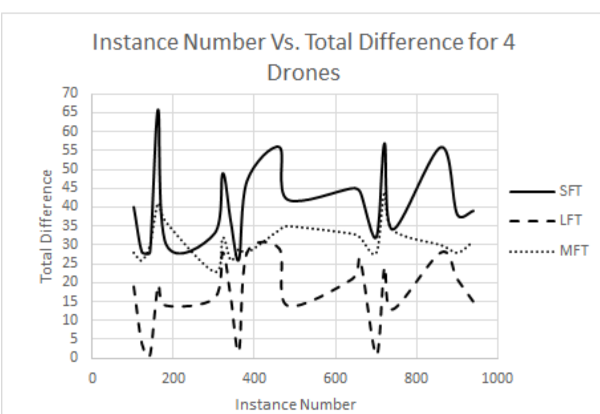

Fig. 3. Total differences for each rule using 4 drones.

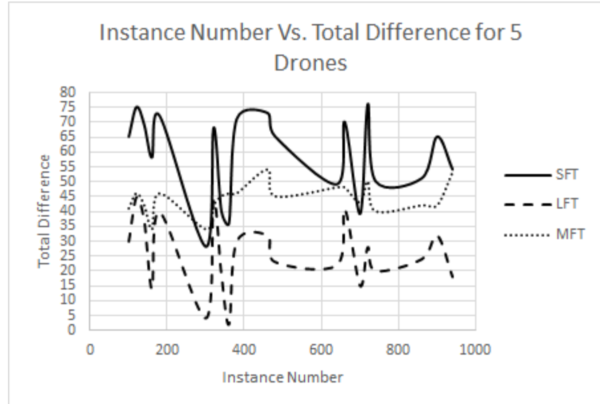

Fig. 4. Total differences for each rule using 5 drones.

presented algorithms handle the routing through two main tasks: the assignment of trips to multiple drones and recharging of drones. It suggested three priority rules in sorting the flying times before assigning them to the drones. The first rule is sorting from the shortest to the longest flying time (SFT) in ascending order. The second rule is sorting from the longest to the shortest flying time (LFT) in descending order. The third rule is sorting the flying times in ascending or descending order first and then starting from the median trip time (MFT). Following each rule, whenever the drones need recharging, two conditions were taken into consideration: recharging the drones just for the time needed to be assigned the next adequate trip or recharging the drones fully, taking their total recharge duration. Hence, the algorithms map routes in minimum time using multiple drones (MTMD).

Moreover, the algorithm's versions were implemented using Java to program was developed validating the algorithm, which produced six cases that test each individual rule (SFT, LFT and MFT) with both recharging conditions (needed and full).

After various testing of the six cases, the output of the program resulted in valuable findings. The LFT rule was proven the current best in assignment of trips to the multiple drones. It almost distributes the trips equally, which means approximately the same total flying time, recharge count and trip count of the drones. The program was tested using common several testing types as well, to assure its effectiveness in following the MTMD algorithm.

B. Future Work

Aggregating the work done, positive improvements are expected to better the research, starting from developing a program with higher performance and dedicating enough time to test all the instances of the dataset using a greater number of drones.

In addition, the Drone Routing Problem (DRP) is progressing continuously; researchers are studying new challenging extensions of it momentarily. Consequently, proposing a better algorithm to develop an enhanced program as a solution to this substantial problem is an aspiration kept in mind. An existing similar problem called the Subset-Sum problem could be beneficial for evolving the rules the MTMD algorithm proposed.

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REFERENCES

[1] M. A. Masmoudi, S. Mancini, R. Baldacci, and Y.-H. Kuo, "Vehicle routing problems with drones equipped with multi-package payload compartments," *Transportation Research Part E: Logistics and Transportation Review*, vol. 164, p. 102757, 2022.

[2] A. Messina, S. Metta, M. Montagnuolo, F. Negro, V. Mygdalis, I. Pitas, J. Capitán, A. Torres, S. Boyle, D. Bull *et al.*, "The future of media production through multi-drones' eyes," in *International broadcasting convention (IBC)*, 2018.

[3] X. Li, P. Yan, K. Yu, P. Li, and Y. Liu, "Parcel consolidation approach and routing algorithm for last-mile delivery by unmanned aerial vehicles," *Expert Systems with Applications*, vol. 238, p. 122149, 2024.

[4] P. Pina and G. Vieira, "Uavs for science in antarctica," *Remote Sensing*, vol. 14, no. 7, p. 1610, 2022.

[5] D. Banik, N. U. Ibne Hossain, K. Govindan, F. Nur, and K. Babski-Reeves, "A decision support model for selecting unmanned aerial vehicle for medical supplies: Context of covid-19 pandemic," *The International Journal of Logistics Management*, vol. 34, no. 2, pp. 473–496, 2023.

[6] D. R. Green, J. J. Hagon, C. Gómez, and B. J. Gregory, "Using low-cost uavs for environmental monitoring, mapping, and modelling: Examples from the coastal zone," in *Coastal management*. Elsevier, 2019, pp. 465–501.

[7] J. Kaabi, Y. Harrath, A. Mahjoub, N. Hewahi, and K. Abdulsattar, "A 2-phase approach for planning of hazardous waste collection using an unmanned aerial vehicle," *4OR*, pp. 1–24, 2022.

[8] G. Macrina, L. D. P. Pugliese, F. Guerriero, and G. Laporte, "Drone-aided routing: A literature review," *Transportation Research Part C: Emerging Technologies*, vol. 120, p. 102762, 2020.

[9] S. I. Khan, Z. Qadir, H. S. Munawar, S. R. Nayak, A. K. Budati, K. D. Verma, and D. Prakash, "Uavs path planning architecture for effective medical emergency response in future networks," *Physical Communication*, vol. 47, p. 101337, 2021.

[10] M. Momeni, H. Soleimani, S. Shahparvari, and B. Afshar-Nadjafi, "Coordinated routing system for fire detection by patrolling trucks with drones," *International Journal of Disaster Risk Reduction*, vol. 73, p. 102859, 2022.

[11] Z. Wang and J.-B. Sheu, "Vehicle routing problem with drones," *Transportation research part B: methodological*, vol. 122, pp. 350–364, 2019.

[12] F. Tamke and U. Buscher, "A branch-and-cut algorithm for the vehicle routing problem with drones," *Transportation Research Part B: Methodological*, vol. 144, pp. 174–203, 2021.

[13] Y. Wang, Z. Wang, X. Hu, G. Xue, and X. Guan, "Truck–drone hybrid routing problem with time-dependent road travel time," *Transportation Research Part C: Emerging Technologies*, vol. 144, p. 103901, 2022.

[14] M. Kang and C. Lee, "An exact algorithm for heterogeneous drone-truck routing problem," *Transportation Science*, vol. 55, no. 5, pp. 1088–1112, 2021.

[15] R. G. M. Saleu, L. Deroussi, D. Feillet, N. Grangeon, and A. Quilliot, "The parallel drone scheduling problem with multiple drones and vehicles," *European Journal of Operational Research*, vol. 300, no. 2, pp. 571–589, 2022.

[16] E. B. Tirkolaee, M. Alinaghian, A. A. R. Hosseinabadi, M. B. Sasi, and A. K. Sangaiah, "An improved ant colony optimization for the multi-trip capacitated arc routing problem," *Computers & Electrical Engineering*, vol. 77, pp. 457–470, 2019.

[17] D. Sacramento, D. Pisinger, and S. Ropke, "An adaptive large neighborhood search metaheuristic for the vehicle routing problem with drones," *Transportation Research Part C: Emerging Technologies*, vol. 102, pp. 289–315, 2019.

[18] G. Barbarosoglu and D. Ozgur, "A tabu search algorithm for the vehicle routing problem," *Computers & Operations Research*, vol. 26, no. 3, pp. 255–270, 1999.

[19] J. Euchi and A. Sadok, "Hybrid genetic-sweep algorithm to solve the vehicle routing problem with drones," *Physical Communication*, vol. 44, p. 101236, 2021.

[20] S.-H. Huang, Y.-H. Huang, C. A. Blazquez, and C.-Y. Chen, "Solving the vehicle routing problem with drone for delivery services using an ant colony optimization algorithm," *Advanced Engineering Informatics*, vol. 51, p. 101536, 2022.

[21] D. Lei, Z. Cui, and M. Li, "A dynamical artificial bee colony for vehicle routing problem with drones," *Engineering Applications of Artificial Intelligence*, vol. 107, p. 104510, 2022.

[22] Q. Wei, Z. Guo, H. C. Lau, and Z. He, "An artificial bee colony-based hybrid approach for waste collection problem with midway disposal pattern," *Applied Soft Computing*, vol. 76, pp. 629–637, 2019.

[23] B. F. Moghaddam, R. Ruiz, and S. J. Sadjadi, "Vehicle routing problem with uncertain demands: An advanced particle swarm algorithm," *Computers & Industrial Engineering*, vol. 62, no. 1, pp. 306–317, 2012.

[24] F. Y. Vincent, A. P. Redi, Y. A. Hidayat, and O. J. Wibowo, "A simulated annealing heuristic for the hybrid vehicle routing problem," *Applied Soft Computing*, vol. 53, pp. 119–132, 2017.

[25] T. Vidal, M. Battarra, A. Subramanian, and G. Erdog˘an, "Hybrid metaheuristics for the clustered vehicle routing problem," *Computers & Operations Research*, vol. 58, pp. 87–99, 2015.

[26] L. C. Montaña, L. Malagon-Alvarado, P. A. Miranda, M. M. Arboleda, E. L. Solano-Charris, and C. A. Vega-Mejía, "A novel mathematical approach for the truck-and-drone location-routing problem," *Procedia Computer Science*, vol. 200, pp. 1378–1391, 2022.

[27] R. Moghdani, K. Salimifard, E. Demir, and A. Benyettou, "The green vehicle routing problem: A systematic literature review," *Journal of Cleaner Production*, vol. 279, p. 123691, 2021.

[28] M. Hannan, M. Akhtar, R. Begum, H. Basri, A. Hussain, and E. Scavino, "Capacitated vehicle-routing problem model for scheduled solid waste collection and route optimization using pso algorithm," *Waste management*, vol. 71, pp. 31–41, 2018.

[29] B.-I. Kim, S. Kim, and S. Sahoo, "Waste collection vehicle routing problem with time windows," *Computers & Operations Research*, vol. 33, no. 12, pp. 3624–3642, 2006.