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Planning Multiple UAVs to Visit Points of Interest Considering Flight Range and Service Time Constraints

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Abstract

Unmanned Aerial Vehicles (UAVs) have proved their value in both civilian and military applications in the recent years even though they have their own limitations such as limited flight ranges and high operation costs. In this work, we propose an optimization problem as to minimize the number of used UAVs to service all the given Points of Interest (PoIs) during the agreed service time windows. To solve this optimization problem, we use a greedy approach to reach a reasonable solution in an acceptable time period. The results of extensive simulation tests show the effectiveness of the proposed heuristic for different flight ranges, PoI topologies, and time windows.

Keywords: Unmanned Aerial Vehicles, Route planning, Genetic Algorithm, Optimization, Simulation

7. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have exhibited their value in both civilian and military applications in the recent years even though they have their own limitations such as limited flight ranges and high operation costs. Applications exploit the mobility of UAVs to service many customers located at Points of Interest (PoIs).One of the important Quality of Service requirements of these applications is to visit the determined PoIs during a given service time period. As the number of UAVs owned by the applications is limited due to the expensive price tag on UAVs, in real life applications, we face with an optimization problem.

In this work, we define this optimization problem as to minimize the number of UAVs used to service all the given PoIs during the agreed service time windows (TW). Moreover, we also aim to minimize the total traveled distance by all UAVs. Thus, the main constraints in the problem are UAV flight range (FR) and time windows (TW) of PoIs. We term this problem the Covering All PoI by Multiple UAVs Problem (CAP/MUP).

Since CAP/MUP can be classified as a combinatorial optimization problem, we opt to use a greedy approach to reach a reasonable solution in an acceptable time period. Thus, we design a heuristic solution called Nearest Neighbor for Maximum PoI/ Multiple UAV (NN-MP/MU) based on Nearest Neighbor (NN) heuristic. Searching for the nearest neighbor is an important problem in a variety of applications, including knowledge discovery and data mining, pattern recognition and classification, machine learning, data compression, multimedia databases, document retrieval, and statistics. Though being a deterministic solution, high-dimensional nearest neighbor problems arise naturally when complex objects are represented by vectors of d numeric features [10]. The Nearest Neighborhood (NN) heuristic is known in the literature for its simplicity and effectiveness in searching the given space. Especially for complex problems, the NN heuristic can reach an acceptable result in a reasonable time.

In generic Nearest Neighbor (NN) heuristic, one selects the nearest PoI as the next one unless it cannot return to base due to the diminished flight range (FR). However, in this case, another optimization problem appears which are related with the delays spent among the PoIs. Therefore, we adopted the NN method into the CAP/MUP such that the developed NN-MP/MU heuristic first finds three nearest PoIs and the PoI causing the least delay is picked up within that set. The critical point is that selected PoI might not be the nearest, but the one from the closest three while satisfying all other constraints.

Vehicle Routing Problem with Time Windows (VRPTW) is closely related with the presented work. Both problems consider that the mobile must visit a location during the given time window. There are many solution methods proposed for VRPTW in the literature. These solutions can be classified into two main groups: exact solutions [3, 4, 5, 6, 7] and heuristic-based solutions [8, 9]. Heuristic-based solutions proposed in the literature employ well known meta-heuristics such as Simulated Annealing, Tabu Search, and Genetic algorithms among others.

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The solutions mentioned above assume that the mobile (vehicle) can wait if it arrives earlier to a given location (depot) compared to the time window and this waiting duration does not have any effects on the traveled distance of the vehicle. This may be an acceptable assumption for the vehicles moving on the ground. However, a flying vehicle (e.g. UAV) has two options for waiting: either UAV can continue fly for passing the time in the air or it can land on, wait, and take off again. Thus, any solution for the UAV routing problem should take into consideration the amount of waiting time due to the limited flight range[2]. In this work, we modify the NN heuristic to generate routes for multiple UAVs considering flight range and waiting times to meet the service time requirement as discussed below.

8. PROPOSED METHOD

The aim of this study is to develop a good adaptation of the NN heuristic for the problem the Covering Maximum PoI by Multiple UAVs Problem (CMP/MUP).

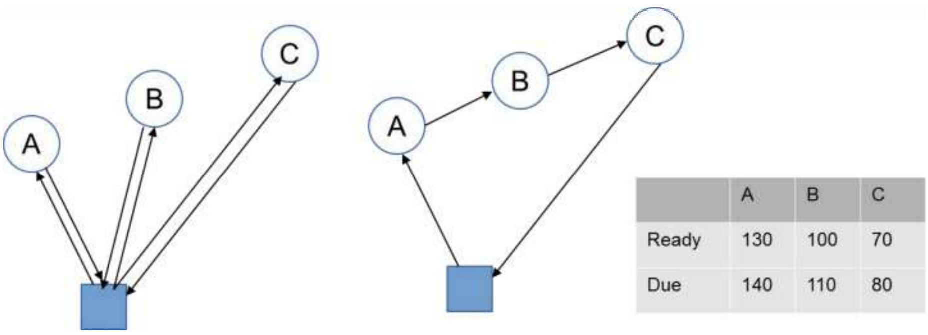
Nearest Neighbor (NN) heuristic is a simple to use, nonetheless effective for specific topology. In generic NN heuristic, one selects the nearest node as the next one. However, in the present study, there is another main constraint which defines when UAV visits each Point of Interest (PoI). As this problem can be classified as a combinatorial optimization problem [6], we use a greedy approach in order to reach a reasonable solution in an acceptable time period.

In generic NN heuristic, route planning begins from the base and continues with the nearest PoI complying with the time window (TW) of the to-be-visited PoI. That is, the NN heuristic eliminates the PoIs whose ready and due times do not fit to the UAV‘s arrival time to them. As the final step, the NN method selects the nearest PoI to the current one provided that the UAV can have enough remaining flight range (FR) for returning to the base.

We improve the generic NN heuristic noticing that in some cases, the nearest PoI might have a rather late ready time than that of the second or the third closest PoIs. If we select the nearest one as the next PoI, this choice would cause UAV to wait in the air until the ready time expires. Explicitly, doing so decreases the flight range of the UAV without visiting any node. Therefore, we propose to select the next PoI among the three closest PoIs according to their ready time. The one with the earliest ready time is selected as the next PoI. This process increases the flexibility of algorithm for maximizing the path travelled and clearly decreases the possible delay times. We name this improved heuristic as the NN heuristic for Maximum PoI/ Multiple UAV (NN-MP/MU).

In fact, this trade-off between ―flight distance” and ―waiting in the air” is believed to be a good sample of greedy approach. We may not select the nearest PoI for the sake of having less delay in the air. But we must keep in mind that this selection is limited to the second or the third closest PoI at most. By the help of this 3-closest PoI set, it has been observed in our experiments that UAVs are able to visit more PoI than that of generic NN heuristic.

Figure 1. Generic NN vs. NN-MP/MU Executions



	A	B	C
Ready	130	100	70
Due	140	110	80

If Fig.1 is examined, the strategies of the generic NN and NN-MP/MU are given. Given the ready-due times of the related nodes the generic NN algorithm on the left-hand side, will assign the PoI C since it has the closest ready time. However, after visiting that node it will miss the time windows for PoIs A and B. Because of that reason, other UAVs have to be assigned for the rest. This situation will be the opposite in NN-MP/MU on the right-hang side. In NN-MP/MU, all the PoIs can be visited by only one UAV which puts forward the aim of this study. Though it may result in more travelling distance, fewer UAVs will be assigned and due to the dataset we might have less travelling distances.

3 EXPERIMENT RESULTS

In this section, NN-MP/MU and generic NN solutions are compared using different VRPTW benchmark problem data files [1] along with various UAV flight ranges.

3.1 Simulation Setup and Parameters

All the test results given in the following tables and figures are obtained by taking the mean of the results of 10 independent runs. We have used both R and C data sets described in [1] in order to observe the effect of different typologies and time windows.

In the experiments, R data sets, R101 thru R105, and C data sets, C101 thru C105, are used. The main simulation parameters and their default values are shown in Table 1. All of the PoIs in the datasets, i.e. 100 nodes, have been included.

Table 1. Simulation parameter settings

Parameter	Default Value	Range	Notes
Data Set	R101	R101-R105, C101-C105	10 Different VRPTW benchmark problems
Number of PoIs	101	101	1st PoI is selected as Base, then the rest 100 are assumed to be the PoIs visited

3.2 Results of Experiments

It is declared in [1] that the geographical data are randomly generated in problem sets R, clustered in C datasets. It is known that the geographical data are randomly generated in problem sets R1 and R2, clustered in problem sets C1 and C2.

Table 2. Simulation test results

Data Set	Generic NN		NN-MP/MU	
	# of UAVs	Total Distance travelled	# of UAVs	Total Distance travelled
R101	29	2276,19	16	1902,67
R102	27	2182,38	16	1969,35
R103	20	1690,22	14	1696,85
R104	14	1431,47	12	1761,97
R105	19	1823,34	13	1856,99
C101	46	3579,40	30	3823,09
C102	36	3076,10	26	3207,15
C103	32	2734,65	28	3019,55
C104	30	2759,30	28	3166,37
C105	32	2587,42	23	3475,92

As seen in Table 2, NN-MP/MU uses less number of UAVs compared to the generic NN for all the considered cases in the tests. We compare the improvement of NN-MP/MU over the generic NN as the percentage of used UAV numbers and traveled distance in Table 3. We observe that NN-MP/MU uses considerable less number of UAVs esp. in R datasets. On the other hand, NN-MP/MU uses 40% fewer UAVs than that of NN algorithm considering all datasets.

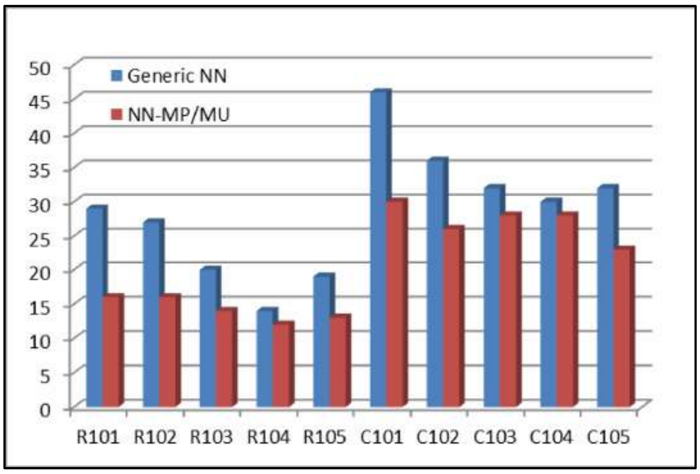
Table 3. Improvement of NN-MP/MU over the generic NN

Data Set	UAV used	Distance Ratio
R101	81,25%	19,63%
R102	68,75%	10,82%
R103	42,86%	-0,39%
R104	16,67%	-18,76%
R105	46,15%	-1,81%
C101	53,33%	-6,37%
C102	38,46%	-4,09%
C103	14,29%	-9,44%
C104	7,14%	-12,86%
C105	39,13%	-25,56%
Average	**40,80%**	**-4,88%**

For the total distance traveled, in general, NN-MP/MU produce 4.88% less distance. Thus, the NN-MP/MU does decrease the total traveled distance slightly. This could be due to generic NN heuristic's success on clustered topologies. In other words, generic NN heuristic assigns more number of UAVS and they travel among a few of them, even go only for one node in most cases. This results in less travel distance in total. In fact, this also shows that NN-MP/MU might be developed in terms of total travelled distance. This is left as a future work.

As it can be clearly seen in Fig.2, NN-MP/MU has superiority over generic NN algorithm in terms of UAV numbers. Moreover generic NN has drawbacks esp. in R datasets where the PoIs are created and placed due to randomly generated geographical data. The performance results between NN-MP/MU and generic NN are apparent in R datasets especially Even though, we can conclude that with respect to different underlying topologies and various time window settings, NN-MP/MU is robust and successful.

Figure 2. Comparison of number of UAVs used by both solutions for different benchmark data sets



4 CONCLUSION & FUTURE WORK

The aim of this study is to present an optimized NN heuristic which can be applied to especially for large number of nodes. In the results , we observe that the optimized NN heuristic generates UAV paths using considerable fewer number of UAVs compared to generic NN. However, total travel distance seems to be slightly lower on the average. Therefore, as a future work, we would like to develop a sophisticated algorithm in order to minimize the total travel distance as well.

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