Two-Echelon Arc Routing Problem with Drones in Traffic Patrol

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#### APPENDIX A

TASK ARC ASSIGNMENT STAGE BASED ON PARTITIONING AROUND MEDOIDS (PAM) METHOD.

In the task assignment stage, we first define the distance between the tasks, which can identify the potential better assignment scheme. Based on the defined distance, |K| path centers are constructed by employing PAM clustering method. All the task arcs are assigned to the |K| path center points to form |K| task arc clusters, which are patrolled in parallel by |K| truck-drone fleets.

#### A. Distance between tasks

Before defining the distance between two tasks, we first define the distance between two nodes in a road network. Considering that the trucks must travel along the road network, while the drones are not constrained by the road network, the distance between two nodes of the road network is different for trucks and drones. We simply take the average of the truck distance and drone distance as the final distance between two nodes.

$$Distance = \frac{(D+Dd)}{2} \tag{1}$$

where D is the shortest distance for trucks computing by Floyd-Warshall algorithm, Dd is the Euclidean distance for drones, Distance is the final distance between two nodes in the road network.

Using the above distance between two nodes, we further define the distance between tasks:

$$\Delta_{task}(te_1, te_2) = \frac{\sum_{i=1}^{2} \sum_{j=1}^{2} \Delta(v_i(te_1), v_j(te_2))}{4}$$
 (2)

where  $\Delta\left(v_i\left(t_1\right),v_j\left(t_2\right)\right)$  is the final distance between the *i*-th end point  $(v_i)$  of task  $te_1$  and the *j*-th end point  $(v_j)$  of task  $te_2$  by formula (2).  $\Delta_{task}\left(t_1,t_2\right)$  is defined as the average of the four distances between the end points of the task  $te_1,te_2$ .

# B. PAM method

Given the distance between two task arcs, we implement PAM method to generate an initial task assignment scheme. Algorithm 1 shows the basic structure of the PAM method.

### APPENDIX B

TASK REALLOCATE BETWEEN DIFFERENT TRUCK-DRONE FLEETS.

To avoid the algorithm falling into the local optima, the task assignments of the truck-drone fleets should be appropriately

# Algorithm 1: PAM method for initial task allocation

```
Input: Set of task arcs TA;
   number of groups |K|, max iterations Iter
   Output: Task allocation scheme
             A = (A_1, A_2, \dots, A_{|K|})
 1 Randomly select |K| task arcs as the cluster center C;
 2 for ta_i \in TA do
       Assign ta_i to nearest A_k by Eq. 2;
       A_k \leftarrow A_k \cup ta_i;
 5 end
 6 Calculate total distance cost;
 7 i = 0:
 8 while i \leq Iter do
       for ta_m \in TA do
10
           for c_n \in C do
                Replace the cluster center with c_n;
11
                Get new scheme A' by reassignment;
12
                Calculate the distance cost;
13
                if the cost reduces then
14
                   c_n \leftarrow ta_m;

A \leftarrow A';
15
16
17
           end
18
       end
       i \leftarrow i + 1
21 end
```

adjusted after the algorithm has been executed for a while. This paper designs a reassignment method for task arcs between different truck-drone combinations. The specific process is described in Algorithm 2.

### APPENDIX C

## A. Information of generated instances

The detail of small-scale instances is shown in Table I, where |N|, |A| and |TA| stands for the number of nodes, arcs, and target arcs, respectively.

As for the large-scale instances, inspired by [1], we select five public transportation networks, namely SiouxFalls, Gold-Coast, Chicago-regional, Philadelphia, and Sydney. From these transportation networks, we further extract several regions with different scales of nodes, arcs and target arcs. It worth noting that the length of links between nodes is scaled up proportionally by a ratio r due to the difference in units of path length and the scale of different transportation networks. The information of generated instances from transportation networks are shown

# Algorithm 2: Task Arc Reassignment Algorithm

**Input:** Routing scheme  $S = (s_1, ..., s_k, ..., s_m)$ , where  $s_k$  is k-th fleet route

**Output:** The adjusted routing scheme  $S^*$ 

- 1 for  $s_k \in S$  do
- 2 Get patrol time of  $s_k$ ;
- 3 end
- 4 if random() < 0.5 then
- 5 | Find  $s_{in}$  with min patrol time;
- 6 Find  $s_{out}$  with max patrol time;
- 7 Get the cluster center  $t_j$  of  $s_{in}$ ;
- 8 | Get  $\triangle_{task}(t_i, t_j) \ \forall t_i \in s_{out};$
- 9 Get  $t_i$  with smallest  $\triangle_{task}(t_i, t_j)$ ;

#### 10 else

- 11 Randomly get routing scheme  $s_{in}$  and  $s_{out}$ ;
- Randomly select a task  $t_i \in s_{out}$ ;
- 13 end
- 14 Reassign  $t_i$  to cluster  $s_{in}$ ;
- 15 Update routes of  $s_{in}$  and  $s_{out}$ ;

 $\label{eq:TABLE I} \begin{tabular}{ll} The detail of small-scale instances. \end{tabular}$ 

Network	$ N_0 $	$ A_0 $	TA	K	KD	Instance
T1	6	13	1 2	1 1	1 2	T1-1-1-1 T1-2-1-2
T2	7	17	1 2 3	1 2 2	1 1 2	T2-1-1-1 T2-2-2-1 T2-3-2-2
Т3	8	23	1 2 3	1 2 2	1 1 2	T3-1-1-1 T3-2-2-1 T3-3-2-2
T4	9	28	2 3 4	2 2 2	1 2 2	T4-2-2-1 T4-3-2-2 T4-4-2-2
T5	10	32	3	2	2	T5-3-2-2
Т6	11	32	4	2	2	T6-4-2-2

in Table II. The  $[x_{min}, x_{max}]$  and  $[y_{min}, y_{max}]$  represent the size of the extracted region.

### B. Results of FT and WST

The results of FT and WST are shown in Table III and Table IV.

# C. Results of sensitivity analysis

The comparison results under different speeds of drones are shown in Table V.

The comparison results under different number of drones are shown in Table VI.

The comparison results under different speed of trucks are shown in Table VII.

The comparison results under different number of trucks are shown in Table VIII.

#### REFERENCES

 B. Xu, K. Zhao, Q. Luo, G. Wu, and W. Pedrycz, "A gv-drone arc routing approach for urban traffic patrol by coordinating a ground vehicle and multiple drones," *Swarm and Evolutionary Computation*, vol. 77, p. 101246, 2023.

 $\label{table II} \textbf{TABLE II}$  The information of generated instances from transportation networks

Networks	r	Instance	$[x_{min}, x_{max}]$	$\left[y_{min},y_{max}\right]$	$ N_0 $	$ A_0 $	TA
		SF-n24-a76-3	[-96.7934, -96.6934]	[43.4906, 43.6129]	24	76	3
		SF-n24-a76-4	[-96.7934, -96.6934]	[43.4906, 43.6129]	24	76	4
C:E-11-	1	SF-n24-a76-5	[-96.7934, -96.6934]	[43.4906, 43.6129]	24	76	5
SiouxFalls	1	SF-n24-a76-6	[-96.7934, -96.6934]	[43.4906, 43.6129]	24	76	6
		SF-n24-a76-7	[-96.7934, -96.6934]	[43.4906, 43.6129]	24	76	7
		SF-n24-a76-8	[-96.7934, -96.6934]	[43.4906, 43.6129]	24	76	8
		GC-n52-a130-4	[153.4020, 153.4108]	[-27.9555, -27.9400]	52	130	4
		GC-n101-a245-8	[153.4005, 153.4123]	[-27.9625, -27.9400]	101	245	8
		GC-n151-a382-12	[153.4002, 153.4164]	[-27.9674, -27.9406]	151	382	12
GoldCoast	15	GC-n200-a514-16	[153.3980, 153.4180]	[-27.9702, -27.9404]	200	514	16
		GC-n250-a617-20	[153.4186, 153.4420]	[-28.0580, -28.0008]	250	617	20
		GC-n300-a743-24	[153.4140, 153.4412]	[-28.0596, -28.0012]	300	743	24
		GC-n300-a743-30	[153.4140, 153.4412]	[-28.0596, -28.0012]	300	743	30
		CR-n50-a144-4	[568600, 582000]	[1957500, 1984400]	50	144	4
		CR-n100-a302-8	[560200, 582000]	[1930800, 1984400]	100	302	8
		CR-n150-a454-12	[555800, 582000]	[1914800, 1984400]	150	454	12
Chicago-regional	1	CR-n201-a614-16	[551200, 582000]	[1907100, 1984400]	201	614	16
		CR-n250-a774-20	[541600, 582000]	[1907100, 1984400]	250	774	20
		CR-n300-a935-24	[522000, 582000]	[1911000, 1984400]	300	935	24
		CR-n300-a935-30	[522000, 582000]	[1911000, 1984400]	300	935	30
		PH-n50-a140-4	[29469, 29681]	[76711, 76886]	50	140	4
		PH-n100-a294-8	[29352, 29837]	[76700, 77096]	100	294	8
		PH-n150-a440-12	[29353, 30100]	[76700, 77126]	150	440	12
Philadelphia	5	PH-n200-a592-16	[29350, 30100]	[76700, 77400]	200	592	16
		PH-n250-a760-20	[29422, 30100]	[76404, 77450]	250	760	20
		PH-n300-a916-24	[29305, 30100]	[76430, 77500]	300	916	24
		PH-n300-a916-30	[29305, 30100]	[76430, 77500]	300	916	30
		SN-n50-a114-4	[151.080, 151.094]	[-33.797, -33.787]	50	114	4
		SN-n101-a238-8	[151.079, 151.095]	[-33.808, -33.787]	101	238	8
		SN-n151-a360-12	[151.071, 151.097]	[-33.809, -33.786]	151	360	12
Sydney	5	SN-n200-a460-16	[151.078, 151.126]	[-33.805, -33.786]	200	460	16
Sydney		SN-n255-a592-20	[151.071, 151.118]	[-33.809, -33.785]	255	592	20
		SN-n302-a698-24	[151.071, 151.127]	[-33.810, -33.785]	302	698	24
		SN-n302-a698-30	[151.071, 151.127]	[-33.810, -33.785]	302	698	30

 $\label{thm:conformal} \textbf{TABLE III} \\ \textbf{Non-parametric statical results on small-scale instances}.$ 

Algorithms	Friedman test	Wilcoxon signed-rank test						
	Ranking	$R^+$	$R^-$	Exact P-value	Asymptotic P-value			
Gurobi	4.9615	-	-	-	-			
TAH-ALNSLS	4.3077	36.00	33.00	0.359425	0.000000			
1-ALNS	5.3462	39.00	40.00	0.634621	0.000000			
LNS	5.1538	34.00	35.00	1.309442	0.000000			
VNS	5.0385	30.50	30.50	2.000000	0.000000			
VND	5.3077	28.50	32.50	0.570099	0.000000			
RVND	5.3077	28.50	32.50	0.570099	0.000000			
VNS-SA	4.4615	40.00	39.00	0.634621	0.000000			
RVND-SA	5.1154	34.00	35.00	1.309442	0.000000			

 $\label{thm:constraint} \textbf{TABLE IV} \\ \textbf{Non-parametric statical results on large-scale instances}.$ 

Algorithms	Friedman test		Wilcoxon signed-rank test						
8	Ranking	$R^+$	$R^-$	Exact P-value	Asymptotic P-value				
TAH-ALNSLS	1.3088	-	-	-	-				
1-ALNS	3.3088	16.50	545.50	0.000005	0.000002				
LNS	5.2353	0.50	561.50	0.000001	0.000001				
VNS	5.7059	3.00	499.00	0.000002	0.000002				
VND	4.6765	0.50	561.50	0.000001	0.000001				
RVND	4.9706	11.50	550.50	0.000003	0.000002				
VNS-SA	5.9412	3.00	499.00	0.000002	0.000002				
RVND-SA	4.8529	3.00	499.00	0.000002	0.000002				

 $\label{table V} TABLE\ V$  The comparison results under different speeds of drones

TABLE VII
COMPARISON RESULTS UNDER DIFFERENT SPEED OF TRUCKS

		Objecti	ve Values	(h) at D	ifferent D	rone Speeds (m/s)
Instances	Algorithms	25	30	35	40	45
	TAH-ALNSLS	9.42	8.44	8.00	7.32	6.94
	1-ALNS	10.52	9.50	8.63	7.32	7.28
	LNS	9.66	8.66	7.99	7.43	6.98
	VNS	9.48	8.70	8.21	7.55	7.14
PH-n200-a592-16	VND	9.67	8.76	8.01	7.50	7.01
	RVND	9.64	8.65	8.00	7.45	6.97
	VNS-SA	9.68	8.87	8.64	8.04	7.54
	RVND-SA	9.61	8.81	8.11	7.78	7.30
	TAH-ALNSLS	10.01	9.25	8.30	7.89	7.26
	1-ALNS	11.95	10.80	9.91	9.19	8.35
	LNS	10.03	9.32	8.41	7.93	7.55
	VNS	10.87	10.05	9.11	8.61	8.06
PH-n250-a760-20	VND	10.20	9.26	8.31	7.89	7.46
	RVND	10.26	9.40	8.37	8.02	7.41
	VNS-SA	11.56	10.50	9.72	9.06	8.49
	RVND-SA	10.58	9.71	8.97	8.29	8.05
	TAH-ALNSLS	13.58	12.54	11.32	10.63	10.04
	1-ALNS	14.18	13.23	12.65	11.72	10.67
	LNS	13.81	13.27	11.73	11.62	10.68
	VNS	13.58	13.38	11.81	11.49	10.58
PH-n300-a916-24	VND	13.89	13.19	11.87	11.70	10.48
	RVND	13.82	13.32	11.99	11.50	10.72
	VNS-SA	13.93	12.97	11.91	11.57	10.73
	RVND-SA	13.68	13.42	12.85	12.02	11.58
	TAH-ALNSLS	14.73	13.56	12.24	11.42	10.24
	1-ALNS	15.63	15.48	12.30	12.09	10.50
	LNS	15.08	13.56	12.30	11.32	10.43
	VNS	16.26	15.08	14.22	13.16	12.48
PH-n300-a916-30	VND	15.18	13.67	12.30	11.39	10.61
	RVND	15.01	13.69	12.61	11.37	10.55
	VNS-SA	17.21	16.13	14.67	14.19	13.62
	RVND-SA	16.05	14.69	12.65	11.84	10.85

		Objecti	ve Value	(h) at Di	fferent Tru	ck Speed (m/s)
Instances	Algorithms	20	25	30	35	40
	TAH-ALNSLS	10.53	9.00	7.96	7.13	6.68
	1-ALNS	11.23	9.33	8.63	7.64	7.23
	LNS	10.64	9.08	8.03	7.23	6.73
	VNS	10.69	9.00	8.08	7.30	6.87
PH-n200-a592-16	VND	10.67	8.96	7.99	7.23	6.68
	RVND	10.55	9.06	7.98	7.26	6.70
	VNS-SA	11.40	10.04	8.90	7.94	7.12
	RVND-SA	11.07	9.22	8.04	7.58	6.99
	TAH-ALNSLS	10.99	9.22	8.34	7.59	6.87
	1-ALNS	12.11	10.05	9.02	8.98	7.50
	LNS	11.15	9.46	8.42	7.67	6.99
	VNS	12.27	10.33	8.99	8.12	7.55
PH-n250-a760-20	VND	11.09	9.31	8.31	7.52	7.00
	RVND	11.29	9.37	8.44	7.51	6.97
	VNS-SA	12.83	10.93	9.59	8.59	7.88
	RVND-SA	12.11	10.60	9.31	8.13	7.89
	TAH-ALNSLS	15.67	13.22	11.28	10.38	9.44
	1-ALNS	18.40	15.15	13.94	12.24	11.47
	LNS	16.43	13.66	11.89	10.75	10.44
	VNS	16.42	13.39	11.81	10.65	9.69
PH-n300-a916-24	VND	16.31	13.37	11.68	10.66	9.87
	RVND	16.44	13.53	11.69	10.67	9.74
	VNS-SA	16.47	13.30	12.17	10.66	9.73
	RVND-SA	16.10	14.24	12.63	11.93	10.59
	TAH-ALNSLS	16.51	13.85	12.19	11.21	10.54
	1-ALNS	17.87	14.23	13.18	11.78	10.15
	LNS	17.41	14.34	13.27	11.63	10.93
	VNS	18.83	15.78	13.83	12.53	11.52
PH-n300-a916-30	VND	16.86	13.91	12.22	11.25	10.58
	RVND	16.91	13.90	12.29	11.26	10.61
	VNS-SA	18.19	16.73	14.86	13.31	12.38
	RVND-SA	17.26	15.21	13.70	12.20	11.24

 $\label{thm:comparison} TABLE\ VI$  The comparison results under different number of drones

TABLE VIII
COMPARISON RESULTS UNDER DIFFERENT NUMBER OF TRUCKS

		Objecti	ve Value	(h) at Di	fferent Dro	one Number
Instances	Algorithms	2	3	4	5	6
	TAH-ALNSLS	8.76	7.89	7.88	7.80	7.80
	1-ALNS	9.07	8.42	8.57	8.46	8.57
	LNS	8.83	7.90	7.94	7.84	7.71
	VNS	8.96	8.18	8.00	7.85	8.11
PH-n200-a592-16	VND	8.84	7.99	7.91	7.81	7.64
	RVND	8.79	8.02	7.94	7.85	7.62
	VNS-SA	9.07	8.34	8.49	8.76	8.20
	RVND-SA	9.06	8.26	8.22	8.04	8.12
	TAH-ALNSLS	9.49	8.19	8.08	8.26	8.52
	1-ALNS	11.18	10.27	9.83	9.79	10.18
	LNS	9.63	8.50	8.30	8.74	8.73
	VNS	10.18	9.12	8.96	8.93	8.97
PH-n250-a760-20	VND	9.72	8.30	8.21	8.53	8.45
	RVND	9.72	8.20	8.28	8.61	8.76
	VNS-SA	9.74	9.57	9.75	9.40	9.95
	RVND-SA	10.40	9.13	9.28	9.11	9.28
	TAH-ALNSLS	12.71	11.25	11.30	11.30	11.39
	1-ALNS	13.44	12.23	12.19	12.16	12.17
	LNS	13.35	11.78	11.81	11.67	11.59
	VNS	13.20	11.83	11.98	11.82	11.56
PH-n300-a916-24	VND	13.46	11.84	11.68	11.62	11.47
	RVND	13.15	11.83	12.10	11.82	11.80
	VNS-SA	13.01	11.71	12.32	12.18	12.12
	RVND-SA	13.25	12.48	12.70	12.69	12.91
	TAH-ALNSLS	13.67	12.21	12.06	12.02	12.04
	1-ALNS	14.30	13.34	13.38	12.89	13.00
	LNS	14.09	12.25	12.20	12.18	12.28
	VNS	15.20	13.96	13.83	13.89	13.88
PH-n300-a916-30	VND	13.74	12.16	12.17	12.02	12.03
	RVND	13.77	12.49	12.32	12.18	12.11
	VNS-SA	14.98	14.15	14.16	14.21	13.91
	RVND-SA	13.67	13.19	13.00	12.83	12.84

		Objec	tive Valu	ue (h) at	Differen	t Truck Number
Instances	Algorithms	2	3	4	5	6
	TAH-ALNSLS	3.07	2.95	2.73	2.33	2.25
	1-ALNS	3.23	3.18	2.94	2.54	2.37
	LNS	3.23	3.19	2.91	2.56	2.68
	VNS	3.18	2.96	2.95	2.48	2.45
PH-n200-a592-16	VND	3.22	3.21	2.84	2.50	2.46
	RVND	3.22	3.20	2.94	2.70	2.56
	VNS-SA	3.20	3.13	2.94	2.36	2.30
	RVND-SA	3.23	3.13	2.89	2.70	2.39
	TAH-ALNSLS	3.92	3.10	2.95	2.79	2.47
	1-ALNS	4.05	3.77	3.55	2.79	2.50
	LNS	4.44	3.53	3.47	3.17	3.25
	VNS	4.43	3.23	3.21	2.88	2.28
PH-n250-a760-20	VND	4.48	3.56	3.49	3.19	3.06
	RVND	4.40	3.45	3.64	3.04	3.38
	VNS-SA	4.31	3.42	3.05	2.85	2.78
	RVND-SA	4.19	3.21	3.38	2.84	3.13
	TAH-ALNSLS	5.07	3.65	3.45	3.26	3.13
	1-ALNS	5.90	4.82	4.07	3.61	3.47
	LNS	6.01	5.13	4.68	4.18	3.69
	VNS	5.55	4.64	3.67	3.48	3.19
PH-n300-a916-24	VND	6.06	5.18	4.77	4.45	3.78
	RVND	6.10	4.81	4.22	4.26	3.73
	VNS-SA	5.46	4.49	4.19	3.97	3.37
	RVND-SA	5.69	4.88	4.62	3.50	3.55
	TAH-ALNSLS	6.23	4.70	4.39	3.92	3.80
	1-ALNS	7.54	4.71	4.42	4.34	4.17
	LNS	8.04	4.62	4.65	4.53	4.36
	VNS	6.26	4.52	4.27	4.26	3.95
PH-n300-a916-30	VND	7.65	4.69	4.72	4.63	4.28
	RVND	7.93	4.60	4.69	4.48	4.42
	VNS-SA	6.70	4.59	4.42	4.39	4.17
	RVND-SA	7.58	4.72	4.73	4.57	4.28