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Unmanned Aerial Vehicle Cargo Delivery Assignment via Time-Varying Constriction Pigeon-Inspired Optimization with Memory Retrospection

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Abstract—**Unmanned aerial vehicles (UAVs) collaboration is a key technology to UAV cargo delivery in the near future. In this paper, distribution requirement parameters are identified to establish a multi-objective cargo delivery assignment model where a large number of tasks are allocated. To optimize high-dimensional multi-UAV task assignment problem, a time-varying constriction pigeon-inspired optimization with memory retrospection (TCMR-PIO) is proposed. A memory retrospection mechanism is developed to increase the multiplicity of pigeon flock and avoid premature convergence. Meanwhile, a time-varying constraint factor is utilized to provide the improved algorithm with higher accuracy and stability. While maintaining the advantage of high convergence speed, an optimized task assignment scheme can be obtained. Comparative simulation experiments with particle swarm optimization (PSO), pigeon-inspired optimization (PIO), quantum pigeon-inspired optimization (QPIO), adaptive weighted pigeon-inspired optimization (AWPIO) and nonlinear dynamic adaptive inertial weight particle swarm optimization (PSO-DAIW) are carried out, and the performance of the TCMR-PIO algorithm validates its effectiveness and superiority on cargo delivery assignment.**

I. Introduction

Unmanned aerial vehicles (UAVs) have significant strengths and broad market prospects in urban low-altitude transportation logistics based on the characteristics of not being limited by ground transportation, strong flexibility, and low cost. Contactless delivery, which means automatic distribution of goods without human face-to-face contact, can also be achieved in UAV cargo delivery. UAVs are predicted to be a main stream in low-altitude air transportation. The market of goods delivery is also in need of unmanned aerial mobility in the near future [1].

Cargo delivery assignment is to assign a group of tasks to multiple UAVs considering the environmental elements and distribution requirements. The optimization of dispatching efficiency and resource consumption based on the completion of tasks is regarded as one of the main challenges in multi-objective task allocation problem in contactless cargo delivery [2]. In order to achieve the subsequent task planning of cargo delivery in the next stage, such as path planning, assigning tasks in advance is a significant procedure in UAV decision making. Requirements of flight safety can be satisfied as well.

Applications of various algorithms in the field of UAV cargo delivery have been proved feasible and effective. Bio-inspired intelligent computing algorithms such as ant colony optimization (ACO), genetic algorithms (GAs) and particle swarm algorithms (PSO) are applied in vehicle routing problem in UAV delivery [3]. An auction algorithm together a quantum PSO is utilized in task assignment and path planning in "the last mile" of cargo distribution [4]. A multi-objective uncontrolled solving ACO algorithm is developed to support the scheduling of delivery [5]. For multi-objective task assignment problem, GAs combined with ACO plays an important role in obtaining task allocation solutions [6-9]. The potential of the PSO algorithm is also thoroughly exploited in this topic [10-12].

However, the algorithms for UAV cargo delivery assignment and task allocation are mostly conducted on occasions where the scale of missions and UAVs is small, usually less than 20 objectives. As to higher-dimensional cases, the condition and constraints would be more complicated. As a global search algorithm, GAs is dominant in obtaining the globally optimal solution, but its deficiency of low convergence speed is exposed in higher-dimensional problems. ACO is similar to GAs in this point. For the PSO, the characteristic of fewer parameters makes it more effective in practical application. However, it has relatively low speed in global convergence, especially in the late stage of evolution.

Pigeon-inspired optimization (PIO) is a new and innovative bio-inspired intelligent computing algorithm originated from the pigeon flock navigation ability in homing, which has been successfully applied to dealing with the problems such as path planning [13], image restoration [14], target defense [15], autonomous control [16] and so on. Although with the advantages of high convergence speed, strong scalability, and interactive information sharing among different individuals, it is difficult for the original PIO to overcome its deficiencies of obtaining sub-optimal solutions and generally limited by premature convergence.

In this paper, a time-varying constriction pigeon-inspired optimization with memory retrospection (TCMR-PIO) is built

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to explore better solutions to the task allocation problem in UAV cargo delivery. The improvement of PIO model consists of two steps: memory retrospection and time-varying constriction. On the one hand, the capability of searching globally optimal solution is enhanced by adding the memory retrospection mechanism. On the other hand, the accuracy and the stability have been greatly enhanced by balancing the global optimal search memory and secondary search memory with the time-varying constriction factor.

II. Model of Cargo Delivery Assignment and Fitness Function

A. Problem Description and Model

Assume that there is a fixed region where D cargoes are pending to be dispatched. The total flight range, maximum waiting time, power consumption, average waiting time of each UAV, maximum cargo capacity and other factors are taken into consideration. n UAVs scattered in k takeoff points are assigned to complete the delivery of the D locations in order. Each mission target is denoted as a three-dimensional spatial coordinate (x_i, y_i, z_i). Additionally, for flight safety, the aircrafts take off and cruise at a fixed height H over the buildings, then descend to the corresponding height z_i of each mission target after reaching the destination (x_i, y_i). Then, UAVs return to the fixed flight altitude H and reach next task target in planned sequence after completing the current delivery. UAV contactless cargo delivery is achieved through the process above.

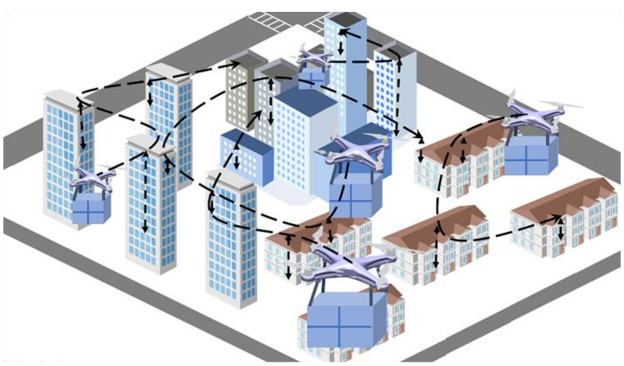

Figure 1. UAV cargo delivery system

B. Cost Functions

Resource consumption and cruising distance are measured with f_1. The flight range of each aircraft while completing the dispatching mission in order and flying back to the airport is L_i.

$$f_1 = \sum_{i=1}^{n} L_i \tag{1}$$

To obtain a relatively short delivery time, a mission target average waiting time function is built to optimize the voyage time of each drone and elevate the delivery efficiency, where L_i is the current UAV flight range and v_i is the UAV cruising speed.

$$t_i = \frac{L_i}{v_i} \tag{2}$$

$$f_2 = \frac{\sum_{i=1}^{n} t_i}{n} \tag{3}$$

The UAVs are expected to conduct cargo delivery within $T_{w\max}$. Once the expected time is exceeded during the dispatching process, extra compensation is provided from the relevant logistic platform for customers, and the overtime payout can be expressed as

$$count = \begin{cases} 0, & t \le T_{w\max} \\ payout, & t > T_{w\max} \end{cases} \tag{4}$$

$$f_3 = \sum_{i=1}^{n} count \tag{5}$$

C. Constraint Functions

The constraint functions employed in this work are established in the form of a penalty function [17]. The weight value of the relevant term of the fitness function is indicated by the penalty factor, which can be set to a positive number that is sufficiently large to ensure that the desired constraint effect is achieved.

The battery capacity is limited, and the maximum power consumption value cannot be exceeded during the whole dispatch process, or the landing is hard to be executed.

$$Battery_i \le Battery_{i,\max} \tag{6}$$

$$c_1 = \begin{cases} 0, & Battery_i \le Battery_{i,\max} \\ 1, & Battery_i > Battery_{i,\max} \end{cases} \tag{7}$$

where $Battery_i$ is the accumulated battery consumption of each UAV, and the maximum power consumption of each drone is $Battery_{i,\max}$.

The number of supplies carried during one mission is controlled within a fixed value.

$$Load_i \le Load_{i,\max} \tag{8}$$

$$c_2 = \begin{cases} 0, & Load_i \le Load_{i,\max} \\ 1, & Load_i > Load_{i,\max} \end{cases} \tag{9}$$

where $Load_i$ represents the amounts of supplies carried by each aircraft, $Load_{i,\max}$ is the maximum quantity of supplies carried by one UAV.

D. Fitness Functions

The fitness function can be expressed as

$$F = w_1 \cdot f_1 + w_2 \cdot f_2 + w_3 \cdot f_3 + w_4 \cdot \sum_{p=1}^{P} c_p \tag{10}$$

where F denotes the value of the fitness function, f_1, f_2, f_3 are the cost functions calculated by (1) to (5), w_1, w_2 and w_3 are the weight coefficients, c_p represents the cumulative number of penalty terms [17], P is the constraint amount, and w_4 is the corresponding penalty factor, which can be set to a positive number that is large enough.

E. Encoding and Decoding Methods

Since the basic formula of the TCMR-PIO is designed for continuous functions, a continuous encoding method is applied. Each UAV takes a number from 1 to n [17]. Each of the D destinations to be dispatched is represented by a real number in the range of $1 \leq x_j < n + 1$. The UAV serial number that completes the dispatch at this target mission location is decided by integer part, and the mission completion order is determined by the fractional part. The case of target number D=9 and UAVs n=4 is illustrated in Fig. 2.

Index X_i is set for each target, and each index generates a random parameter in the range of (1, 5). After sorting, the order of task execution is determined, such as the index X_6 and X_8 in the figure, whose corresponding parameters are 2.45 and 2.01 respectively, and the integer parts are 2. Therefore, task D_8 is executed first by aircraft whose serial number is 2, then task D_6 is performed in sequence.

assignment	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	···
index	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	···
parameter	2.58	3.97	4.32	1.56	1.23	2.45	3.66	2.01	3.69	···

sort

index	X_5	X_4	X_8	X_6	X_1	X_7	X_9	X_2	X_3	···
parameter	1.23	1.56	2.01	2.45	2.58	3.66	3.69	3.97	4.32	···
UAV	U1		U2			U3			U4	···
sequence	$D_5 \to D_4$		$D_8 \to D_6 \to D_1$			$D_7 \to D_9 \to D_2$			D_3	···

Figure 2. Encoding and decoding process of task assignment

III. TCMR-PIO: An Improved Pigeon-Inspired Optimization Model

In order to increase the success rate of UAV cargo delivery assignment as well as lower the overall resource consumption. A memory backtracking mechanism is proposed to increase the diversity of pigeon population, which is conductive for pigeons to escape from the local optimal destination. The accuracy of algorithm is improved by time-varying constriction factor as well.

A. Basic Pigeon-Inspired Optimization

Inspired from the pigeon flock's ability to perceive the earth's magnetic field and the sun's altitude, pigeon-inspired optimization [13] is put forward in 2014. The flight direction of pigeons is guided towards to destination. In the next stage of the geomagnetic operator, when the pigeons are approaching the search target, the guidance from geomagnetic and the sun's altitude for the pigeon flock is gradually weakened. At the same time, the information exchange in the flock will occupy the dominant position. The summarized formula is as follows

$$V_i(t) = V_i(t-1) \cdot e^{-Rt} + rand \cdot \left(X_{gbest} - X_i(t-1)\right) \tag{11}$$

$$X_i(t) = X_i(t-1) + V_i(t) \tag{12}$$

where R is the map and compass factors, $rand$ is a random number taking values in the range of (0,1), t is the value of newest iterations, and X_{gbest} denotes to the optimal position in the memory of all members in the flock after t rounds of search. The evolution lasts for T_1 iterations.

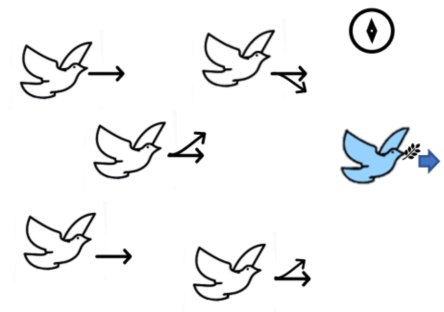

Figure 3. Map and compass operator mechanism of PIO

In the later stage of searching, the pigeon flock is led by individuals with deeper memory of the landmarks to locate to the optimal destination. After one iteration of evolution, few marginalized pigeons that are less acquainted with the landmark leave the flock. The updating process will last T_2 rounds of iterations until the whole group of pigeons find the best destination.

$$N_p = \frac{N_p(t-1)}{2} \tag{13}$$

$$X_c(t) = \frac{\sum X_i \cdot f\left(X_i(t)\right)}{N_p \cdot \sum f\left(X_i(t)\right)} \tag{14}$$

$$X_i(t) = X_i(t-1) + rand \cdot \left(X_c(t) - X_i(t-1)\right) \tag{15}$$

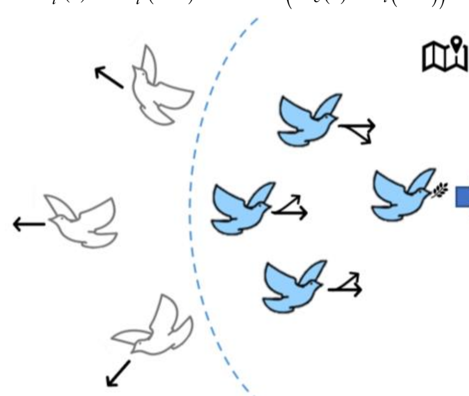

Figure 4. Landmark operator mechanism of PIO

B. Memory Retrospect Mechanism

In the first stage of searching, the globally optimal position of the past experience in pigeons' brain is recognized as the guiding direction for the next search to locate to the optimal destination in the searching range quickly. A memory retrospection mechanism of the pigeons is designed. The optimal solution of each round of search is stored in the pigeon brain. The median solution of the preoccupied ε_m% optimal solutions will be regarded as the secondary search memory, which will decide the search direction together with the current global optimal search memory in next iteration. In this way, with the other feasible solutions as guidance, the flock's ability to skip the local optimal solution and search for better destination is obtained. The parameter of the secondary search memory can be expressed as

$$N_t = \begin{cases} t, & t \leq \varepsilon_m \cdot T \\ \varepsilon_m \cdot T, & t > \varepsilon_m \cdot T \end{cases} \tag{16}$$

$$m = \frac{N_t}{2} \tag{17}$$

The map and compass operator function can be updated as follows

$$\begin{aligned} V_i(t) &= V_i(t-1)\cdot e^{-Rt} + \varepsilon_1 \cdot rand \cdot \left(X_{gbest} - X_i(t-1)\right) \\ &+\varepsilon_2 \cdot \left(X_m - X_i(t-1)\right) \end{aligned} \tag{18}$$

$$X_i(t) = X_i(t-1) + V_i(t) \tag{19}$$

where ε_m is the memory coefficient of the flock, ε_1 and ε_2 are the activation coefficients for the global-best search memory and the secondary search memory, and N_t is the secondary search memory space.

C. Time-Varying Constriction

Time-varying constriction factor can balance the contradiction between the two models in particle swarm optimization [18]. The influence of the globally optimal search memory and secondary search memory of the pigeon flock on the flight direction is balanced by the constriction, improving the global search ability further while enhancing the accuracy of the algorithm at the same time. The equations are as follows

$$C_1 = C_{1\min} + (C_{1\max} - C_{1\min})\frac{t}{T_1} \tag{20}$$

$$C_2 = C_{2\min} + (C_{2\max} - C_{2\min})\frac{t}{T_1} \tag{21}$$

$$\psi = C_1 \cdot r_1 + C_2 \cdot r_2 \tag{22}$$

$$\chi = \frac{2}{\left|2-\psi-\sqrt{\psi^2-4\psi}\right|} \tag{23}$$

where r_1 and r_2 take random numbers in the range of (0,1) respectively, $C_{1\max}$ and $C_{1\min}$ are the maximum and minimum time-varying activation coefficient of the global optimal search memory respectively, $C_{2\max}$ and $C_{2\min}$ are the maximum and minimum time-varying activation coefficient of the secondary search memory as well, T_1 is iterations of map and compass operator, Coefficient χ is the time-varying constriction factor to balance the effects of two kinds of guidance calculated according to (23).

The improved map and compass operator update functions can be expressed as follows

$$\begin{aligned} V_i(t) &= \chi \cdot \left[V_i(t-1)\cdot e^{-Rt} + C_1 \cdot rand \cdot \left(X_{gbest} - X_i(t-1)\right) \right. \\ &\left. +C_2 \cdot \left(X_m - X_i(t-1)\right)\right] \end{aligned} \tag{24}$$

$$X_i(t) = X_i(t-1) + V_i(t) \tag{25}$$

IV. Procedure of UAV Cargo Delivery Assignment via TCMR-PIO

The UAV cargo delivery assignment approach optimized by our proposed TCMR-PIO algorithm is demonstrated in following steps:

Step 1: Initialize the values of control variables in cargo delivery assignment model in section 2.

Step 2: Input the parameters of our TCMR-PIO algorithm, and generate the original pigeon flock.

Step 3: Update the location and velocity of pigeons according to (24)-(25), and calculate fitness values with (1)-(10).

Step 4: Store optimal solution of each iteration of pigeon flock, and update secondary search memory. Check the iterations and return to **Step 1** if $t < T_1$.

Step 5: Update the pigeon flock, and search for center pigeon together with position of each pigeon according to (13)-(15).

Step 6: Select the optimal UAV cargo delivery assignment solution globally and individually. Check the iterations and return to **Step 5** if $t < T_2$.

Step 7: Output globally optimal result as UAV cargo delivery assignment approach.

V. Simulation Results

In order to test the application effect of the proposed TCMR-PIO algorithm for UAV cargo delivery assignment, a series of comparative simulation experiments are conducted in MatlabR2020a simulation environment.

In the simulation, 5 different locations of takeoff points are available for UAVs with their center coordinates of (150, 150, 0), (200, 300, 0), (350, 200, 0), (275, 400, 0), (400, 350, 0). The cruising height is set to 55m. 31 target locations are randomly gained at a certain distance from each other in three dimensions. The performance of TCMR-PIO is compared to results from PSO, PSO-DAIW [19], PIO, AWPIO [20], QPIO [21].

Coordinates of targets are listed in Table I.

TABLE I. COORDINATES OF DISPATCH TARGET LOCATIONS

NO.	Central Coordinate	NO.	Central Coordinate	NO.	Central Coordinate
1	(130, 231, 10)	2	(363, 131, 3)	3	(417, 224, 7)
4	(371, 139, 9)	5	(332, 155, 45)	6	(348, 153, 50)
7	(323, 122, 36)	8	(419, 104, 17)	9	(431, 79, 2)
10	(438, 57, 25)	11	(300, 197, 37)	12	(256, 175, 22)
13	(278, 149, 17)	14	(238, 167, 47)	15	(133, 65, 7)
16	(371, 167, 9)	17	(391, 219, 46)	18	(406, 237, 28)
19	(378, 221, 50)	20	(367, 257, 25)	21	(402, 283, 47)
22	(426, 293, 39)	23	(342, 190, 4)	24	(350, 376, 47)
25	(339, 264, 36)	26	(349, 321, 28)	27	(295, 324, 12)
28	(314, 350, 13)	29	(255, 235, 33)	30	(278, 426, 21)
31	(230, 275, 16)				

For the TCMR-PIO, $C_{1\max} = C_{2\max} = 4.5$, $C_{1\min} = C_{2\min} = 1.5$, $R = 0.2$. Parameters in PSO, PSO-DAIW algorithm are set to values [22], where $c_1 = c_2 = 2.05$, $w = 0.8$, $w_{\max} = 0.9$, $w_{\min} = 0.4$. The parameters of PIO, AWPIO, and QPIO algorithms are set to reasonable values while following the principle of comparison to control variables, where $R = 0.2$, $w_{\max} = 4.5$, $w_{\min} = 1.5$, $P_0 = 0.05\pi$.

The simulation on each type of algorithm is repeated 20 times under the same condition, and the initial population is set to the same.

A. Comparative Simulation Results

The variation of optimal values with the number of iterations for the six algorithms is illustrated in Fig. 5, where the results that succeed in completing task assignment are taken into consideration. It is obvious that the convergence speed of PIO, TCMR-PIO, AWPIO algorithms is much higher than QPIO. The basic PSO and PSO-DAIW have little difference in the initial speed of seeking the optimal value compared to TCMR-PIO, but are left behind in the late stage of evolution.

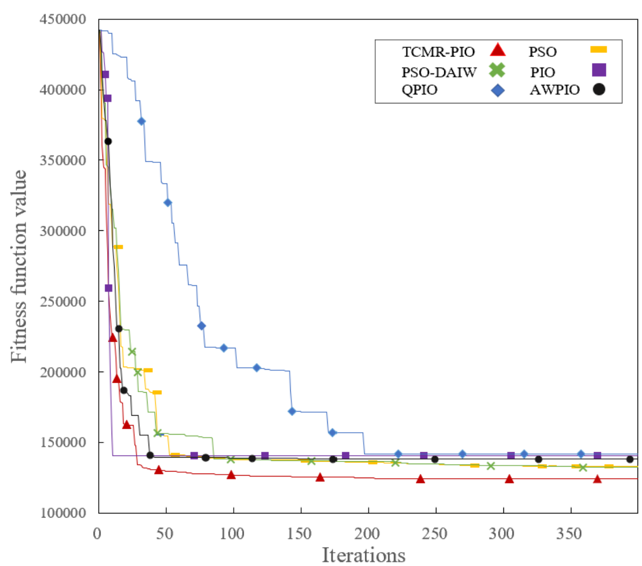

Figure 5. Comparison of algorithm convergence curves

From Fig. 5, it can be concluded that TCMR-PIO has superiority over other algorithms on the aspects of convergence speed and fitness function value. For other algorithms such as the PSO and PSO-DAIW, it can be observed from the figure that the curves are still converging slowly when the number of iterations meets 350. The TCMR-PIO converges quickly when the number of pigeon generations reaches 50, stabilizing when the number of iterations reaches 200. The lowest final fitness function value among the six algorithms is also presented in the TCMR-PIO.

The average value of the optimal solution, the optimal value, the standard deviation, and the average computing time are given in Table II.

TABLE II. STATISTICAL DATA

Algorithm	Average	Optimal	Computing Time	SD
PIO	140772.14	136050.84	25.58s	2887.18
TCMR-PIO	**124056.46**	**117533.81**	**17.25s**	**2463.04**
AWPIO	138454.70	132755.04	23.72s	4276.05
QPIO	141800.71	123713.08	270.77s	7926.61
PSO	132729.37	129649.02	18.00s	2594.53
PSO-DAIW	132583.72	129722.23	16.44s	2466.60

From the aspect of success rate of the task assignment scheme, the success rate in the basic PIO algorithm is 28.99%, in QPIO is 86.97%, while the other algorithms can produce task assignment schemes with the constraints at the percentage of 100%.

On the one hand, it is obvious in Fig. 6 that our proposed TCMR-PIO algorithm can contribute to a sharp reduction in the mean and optimal values of 11.87% and 13.61% compared to the PIO algorithm, 10.40% and 11.47% compared to the AWPIO algorithm, 12.51% and 5.00% compared to QPIO, respectively. Compared to both of the PSO and PSO-DAIW algorithm, the average fitness values see a decreased by nearly 7.00%, and the optimal value sees a decline of around 10.00%.

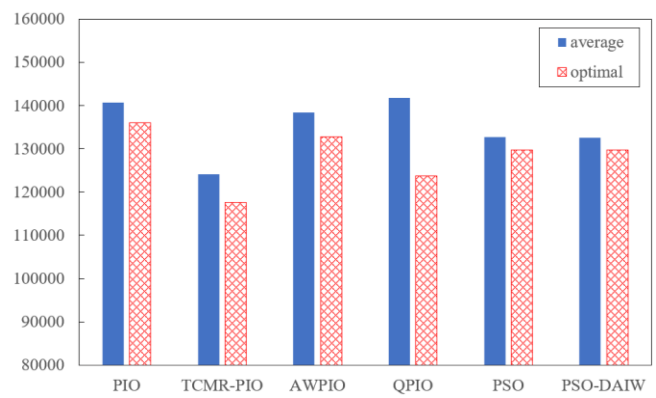

Figure 6. Comparison of average and optimal values

On the other hand, from the statistical analysis in Table II, it is obvious that TCMR-PIO presents a better performance on the aspects of computation time, algorithm accuracy and stability. Computation time of TCMR-PIO is reduced by 32.56% and stability is improved by 14.69% in comparison to the PIO algorithm. The computing time and stability sees a decline by 27.28% and 42.40% relative to AWPIO algorithm, respectively. Compared with QPIO, the computation time and the stability can be reduced by 93.63% and 68.93% respectively. Compared with PSO-DAIW algorithm, the TCMR-PIO algorithm performs slightly inferior in aspects of computation time, but it shows the best overall performance among all the other comparative algorithms.

B. Task Assignment Scheme

The UAV task assignment scheme given by TCMR-PIO is demonstrated in Fig. 7, where the locations of 5 takeoff points are represented by red solid spots and 31 targets are shown in blue circle, distance between takeoff point to the first target destination is denoted as red arrow, the sequence of task completion is indicated as arrows in different colors.

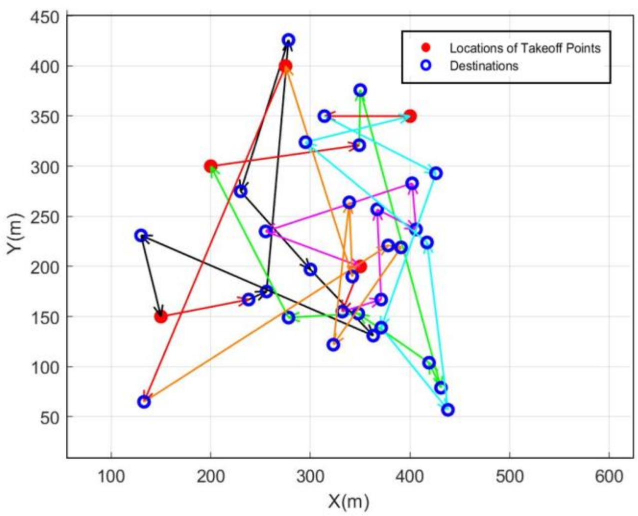

Figure 7. Task assignment scheme from TCMR-PIO

VI. CONCLUSION

In this paper, a mathematical model of multi-UAV cooperative cargo delivery is established. An improved TCMR-PIO algorithm is developed, and a novel memory retrospection mechanism and reliable time-varying constriction factor is adopted in the improved PIO model. The comparative simulation results verified that the performance of the proposed TCMR-PIO algorithm is much better in searching optimal solution and convergence speed for UAV cargo delivery.

REFERENCES

[1] A. P. Cohen, S. A. Shaheen and E. M. Farrar, "Urban air mobility: History, ecosystem, market potential, and challenges," *IEEE Trans. Intelligent Transportation Systems*, vol. 22, no. 9, pp. 6074-6087, Sept. 2021.

[2] X. G. Qi, B. Li, Y. S. Fan, "A survey of mission planning on UAVs systems based on multiple constraints," *CAAI Trans. Intelligent Systems*, vol. 15, no. 2, pp. 204-217, 2020.

[3] J. Mańdziuk, "New shades of the vehicle routing problem: Emerging problem formulations and computational intelligence solution Methods," *IEEE Trans. Emerging Topics in Computational Intelligence*, vol. 3, no. 3, pp. 230-244, June 2019.

[4] X. H. Guo, M. J. Ji, D. S. Wen, X. Zhang, S. Tian, "Task assignment and path planning for distributed multiple UAVs in the "last mile"," *System Engineering Theory and Practice*, vol. 41, no. 4, pp. 946-961, April 2021.

[5] Liu, C., Qian, Y. "Optimal allocation of cargo delivery in emergency events using multi-objective constraint for vehicular networks," *Wireless Networks,* vol. 28, no. 8, pp. 3715-3727, Nov.2022.

[6] I. M. Ali, K. M. Sallam, N. Moustafa, R. Chakraborty, M. Ryan and K. -K. R. Choo, "An automated task scheduling model using non-dominated sorting genetic algorithm II for fog-cloud systems," *IEEE Trans. Cloud Computing*, vol. 10, no. 4, pp. 2294-2308, Oct. 2022.

[7] D. Pradhan, S. Wang, A. Shaukat, T. Yue, L. Marius, "CBGA-ES+: A cluster-based genetic algorithm with non-dominated elitist selection for supporting multi-objective test optimization," *IEEE Trans. Software Engineering*, vol. 47, no. 1, pp. 86-107, Jan. 2021.

[8] W. -N. Chen and J. Zhang, "Ant colony optimization for software project scheduling and staffing with an event-based scheduler," *IEEE Trans. Software Engineering*, vol. 39, no. 1, pp. 1-17, Jan. 2013.

[9] X. Hu, H. Ma, Q. Ye and H. Luo, "Hierarchical method of task assignment for multiple cooperating UAV teams," *Journal of Systems Engineering and Electronics*, vol. 26, no. 5, pp. 1000-1009, Oct. 2015.

[10] S. -Y. Ho, H. -S. Lin, W. -H. Liauh and S. -J. Ho, "OPSO: Orthogonal Particle Swarm Optimization and Its Application to Task Assignment Problems," *IEEE Trans. Systems, Man, and Cybernetics - Part A: Systems and Humans*, vol. 38, no. 2, pp. 288-298, March 2008.

[11] J. Wu, C. Song, J. Ma, J. Wu and G. Han, "Reinforcement learning and particle swarm optimization supporting real-time rescue assignments for multiple autonomous underwater vehicles,"*IEEE Trans. Intelligent Transportation Systems*, vol. 23, no. 7, pp. 6807-6820, July 2022.

[12] H. Duan, P. Li and Y. Yu, "A predator-prey particle swarm optimization approach to multiple UCAV air combat modeled by dynamic game theory," *IEEE/CAA Journal of Automatica Sinica*, vol. 2, no. 1, pp. 11-18, Jan. 2015.

[13] H. B. Duan, P. X. Qiao, "Pigeon-inspired optimization: A new swarm intelligence optimizer for air robot path planning," *IEEE Trans. Cybernetics*, vol. 7, no. 1, pp. 2-21, March 2014.

[14] H. B. Duan, X. H. Wang, "Echo state networks with orthogonal pigeon-inspired optimization for image restoration," *IEEE Trans. Neural Network Learning System*, vol. 27, no. 11, pp. 2413-2425, Nov. 2016.

[15] H. B. Duan, H. B. Tong, J. C. Liu, "Coordinated target defense for multi-UAVs based on exponentially averaged momentum pigeon-inspired optimization," *Journal of Beijing University of Aeronautics and Astronautics*, vol. 48, no. 9, pp. 1624-1629, Sept. 2022.

[16] Y. Wan, H. B. Duan, "Multi-UAV obstacle avoidance control via multi-objective social learning pigeon-inspired optimization," *Journal of Zhejiang University (English Version) (Part C: Computer and Electronics)*, vol. 21, no. 5, pp. 740-748, May 2020.

[17] X. Y. Zhang, S. Xia, T. Zhang, "Adaptive genetic learning particle swarm optimization based cooperative task allocation for multi-UAVs," *Control and Decision*, doi.org/10.13195/j.kzyjc.2022.0240.

[18] M. Clerc, J. Kennedy, "The particle swarm – explosion, stability, and convergence in a multidimensional complex space," *IEEE Trans. Evolutionary Computation*, vol. 6, no. 1, pp. 58-73, February 2002.

[19] S. L. Wang, G. Y. Liu, "A nonlinear dynamic adaptive inertial weight particle swarm optimization," *Computer Simulation*, vol. 38, no. 4, pp. 249-253, 451, April 2021.

[20] N. Lin, S. M. Huang, C. Q. Gong, "UAV path planning based on adaptive weighted pigeon-inspired optimization algorithm" *Computer Simulation*, vol. 35, no. 1, pp. 38-42, 125, Jan. 2018.

[21] H. Gao, G. H. Xu, Z. R. Wang, "An improved quantum evolutionary algorithm and its application to a real distribution routing problem," *Control Theory and Applications*, vol. 24, no. 6, pp. 969-972, Dec. 2007.

[22] A. Samane, J. Shahram, F. Reza, N. Mahdi, "Performance-aware placement and chaining scheme for virtualized network functions: A particle swarm optimization approach," *Journal of Supercomputing*, vol. 77, no. 11, pp. 12209-12229, Nov. 2021.