Synergistic Path Planning of Multi-UAVs for Air Pollution Detection of Ships in Ports

Abstract: The phenomena of the COVID-19 outbreak and the Arctic Iceberg melting over the past two years make us reconsider the impact our way of life has on the environment and the responsibility of business toward minimizing and potentially eliminating emissions. Increasing ship traffic in ports leads to the growing emission of air pollutants, which influences the air quality and public health in the surrounding areas. The International Maritime Organization (IMO) has adopted relevant regulations (e.g., Annex VI of IMO's pollution prevention treaty (MARPOL) and mandatory energy-efficiency measures) to address ship emissions. To ensure the effective implementation of such regulations and measures, air emission detection and monitoring has become crucial. In this paper, a dynamic multitarget path planning model is developed to realize multi-UAVs (Unmanned Aerial Vehicles) performing synergistic detection of ship emissions in ports. A path planning algorithm under a dynamic environment is developed to establish the model. This algorithm incorporates a Tabu table into particle swarm optimization (PSO) to improve its optimization ability, and it obtains the initial detection route of each UAV based on a "minimum ring" method. This paper describes a multi-UAVs synergistic algorithm to formulate the path reprogramming time in a dynamic environment by judging and cutting the "minimum ring". This finding proves the improved efficiency of air pollution detection by UAVs. It provides useful insights for maritime and port authorities to detect ship emissions in practice and to ensure ship emission reduction for better air quality in the postpandemic era.

Keywords: UAVs, Ship emissions, Air pollution, Path planning, Dynamic multiobjective, PSO

1. Introduction

The phenomena of the COVID-19 outbreak and Arctic Iceberg melting over the past two years make us reconsider the impact our way of life has on the environment and the responsibility of business toward minimizing and potentially eliminating emissions. Over 90% of world trade is carried by sea (UN, 2019). With increasing ship traffic in ports, the environmental pollution from ships is on the top agenda of the international maritime society. Shipping contributes to the third largest air pollution after motor vehicles and industrial production (Liang, 2016). Exhaust gas from shipping activities is composed of carbon dioxide (CO2), nitrogen oxides (NOx), and sulfur oxides (SOx), among other components (see e.g., UNCTAD, 2017; Zheng et al., 2017). According to the International Maritime Organization (IMO), shipping operations account for almost 10–15% of anthropogenic SOx emissions around the world, with most of these emissions coming from densely populated coastal regions (IMO, 2018).

High shipping emissions result in strong motivation for local governments and the IMO to adopt a variety of regulations to ameliorate the polluted environment. In 2009, the International Maritime Organization (IMO) revised and implemented the International Convention for the prevention of pollution from ships (MARPOL) on the basis of the International Convention for the prevention of marine oil pollution (IMO, 2009). In 2011, IMO adopted the amendment to Annex VI of MARPOL Convention. According to the requirements of the resolution, the emission control zones of the Baltic Sea, the North Sea, the North American Sea and the Caribbean Sea have implemented the standard of sulfur content of ship fuel to not exceed 0.1% since January 1, 2014 (IMO, 2011). In 2016, the IMO MEPC announced the establishment of NOx emission control areas in the Baltic Sea and the North Sea, which will come into force on January 1, 2021 (International ship network, 2016). The IMO MEPC also decided to implement the global sulfur limitation in 2020, which requires all ships that sail outside the sulfur emission control areas to use fuel with a sulfur quantity that does not exceed 0.5% (Sindh marine, 2016). In China, during berthing (except for after berthing and one hour before departure), vessels shall use fuel oil with sulfur content that does not exceed 0.5% m/M (Ministry of transport of the people's Republic of China, 2015). In 2020, the Maritime Safety Administration, the Ministry of Communications of China, announced the formal implementation of the Implementation Plan for global Marine Fuel Sulphur Restriction 2020 and the Guidelines for the Supervision and Management of Air Pollutant Emissions from Ships. The requirements for ship exhaust emission limitations are as follows: The sulfur content of Marine fuel used by all types of Marine vessels in inland river discharge control areas shall not be greater than 0.1% m/m. The sulfur content of Marine fuel used by all types of sea-going and river-sea direct vessels in coastal air pollutant discharge control zones and international navigation vessels in nondischarge control zones shall be no more than 0.5% m/m (Soarabolity, 2020).

The expansion of the detection range and the improvement of the detection standards pose more severe imitations; however, since using low-sulfur fuels leads to high operation costs, many shipowners take the risk of not complying with the regulations. Such noncompliance ratios even reach up to 12.3% according to historical cases (OECD, 2018). All of the above are a challenge to the detection technology.

UAVs have the characteristics of low cost, fast flight speed and portable mission load, which makes them have unique advantages in performing complex tasks. With the rapid development of UAV technology, its flight speed, stability and wind resistance level have been greatly improved. At present, UAVs have played an important role in maritime search and rescue, such as sea patrol, channel mapping and other aspects (Zhu, 2020; Zhang, 2020; Jing et al., 2017). Over the past two years, UAVs have been attempted to detect the air pollution of ships. For instance, on April 23, 2020, Yangzhou MSA used Dajiang M210 UAV (rotor UAV, with a maximum speed of 82.8 km/h) equipped with sniffers to monitor the exhaust gas of dozens of ships through the supporting software enabling real-time visualization analysis. On May 20, 2020, Dajiang M210 UAV was equipped with a sniffer to measure the ship exhaust gas around the perimeter zone of Han River Maritime Department of Yangzhou maritime administration (Soarabolity, 2020). However, the application of UAVs in ship air pollution detection is still in its infancy. There are still many problems that must be studied and solved, such as the paths of UAVs detect planning, UAV air traffic control, and so on. In this paper, we propose new path planning model and algorithm to optimize the use of multiple UAVs to detect the air pollution of ships in real time.

The core of the decision is to assign each UAV a sequence of detection tasks with time schedules that regard the characteristics of ship emission detections by multi-UAVs, Decisions involved must be made by considering the following aspects: the number of ships for detection can be very large in certain time periods, and the positions and quantity of the ships to be detected in the detection area are dynamic; assigning multiple detection tasks for each operated tour to increase the utilization of the UAV fleet; the length of time required to detect each ship is dynamic; multiple-UAVs are used for synergism detection; and the flight time of the UAVs is limited because of their limited battery capacity.

Synergism detection of ship air pollution by multiple UAVs is attributed to a special traveling salesman problem (TSP). It is a dynamic multiperson and multiobjective traveling salesman problem Called the dynamic traveling salesman problem (DTSP), which is known to be an NP-hard problem (Michael R, 1979). Although there are many effective models and algorithms for solving dynamic multi-person multiobjective TSP problems and the related problems also, most of them cannot be directly applied to tackle a generalized setting of multi-UAVs with synergistic detection of dynamic ships' air emissions (Strąk, 2019).

The contribution of this study can be summarized as follows. First, this paper provides a new solution for path planning that demonstrate how UAVs can be used as a detection tool for air emission of ships in ports to improve the efficiency of detecting air pollution of ships. COVID-19 changes social behaviors, and the use of autonomous vehicles for mobility is growing. Under such a circumstance, the issue of investigating how UAVs can be used to replace or relieve in part or full ship air emissions detection by human beings becomes emerging and significant. It obviously has a potential impact on improving environmental protection regulations enforcement. Second, the number and positions of the investigated ships are defined as dynamic parameters in this study to well reflect the practical scenarios. Routing UAVs among sailing ships with less detection cost and higher detection efficiency is derived in a new DTSP problem in this paper. It has academic significance because of the involvement of specific features that generalize the well-known DTSP from the literature. We model the dynamics of ships' emission detection through comparing a preset threshold and the change in the "minimum loop" length to determine the path reprogramming time. Third, an improved PSO algorithm based on Tabu is proposed; the case of Yangzhou is referred to simulate data and experimentally solve the proposed formulation, and we compare the new algorithm with the traditional PSO algorithm. The experiment proves that the new algorithm has a faster iterative speed.

This paper is organized as follows. Following the introduction in Section 1, Section 2 presents the previous studies on the air pollution of ships, with applications of UAVs in the field of logistics and path planning. Section 3 describes the problem of synergistic path planning of multi-UAVs for air pollution detection of ships in ports. Section 4 establishes the model of synergistic path planning of multi-UAVs. Section 5 proposes the solution based on a PSO. Section 6 describes the experimental data and results. Section 7 concludes the paper.

2. Literature Review

In this section, we summarize the current research on ship air pollution emissions, the impact of ship air pollution on the environment and the ship air pollution detection methods. In Section 2.1, we address the research results of UAVs and introduced their applications in logistics, traffic inspection and other relevant fields. In Section 2.2, we review the state-of-the-art techniques for path planning models and algorithms involved in DTSP, especially for UAV routing problems of DTSP in Section 2.3.

2.1. Related work on ship air pollution

In recent years, ship air pollution has become a hot issue. It was found that ship emissions increased the concentration of pollutants in the area rapidly and caused serious adverse effects on the environment. Liu et al. (2019) found that the total amount of air pollutants emitted by container ships, bulk carriers and cruise ships accounted for approximately 90% of the total pollutants from ships. In terms of the impact of ship air pollution on the environment, Lou et al. (2019) studied the gaseous intermediate volatile organic compounds (IVOC) produced by ships burning heavy fuel oil (HFO) and found that a large amount of emitted IVOC seriously affected the air quality. Ship exhaust is an important cause of haze, and a general circulation model shows that haze was significantly disturbed by a tropical rainfall model and hydrological cycle, and it had an impact on the global climate (Ramanathan et al., 2001). Boersma et al. (2015) analyzed the changes of nitrogen oxide emissions in European shipping and found that the total nitrogen oxide emissions of shipping in Europe kept increasing, which suggested that more attention should be paid to NOx emission in the shipping industry. Alahmadi et al. (2019) used a local geographic weighted regression (GWR) model under the geographic information system (GIS) environment to characterize and quantify the contribution of marine sector emissions to the concentration of NO_2 in the Red Sea region.

Therefore, it is urgent to strengthen the detection of ship exhaust gas for the purpose of controlling ship air pollution effectively. The traditional detection methods for air pollution of ships include manual boarding detection and detection by fixed position loading equipment. For manual boarding detection, one type of approach is checking the oil change records in the logbook and taking oil samples for testing, then bringing the data into a unified data system for analysis. However, such sampling inspection is blind and lagging, and the inspection efficiency is limited (Wu, 2020). Another method of manual boarding detection is using a marine fuel sulfur content rapid detector for detection. Relatively speaking, the efficiency has improved, but the work process is relatively complex and must be operated by a large number of people on board the ship for on-site determination. As is known, the manual boarding method obviously affects the detection's immediacy and convenience (Ministry of transport of the people's Republic of China, 2020). Moreover, given the effect of Covid-19, the method of boarding inspection will become risky. For the method of detection by fixed positions loading, we have the following situation: In 2012, sniffers were installed on ships for air pollution detection in Neva Bay and Gulf of Finland. In early 2014, Denmark installed a sniffer on the Great Belt Bridge to detect air pollution from ships (Chang et al, 2017). Fixed sniffer technology and optical remote sensing technology have the features of mature technology and lower cost. However, they are types of passive detection methods, which lack flexibility and have limitations in their detection effect because the location relationship between the sniffers and the pollution sources have a large impact on the detection results (Chang et al, 2017). Therefore, there is an urgent need to adopt new technologies and new ideas to develop the real-time detection of port ship air pollution (Wu, 2016).

With the development of technology, recent studies have shown that UAVs that carry sniffers for ship air emissions detection can greatly improve the efficiency of sniffing (Soarabolity, 2020). However, there is only a limited number of applications and academic research related to this field at present.

2.2 Existing studies for routing UAVs in various applications

Currently, given their low costs in both capital and operations, UAVs have been widely used in many fields, such as military surveillance (see, e.g., Xia et al., 2017), logistics delivery operations (see, e.g., Murray and Chu, 2015; Wang et al., 2017; Carlsson and Song, 2017) and traffic inspection (Wang et al., 2018). Because the UAVs' tasks are quite different in different fields, the models and algorithms are designed differently. For example, military surveillance problems are often considered to have dynamics and uncertainties, and the solutions must always consider the dynamic appearances of new targets or the uncertain information collected from locations that have very limited communications (Xia, 2017). At present, UAV has played an important role in maritime search and rescue, Sea Patrol, channel mapping, ship air emission and other aspects (Zhu, 2020; Zhang, 2020; Jing et al., 2017; Soarabolity, 2020).

Synergistic mission of UAVs is also an important research direction of UAV applications. For example, Chen et al. (2016) provided theoretical support for synergistic path planning of multiple UAVs by analyzing the constraints and common algorithms of path planning. Yan (2017) proposed a strategy for UAVs to collect battlefield information based on scenario analysis. Rastgoftar et al. (2019) proposed that the UAV multicluster cooperation protocol also extended the previous synergistic control mechanism, and they realized location detection and collision avoidance technologies when multiple cooperation clusters had different destinations. Ding et al. (2019) studied the UAVs path planning problem for a team of cooperating heterogeneous vehicles composed of one UAV and multiple unmanned ground vehicles (UGVs).

Nowadays, UAVs have been widely used in some fields, the characteristics of UAVs are quite suitable for the detection of ships' emission in motion without manual boarding. However, researches and applications involved ship air emission detection by UAVs are still in their infancy. Solution for routing UAVs is the key in this field. Much fewer works related synergistic mission of UAVs have been mentioned in the references.

2.3 Related work on the DTSP

The Traveling Salesman Problem (TSP) is an optimal combinatorial problem, and DTSP is the dynamic traveling salesman problem, which belongs to NP hard problems (Michael R, 1979). The research on path planning in a dynamic environment mainly started approximately in year 2000. Carlisle and Dozier (2000) began to apply a PSO algorithm to solve dynamic tracking problems in 2000. Based on the analogy of electrostatic field energy, Blackwell et al. (2002) proposed a "charged particle" PSO algorithm. To keep the diversity of the population and address the dynamic environment, an additional acceleration factor was added to simulate the repulsion effect of charged particles on other charged particles. Jatmiko et al. (2006) combined a CPSO algorithm with the standard PSO algorithm and added a rejection function to keep the balance of the system diversity, to address the dynamic changes in the environment. Hu et al. (2015) studied a dynamic closed-loop vehicle routing problem, which was an extension of the dynamic closed-loop vehicle routing problem in closed-loop logistics. Liu et al. (2018) proposed an optimization algorithm based on decomposition and prediction of multiple PSOs to solve dynamic multiobjective optimization problems. Wang et al. (2018) established an online optimization scheduling method based on multi-prediction scenarios for real-time distribution in the same city, and they integrated multiple scenarios with predicted orders into the path planning process. Strąk and Łukasz (2019) proposed a self-adaptive discrete PSO algorithm with heterogeneous parameter values for the DTSP. Through the above review, the PSO is found to be an effective and efficient algorithm to solve the problems involved in the DTSP. However, the PSO has the problem of slow convergence speed and ease of falling into a locally optimal solution in the later stages of the algorithm. A Tabu table is considered, which is incorporated into the iterative calculation of the PSO to improve the optimization ability of the algorithm and to overcome the disadvantages of the PSO in this paper.

UAV path planning in a dynamic environment is an NP-hard problem, and the available solutions in the literature include the reinforcement learning methods based on Markov decision process, such as the Q-learning algorithm (e.g., Zhao, 2017). They use a reward function and a state transition strategy to explore and predict the environment step by step, and they improve the UAV's ability to address a complex unknown environment through an autonomous learning process. An adaptive random exploration method that is combined with reinforcement learning is used to guide UAV navigation and obstacle avoidance tasks within the context of the path planning of UAVs used to detect ship emissions in a dynamic environment. Bouman (2018) proposed an algorithm based on dynamic programming to solve the new task assignment problem generated by the synergism of UAVs and trucks. Xia et al. (2019) proposed path planning methods for UAVs' detection of ship air pollution. They regarded the UAVs' scheduling problem as a generalized team-orienteering problem and modeled the dynamics of each sailing vessel based on the advanced prediction of ship positions creatively. To solve this proposed formulation, they developed a Lagrangian relaxation-based method that can obtain near-optimal solutions. Numerical experiments were conducted to validate the effectiveness and efficiency of the proposed method. However, the ship's trajectory is often difficult to predict accurately, even though there could be an automatic identification system. Ships' real-time locations are uncertain in practice; for example, a vessel can occasionally adjust its sailing speed and course rather than stick to a given plan for safety or congestion reasons (Qu et al., 2011; Weng et al., 2012). However, Xia's paper discussed two simple extensions for deviation correction of the prediction. Thus, we attempt to provide another idea to solve the dynamic ships' emissions detection by UAVs: we model the dynamics of ships through comparing a preset threshold and the change in the "minimum loop" length to determine the path reprogramming time.

From what has been reviewed and discussed above, we find it is urgent to adopt new technologies and ideas to strengthen the real-time detection of air pollution of ships in ports based on the discussion on the impact on the environment and measurement of emission. In recent years, UAVs have been attempted to detect the air pollution of ships. However, the applications of UAV for ship air pollution detection are still at its infancy stage. How to plan the flight path of UAV is the key to improve the detection efficiency and reduce the detection cost. In this paper, UAVs path planning in dynamic environment is derived as a DTSP problem, which is a NP hard problem. The research serves as a more general solution for routing UAVs regarding ship emission detection's specialties , such as the number of ships for detection can be very large in certain time periods and the positions and quantity of the ships to be detected in the detection area are dynamic. Moreover, assigning multiple detection tasks for each operated tour for one UAV and multiple-UAVs are used for synergism detection and flight time of a UAV is considered with the limitation of its battery capacity.

3. Problem Description

The investigated problem in this paper is how to plan the routes of multiple UAVs for detecting ships' emissions in ports in a synergistic way. First, the initial positions and number of ships to be detected are determined, which is regarded as part of the detection tasks of the UAVs. Then, these detection tasks are merged into the control platform to assign the detection tasks for each UAV. Then, multiple UAVs (each carrying a portable multigas detector) work together to conduct real-time emissions detection of ships in the port, and the detection results can be transmitted to the control center through wireless transmission. Fig. 1 illustrates the main process of air detection by UAVs.

[Please insert Fig 1 here]

The specific process of multi-UAVs detection of air pollution from ships is as follows: (1) The flight paths of UAVs are represented by lines. The UAVs start from the ports and fly to the ships that are to be detected in sequence according to the assigned tasks. Because the ships are in motion, when any UAV has completed the first detection of a ship, it is necessary to determine whether to replan the UAV detection path. If it is necessary, then they replan the flight path of the UAVs to the ships that have not been detected and the ships newly added to the detection queue; otherwise, when the ship has been completely detected, they replan the UAVs' detection path to the new ship to be detected. (2) In the process of detection, if there are UAVs that are idle when they complete their own workload, they need to be synergistic with other UAVs to complete their detection tasks. (3) When the quantity of UAVs flying in the port is more than the quantity of ships detected, the redundant UAVs flying back to the ports will no longer be assigned with detection tasks. At this moment, the working state of these UAVs is called "nonworking state". The battery power of each UAV is limited, and it must fly within the battery power limit. When the power of the UAVs is insufficient, it must return to the charging pile. At this time, a standby UAV from shore is assigned to detect the ship. In the whole detection process, weather factors (such as strong winds) and air flow around the running ship will not be considered in this paper.

The flight path problem of UAVs detecting air pollution of ships is abstracted into a topology structure (see Fig. 2). The lines in the figure show the possible flight paths of the UAVs. It can be seen from the figure that the UAVs can fly to the ship to be detected and the charging pile, and the UAVs in the charging pile can fly to the ships.

[Please insert Fig 2 here]

4. Establishing the Model

4.1 Model assumptions

In reality, it is very complex to use UAVs to detect sailing ships. To simplify the model, the following assumptions are set for the model formulation .

a. The flight formation composed of UAVs detects D ships (the value of D is variable).

b. Each ship is detected by only one UAV, while one UAV can detect multiple ships.

c. The time and cost of the UAVs going from one ship to another are calculated based on only the distance between the two ships.

d. UAVs move in only two dimensions.

e. When one UAV is in charge, the standby UAV is automatically added to the detection tasks.

f. The influence of weather and air flow around the ships on the detection is not accounted for.

h. Ships move slowly when they are in the waters in port. The flight speed of the UAVs is much faster than the ship speed (Shi et al., 2014; Huang et al., 2016), and thus, the influence of the ship speed is ignored in the model formulation.

4.2 Indicators and sets

$G(N,E)$ is a network with vertex set N and directed edge set E.

$i,j \in N, N = \{0,1,\cdots,|N|\}, (i,j) \in E.$

p —— the real-time position of the ship to be detected.

$\bar{N}$ —— a set of ships to be detected, $p \in \bar{N}$.

g —— UAVs' charging pile.

c —— UAV's position.

k —— index of UAVs.

K—— set of all UAVs, $K = \{1,2,\dots,k,|K|\}$.

$t_{i,j}$—— flight time of UAVs from i to j.

$C_{i,j}$—— power required by UAVs from i to j.

T_P—— time needed to detect ship p.

C_c^{min}—— minimum total cost of detection.

C_T^{min}—— minimum the total time of detection.

$d_{i,j}$—— 0-1 variable, the connection between two points is 1, $(i,j) \in N$, otherwise is 0.

$\bar{Q}$—— battery capacity of UAVs.

δ_k—— current electric quantity of UAVs.

$r_{i,j,k}$—— 0-1 variable. When the UAV k passes the route$(i,j) \in E$, it is 1; otherwise, it is 0.

η_k—— 0-1 variable. When the UAV is not working, it is 1; otherwise, it is 0.

u,z,λ—— constant.

M—— a sufficiently large positive number.

4.3 Synergistic path planning model of multi-UAVs

4.3.1 Cost minimization objective

The cost of using UAVs to detect the ships mainly includes the electricity cost of the UAV's flight, the communication cost between UAVs, the extra cost of exhaust gas detection involving sniffers, UAV's maintenance, and depreciation cost. This paper mainly considers the electricity cost of the UAV's flight, which is strongly associated with the path programming. In addition, the length of UAV's flight path determines the flight cost of the UAV, and it also affects the efficiency of detection, timeliness of detection, carbon emissions per kilometer, and more, which are important indicators for judging the quality of the path planning(Li, 2020). Therefore, the power cost of a UAV from one ship to another is directly proportional to the distance between the two ships.

The total electricity cost of flight for UAV k is $\sum_{i \in N} \sum_{j \in N} (C_{i,j} r_{i,j,k})$.

The total cost of the flight electricity for the whole UAVs fleet is $\sum_{i \in N} \sum_{j \in N} \sum_{k \in K} (C_{i,j} r_{i,j,k})$.

4.3.2 Time minimization objective

The UAV's detection time mainly consists of two parts, which are the time needed for the UAV's flight and the time needed for the ship detection.

The flight time of UAV k is $\sum_{i \in N} \sum_{j \in N} (t_{i,j} r_{i,j,k})$;

The total time of the UAV's formation detection is $\max(\sum_{i \in N} \sum_{j \in N} (t_{i,j} r_{i,j,k} + T_j))$.

In the detection process, to shorten the total detection time, if there is a free UAV or lower workload UAV, when it completes its work, it will be assigned to the detection route of other UAVs to help other UAVs to detect, but this action will increase the total cost of detection. Therefore, the objective of cost minimization is not the same as the objective of time minimization. Instead, they can conflict with each other. Therefore, this paper gives the two objectives a certain weight u and z, and then, it adds the two goals to transform the problem into a single objective problem for an optimal solution. Here, u and z reflect the importance of the two objective functions, respectively. When the air pollution of the ships in the ports is serious, it is necessary to reduce the value of u/z. When the air pollution control of the ships has reached the specified goal, it can increase the value of u/z accordingly.

4.3.3 Mathematical model

The mathematical model of the UAVs' path planning established in this paper is as follows:

$Obj.$

$$\text{Min } C = u * \frac{C_C - C_C^{min}}{C_C^{min}} + z * \frac{C_T - C_T^{min}}{C_T^{min}} \tag{1}$$

$\boldsymbol{s.t.}$

$$C_C = \sum_{i \in N} \sum_{i \in N} \sum_{k \in K} (C_{i,j} r_{i,j,k}) \tag{2}$$

$$C_T = \max(\sum_{i \in N} \sum_{j \in N} (t_{i,j} r_{i,j,k} + T_j)), k \in K \tag{3}$$

$$u + z = 1 \tag{4}$$

$$\sum_{k \in K} (r_{i,j,k} + r_{j,i,k}) \leq 1, \forall (i,j) \in E \tag{5}$$

$$\sum_{i \in N} \sum_{j \in N} (C_{i,j} r_{i,j,k}) \leq \delta_k, \forall k \in K \tag{6}$$

$$\exists g, C_{k,g} < \delta_k, g \in \bar{N} \tag{7}$$

$$r_{i,j,k} \leq M(1-\eta_k), \forall k \in K, i,j \in N \tag{8}$$

$$\delta_{k,o} = \bar{Q}, \forall k \in K \tag{9}$$

$$r_{g,c,k} = 0 \tag{10}$$

$$0 \leq \delta_k \leq \overline{Q_k}, \forall k \in K \tag{11}$$

$$d_{i,i} = 0, i \in E \tag{12}$$

$$d_{i,j} \geq r_{i,j,k} \tag{13}$$

$$C_g = 0 \tag{14}$$

$$T_g = 0 \tag{15}$$

$$r_{i,j,k} \in \{0,1\}, \forall (i,j) \in E, \forall k \in K \tag{16}$$

$$\alpha_k \in \{0,1\}, \forall k \in K \tag{17}$$

$$\delta_k \geq 0, \forall k \in K \tag{18}$$

$$d_{i,j} \in \{0,1\} \tag{19}$$

Objective (1) is to minimize the weighted sum of the total cost and time. Constraint (2) represents the total cost of detection. Constraint (3) represents the total time of detection. Constraint (4) specifies that the sum of u and z is equal to 1. Constraint (5) means that at most one UAV passes through each side. Constraint (6) describes the UAV's electric quantity constraint, which means that the power consumed by a UAV cannot exceed its remaining power. Constraint (7) means that the remaining electric power can fly to the nearest charging post. Constraint (8) indicates that the UAV does not perform the detection task when it is not working. Constraint (9) indicates that the initial electric power of the UAV’s battery is the battery capacity. Constraint (10) indicates that the UAVs can only fly to the charging pile or the ships to be detected. Constraint (11) indicates the UAV’s electric power constraint. Constraint (12) indicates that the distance between the same points is 0. Constraint (13) indicates that the UAVs can fly along the line only when there is a connection between two points. Constraint (14) indicates that the UAVs do not consume cost when charging. Constraint (15) indicates that the UAVs do not consume time when charging (the standby UAVs will join the operation immediately). Constraint (16) (17) (18) and (19) are self-explanatory constraints.

5. The New Improved PSO Algorithm

The above model is an NP-hard problem, which must be solved by a heuristic algorithm. The PSO, which has been widely used to solve dynamic path planning, is adopted in this paper to tackle the real-time requirements of dynamic ship pollution detection problems. Therefore, this paper chooses the improved PSO algorithm to solve the model.

5.1 Basic PSO

The basic PSO seeks the optimal solution by tracking two optimal values, one of which is the optimal value p_{best} of the particle itself in the whole process of motion, while the other is the optimal solution g_{best} of the whole PSO thus far. In the basic POS algorithm, the calculation formula of the d-dimensional neighborhood function of the ith particles at time $k+1$ is as follows:

$$v_{id}^{(k+1)} = \omega * v_{id}^{(k)} + c_1 * r_1 * \left(p_{id}^{(k)} - x_{id}^{(k)}\right) + c_2 * r_2 * (p_{id}^{(k)} - x_{id}^{(k)}) \tag{20}$$

$$x_{id}^{(k+1)} = x_{id}^{(k)} + v_{id}^{(k+1)} \tag{21}$$

$$|v_{id}^{(k)}| \leq V_{max} \tag{22}$$

where ω is the inertia factor, k is the iteration period, $v_{id}^{(k)}$ is the particle velocity, $p_{id}^{(k)}$ is the optimal position of the particle, $x_{id}^{(k)}$ is the current position of the particle, c_1, c_2 is the acceleration factor, r_1, r_2 is the random number between (0,1), and V_{max} is the velocity vector limit constant.

Formula (20) is mainly composed of three parts: the first part is the velocity inertia of the particles in advance. The second part is the self-cognition part, which represents the thinking of particles themselves, which can be understood as the distance between the current position of the particles and their best position. This part enables the particle to have the global searching ability and to avoid falling into a locally optimal solution. The third part is the social part, which embodies the information sharing between particles. It can be understood as the distance between the current position of the particles and the optimal position of the group. A fitness function is used to judge the fitness of the particles.

5.2 PSO based on a Tabu Search (TS)

At the later stage of the PSO, when an optimal position is found in a certain iteration, all of the particles will move closer to that position, and the particle swarm tends to be the same point, which results in a failure to search again in the solution space, a slow convergence rate, and ease of falling into a locally optimal solution. At this point, based on the classical Tabu search algorithm, a Tabu table is introduced to improve the optimization ability and precision of the algorithm.

5.3 Thoughts and flows of synergistic path planning of multi-UAVs

In this paper, the path planning of multi-UAVs synergistic detection of ship pollution is solved based on "minimum ring". A "minimum ring" is a concept in graph theory that refers to a loop (i.e., "ring") that returns to the starting point by passing through any number of vertices on the graph at most once each. The "minimum ring" is the ring with the smallest length added to the edges of all rings. Specific strategies are as follows.

(1) Acquisition of each UAV detection path. According to the positions of all UAVs and the ships to be detected at a certain time, we calculate the "minimum ring" R_1 (see solid line ring in Fig. 3) that connects all UAVs to the ships to be tested and the "minimum ring" R_2 (see dotted line ring in Fig. 3) that connects the ships to be tested. Then, we cut R_1 to obtain the flight detection path of each UAV. The cutting method is based on the principle of the shortest general route, and one of the two adjacent lines of each UAV is disconnected to obtain multiple paths starting from the UAV (as shown in Fig. 4, ***strategy 1***). The UAV will be detected according to this path.

[Please insert Fig 3 here]

[Please insert Fig 4 here]

(2) According to the dynamic environment change, the UAV detection reprogramming path is acquired. Since the ship is always in motion, every time a ship is detected, the ship is taken as a fixed point, and the length of R_2 at that time is calculated. If the difference between the current length of R_2 and the minimum value of R_2 at all times exceeds the preset threshold. The threshold value here refers to the gap between existing length of the minimized circle and the shortest one over the past moment n. In practice, this threshold value indicates the maximum flying distance of the drone for completing all asked inspection tasks but without rescheduling the route. The "minimum ring" composed of the UAV, undetected ship and incoming ship will be regenerated. Otherwise, after all of the ships in the "minimum ring" have been detected, the flight path of the UAV to detect the new ship to be tested is replanned (***strategy 2***).

(3) UAV coordinated operation. During the detection process, if there is an idle UAV, it will be synergistic with the other UAVs to complete the detection task. The specific methods are as follows. First, we calculate the remaining tasks of the other assigned UAVs on their respective "loop lines" (number of ships + length of loop lines), and we sort the "loop lines" in turn according to the size of the remaining tasks. Second, on the basis of the sorted loop lines, the unassigned UAV is calculated one by one to evaluate whether the value of the objective function relating to each ship can be reduced. The ship that can reduce the value of the objective function the most, which is called the asterisk ship (i.e., ship B in Fig. 5 and ship D in Fig. 6). Third, if an asterisk ship is not the last one of the "loop lines" (e.g., ship B in Fig. 5), then we disconnect the edge between the ship and the adjacent ship in the opposite direction of the loop line (the edge between ship B and C in Fig. 5), and a new detection route of idle UAVs and ships to be tested (ships B, C and D in Fig. 5) is formed. If the asterisk ship happens to be the last one on a "loop" (e.g., ship D in Fig. 6), then ships along this route are relatively evenly distributed with respect to the associated UAVs for detection (see Fig. 6, the ships detected by idle UAVs are D and C). At the same time, we cancel other UAVs' detection tasks (***strategy 3***).

Because it is difficult to calculate the shortest time of each UAV in advance, we develop a method to calculate the approximate shortest time.

$$C_T{}^{min} = \left\lceil \frac{Sum(P_i)}{Sum(y_i)} \right\rceil * T + \frac{X_{min} - max(\sum_{i \in K} Y^i_{right}, \sum_{i \in K} Y^i_{left})}{v * Sum(y_i)} \tag{23}$$

$Sum(S_i)$ represents the number of ships to be detected. $Sum(P_i)$ represents the total number of UAVs. T is the expected average detection time of each ship. X_{min} is the length of the "minimum loop" formed by the connection of UAVs and ships. Y^i_{right} represents the length of the first flight path of the UAVs in the counterclockwise direction (see Fig. 4), and v is the average flight speed of the UAVs.

[Please insert Fig 5 here]

[Please insert Fig 6 here]

(4) Due to the limitations of the UAV battery power, when the UAV power is low, the UAV must fly back to the charging pile (i.e., g) for charging. At this point, a backup UAV sets off from the port to replace the UAV that has low power to ensure the overall efficiency of the UAV fleet detection. At the same time, the paths of all UAVs are reprogrammed to find the optimal flight path of each UAV. In this paper, the weighted sum of the cost of the UAV detection and the minimum of the detection time is taken as the target, and as many ships are required to be inspected as possible.

5.4 Algorithm implementation

To describe the improved PSO in the context of ship emission detection, this section first defines the important symbols involved in the algorithm, as shown in Table 1.

[Please insert Table 1 here]

Second, an optimized PSO is implemented. The implementation process of the algorithm is as follows.

Step 1 Initialize the particle swarm and Tabu table. Set NC_MAX, particle position, initial speed, $Beta$, $Alpha, l, TS\_MAX$.

Step 2 Calculate the fitness value of the individual (the fitness value is the total path length selected), and leave the Tabu table blank.

Step 3 update p_{best} and g_{best}.

Step 4 Use formulas (20) and (21) to update the speed and position of an individual.

Step 5 Determine whether the maximum number of iterations of the PSO has been reached or the convergence condition has been met. If not, go to ***step 2***. Otherwise, perform the next step.

Step 6 A certain number of neighborhood solutions is generated by the current solution, and a Tabu search is conducted, and some candidate solutions with the best adaptability are selected.

Step 7 Determine whether there is a candidate solution that meets the amnesty criteria. If yes, then replace the current solution with the best candidate solution that meets the amnesty criteria, and replace the object that first enters into the Tabu table with the corresponding Tabu object. At the same time, replace the historical optimal solution with the candidate solution, and then, turn to ***step 9***. Otherwise, perform the next step.

Step 8 The Tabu attribute of each object that corresponds to the candidate solution is determined, and the best state that corresponds to the non-Tabu object in the candidate solution set is selected to replace the current solution. At the same time, the corresponding Tabu object is replaced by the first Tabu object in the Tabu list.

Step* 9** Determine whether the maximum number of iterations of the Tabu search algorithm is reached. If the maximum number of iterations is reached, then $X_{min} = (y_1, x_1, x_2, \dots y_2, \dots, x_i, y_j, \dots, x_k)$ to perform the next step; otherwise, go to ***step 6.

Step* 10** According to Strategy 1, cut the obtained loop line X_{min}, and the objective function is combined to obtain the scheduling scheme of each UAV. Next, we will discuss the details of ***Strategy 1.

Step* 11** Every time a ship is detected, the ship is regarded as a fixed point, and the environment is tested according to ***Strategy 2. If it is determined that the environment changes, ***Step 1*** is executed; otherwise, ***Step 11*** is executed.

***Strategy 1*: Route segmentation strategy of X**

Strategy 1: Route segmentation strategy of $\mathbf{X_{min}}$ (obtain the initial detection path of each UAV).

if $\sum Y^i_{right} > \sum Y^i_{left}$ then
  Disconnect all Y^i_{right};
else
  Disconnect all Y^i_{left};
In the whole process of detecting the air pollution of ships,
if y_i is idle then
  Strategy 3;

Strategy 2: Environmental detection method (minimum loop method) (determine the path rescheduling time).

if $\Delta \mathrm{d} > X^{ship}_{now} - min(X^{ship}_{min})$ or the UAV's electric quantity shortage then
  Path replanning;
else Continue detecting as originally planned;

Strategy 3: Allocation strategy of idle UAV y_j (synergistic strategy) (see Fig. 5, Fig. 6).

Z= Sort (X_i);
for x in Z:
  for X^i_{late} in x:
    if y_j detects X^i_{late} make max ($C_{now} - C_{expect}$)
      if X^i_{late} is not the last ship on the route then
        y_j detects X^i_{late} and later ships;
        Disconnect the previous path of X^i_{late};
      else
        Divide the undetected ships of this route into two UAVs for monitoring;
        Disconnect the line at the junction;
    else X^i_{late} is the previous ship of X^i_{late}.
  end;
end;

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6. Experiment and Analysis

In this paper, we use MATLAB r2010b to simulate the data in the Windows 10 i5-2.11ghz 8GB 64-bit operating system.

6.1 Data preparation

In this paper, the ships sailing in the ports on a certain day are derived from real cases for the experiment. Some parameters involved in the experiment are shown in Table 2.

[Please insert Table 2 here]

Statements about the main parameters in Table 2 are as follows:

Average Flight Speed of UAV: The average flight speed of UAVs was referred to the experiment results by Yangzhou Maritime Administration of China in which the max speed was 82.8km/h (Soarabulity, 2020). Based on such information and taking into account the wind effect at seas (IT home, 2017), we set the average speed as 50 km/h in this study.

Estimated Average Inspection Time of Each Ship: We set the estimated average inspection time of each ship as 2min / ship based on the experiences of Yangzhou maritime administration When UAV works, it can be measured in the air without emission to obtain the background concentration value of corresponding gas components. Then, the UAV flies to the bottom of the ship's tail gas plume and keeps following for about 1 minute. Then, the real-time estimated sulfur content of the ship can be viewed on the ground software (Soarabulity, 2020).

Number of UAVs used: According to the case of Yangzhou Maritime Safety Administration measuring exhaust gas from ships, we set the number of UAVs to 3.

Detection range: The endurance of Dajiang M210 UAV (rotor UAV) is 35 minutes. According to the average flight speed of 50km / h, the max light distance of the UAV after full charging is about 29km. Considering the limitation of the number of UAV and ensuring that UAV can detect a certain number of ships in one endurance time, the detection range of ships is set as 3nmi * 3nmi, that is about 31 square kilometers.

Threshold: If the threshold value is too large, it cannot adjust the flight path of UAVs in time according to the change of ships position. If the threshold value is too small, the UAVs' path re planning will be too frequent. After the test for the algorithm, when the threshold value is about 5, the algorithm obtains relatively good path planning effect.

In this paper, the detection range and ship coordinates are scaled to $10 * 10$ coordinates in the proportion ψ. We randomly generated some data as the initial ship position coordinates for simulation. (see Table 3), and UAV (see Table 4) are set randomly for the experiment (S_i represents the ith ship, P_i represents the ith UAV, (X, Y) represents the position coordinates). Fig. 7 shows a schematic diagram of the positions of the ship to be detected and the UAVs.

[Please insert Table 3 here]

[Please insert Table 4 here]

[Please insert Fig 7 here]

6.2 Algorithm contrast

In this paper, the UAV and ship position data obtained in Fig. 7 are used to compare the performance of the TS-based PSO with the classical standard PSO. Fig. 8 presents comparison results between the PSO and the TS-based PSO.

[Please insert Fig 8 here]

After the experiments, it is verified that the PSO based on TS can jump out of a locally optimal solution, and the experiments revealed a better optimization ability than the PSO. The optimal parameter combination of the improved PSO algorithm is obtained after several experiments. The basic parameters are set as follows: $Alpha = 0.35, Beta = 0.45, NC\_MAX = 700, TS\_MAX = 300$, and we set $u = 0.1$, $z = 0.9$, with threshold $\Delta d = 5$, and random setting of the other parameters.

6.3 Solving the UAVs' flight paths

Based on the condition of minimizing the cost of UAV detection of ship air pollution, the total time for the UAV-to-ship air pollution detection is optimized, and finally, the allocation of the UAV initial detection tasks is obtained under the consideration of cost and efficiency.

(1) Acquisition of the initial detection path of each UAV

First, with the minimum cost in the UAV path planning model, the improved PSO algorithm is used to solve the initial flight path of each UAV (as shown in Fig. 9), as well as the flight distance and total detection time of each UAV (as shown in Table 5).

[Please insert Fig 9 here]

[Please insert Table 5 here]

(2) UAV rerouting and synergistic operation

When a UAV, such as P2, completes its current mission, it must work with other UAVs. According to the calculation of (***Strategy 2***), the new operation paths of UAV P2 and P3 are obtained (as shown in Fig. 10). Table 6 shows the task allocation of the UAV synergistic operation under the consideration of both cost and efficiency.

[Please insert Fig 10 here]

[Please insert Table 6 here]

(3) UAV path reprogramming

Since the ship is moving and is always in a dynamic state, the ship position change data is simulated to show how the UAV adapts to the change in the external environment through continuous rerouting. In Table 7, for each detection after a ship (see S_3), we allocate the ship as a stationary point and calculate the moment R_2 length (as shown in Fig. 3). If the difference between the current length of R_2 and the minimum value of R_2 at all times exceeds a preset threshold, then the "minimum ring" R_1 is regenerated, and the newly generated R_1 is cut. After the calculation, when testing the S_4, namely, 6.83 min, $X_{now} - \min(X_i) = 41.97 - 31.66 = 10.31 >$

$\Delta d =\ 5$, and the UAV path is submitted for rezoning.

[Please insert Table 7 here]

At this time, the ships that have not been detected, the ships that have newly joined the detection task and the coordinates of the UAV are as follows:

[Please insert Table 8 here]

[Please insert Table 9 here]

It can be seen from Table 8 that ship S_7 has moved out of the detection range, and thus, the re-planned route does not include ship S_7. The method of path re-planning is the following: first, the ships S_3, S_4, S_8, S_9, which have been detected, and ship S_7, which has been driven out of the detect range, are eliminated; then, the new ships S_{10}, $S_{11}\ldots S_i$, which are to be detected, are added, and finally, the UAV has a plan created to detect the paths of the ships (S_1, S_2, S_5, S_6, S_{10} … S_i) to be detected (as shown in Fig. 11), and so on.

[Please insert Fig 11 here]

(4) More test scenarios

We added new test scenarios based on the original test data. For the ships that have not been detected in the first group of data and the newly added ships that have not been detected, the UAV detection path planning is continued. The new test results show the effectiveness of the algorithm.

[Please insert Table 10 here]

[Please insert Table 11here]

[Please insert Table 12 here]

6.4 Results discussion

An analysis of the efficiency of the UAVs' detection of the ships' air pollution was made. Table 13 shows the efficiency of the UAVs' detection of the ships' air pollution. According to Table 13, the average time for completing the first ship's detection is 4.23 min/ship, 2.51 min/ship is for the second ship and when the fourth ship detection is completed, the average detection time becomes 1.71 min/ship. It can be seen that with the UAVs' detection of the ships' air pollution, the detection efficiency is gradually improved. Then, we simulated more test scenarios as shown above and analyzed the efficiency of the UAVs' detection of ships' air pollution based on the new scenario. According to the analysis results in Table 14 and Fig. 12, the average detection time (including the gas detection and flight time) of the UAVs' detection of ships gradually decreases with an increasing number of ships to be detected in the port.

[Please insert Table 13 here]

[Please insert Table 14here]

[Please insert Fig 12 here]

Then, we analyzed the influences of the changes in the u and z values on the route strategy of the UAVs detecting ships' air pollution (see Table 15). Based on the above analysis, the changed in the u and z value will affect the flight path of the UAVs. When u > z, the path planned for the UAVs will be more inclined to sacrifice certain efficiency and reduce the cost of detection. When u < z, the path planned for the UAVs will be more inclined to invest more into improving the detection efficiency.

[Please insert Table 15 here]

The above analysis shows that the changes in u and z have an impact on the flight strategy of the UAVs detecting ships. These analysis results implicated that the u/z ratio should be reduced appropriately in the ports that face high air pollution to improve the detection efficiency, while in the ports with low air pollution, the u/z ratio should be increased to reduce the total detection cost.

7. Conclusions

In this paper, a new synergistic path planning model of multi-UAVs is developed for ship air pollution detection in a dynamic environment, and an improved PSO is used to solve the model. The contributions of this paper are as follows:

(1) This paper provides a new solution on path planning for demonstrating how UAVs can be used as a detection tool for air pollution of ships in ports to improve the efficiency of detecting air pollution of ships and reduce the cost of detection. COVID-19 changes social behaviors and use of autonomous vehicles for mobility is growing. Under such a circumstance, the issue of investigating how UAVs can be used to replace or relief in part or full ship air emission detection by human beings becomes emerging and significant. It focuses on the decision making of scheduling and routing of UAVs, and the results can be incorporated into and provide useful insights for any tested in which UAVs are used to detect ship emission in practice.

(2) The core of the decision is to assign each UAV a sequence of detection tasks with time schedules that regard the characteristics of ship emission detections by multi-UAVs, Decisions involved must be made by considering the following aspects: the number of ships for detection can be very large in certain time periods, and the positions and quantity of the ships to be detected in the detection area are dynamic; assigning multiple detection tasks for each operated tour to increase the utilization of the UAV fleet; the length of time required to detect each ship is dynamic; multiple-UAVs are used for synergism detection; and the flight time of the UAVs is limited because of their limited battery capacity.

Synergism detection of sailing ship air pollution by multiple UAVs in this paper is attributed to a problem of DTSP, which is known to be an NP-hard problem. Although there are some effective models and algorithms for solving DTSP problems and the related problems also, most of them cannot be directly applied to tackle a generalized setting of multi-UAVs with synergistic detection of dynamic ships' air emissions.

(3) UAV path planning in dynamic environment is a NP hard problem, fewer available solutions in the literature include the reinforcement learning methods based on Markov decision process, such as a Q-learning algorithm (e.g. Zhao, 2017). Xia et al. (2019) used AIS data to undertake ship location prediction, and then established a path planning model for UAV detection of ship air pollution. It developed a new method based on Lagrange relaxation to solve the problem. Although showing some attractiveness, the effectiveness of previous prediction-based methods depend on the accuracy of ship position prediction. In port, ships often change their speeds and

courses for various reasons (e.g. anti-collisions), it is therefore difficult to accurately predict the ship position (Qu et al., 2011; Weng et al., 2012).

To cope with the detection of the different number of ships using different UAVs under uncertainty caused by the dynamic position of the ships, it proposes a multi UAVs cooperative detection strategy with less detection cost and higher detection efficiency. The time of path reprogramming in dynamic environment is determined by comparing the preset threshold with the change of "minimum loop" length. The threshold value is defined as the gap between existing length of the minimized circle and the shortest one over the past moment n. In practice, this threshold value indicates the maximum flying distance of the drone for completing all asked inspection tasks but without rescheduling the route.The algorithm proposed in this paper is based on the threshold to determine the path re planning time of each UAV in dynamic environment, which provides a new idea for solving the path planning problem in dynamic environment.

(4) In order to adapt to the real-time requirements of dynamic environment, this paper improved PSO algorithm based on Tabu search algorithm and the "minimum ring" method to solve the dynamic path planning model, and compares the new algorithm with the traditional PSO algorithm. The experiment proves that the new algorithm has a faster iterative speed, providing a new direction on solving the dynamic scheduling problem of UAVs.

However, there are still some limitations in this study. For example, the influence of the sea wind speed and the influence of air control on the UAV flight path, and testing with more large-scale data in scenarios must be further studied. Moreover, in this study, there can be escaped ships to be detected. Therefore, it is an important research topic to divide the detection area and study the synergism among multiple areas to reduce the appearance of escaped ships. In addition, the solution method based on PSO is essentially a heuristic method, and using a heuristic algorithm to solve VRP is still a challenging subject. These limitations will be our research directions in the future.

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