**Scheduling drones for ship emission detection from multiple stations**

Zhi-Hua Hu 1\*, Tian-Ci Liu 1, Xi-Dan Tian 1

1 Logistics Research Center, Shanghai Maritime University, Shanghai 201306, China

\*Corresponding to: zhhu@shmtu.edu.cn

# Abstract

Various port cities and authorities set up emission control areas (ECA) to constrain the ships’ fuel usage in a specified offshore geographical range. However, the ECA policy faces high costs and low monitoring and regulation enforcement efficiency. In this study, the drone scheduling problem is investigated, considering the simultaneous movements of drones and ships. Set-covering integer linear programs are developed to formulate the assignments of drones to ships. And a model and solution algorithm are devised to formulate the moving times and meeting positions between a drone and a ship. The proposed models and algorithms are demonstrated and verified by experiments. Numerical studies present that considering simultaneous movements in the model can save drone flying distances and increase efficiency. Based on the modeling and experimental studies, managerial implications and possible extensions are discussed.

# Keywords

Drone scheduling problem;

Ship emission detection;

Emission control area;

Integer linear program.

# 1. Introduction

Shipping is the primary transport mode of commodity trade and emits many air pollutants. The atmospheric pollutants discharged by ships will seriously impact the natural environment and public health, and its fundamental source is heavy oil [[1](#_ENREF_1)]. The pollutants emitted from the combustion of ship fuel mainly include sulfur oxides, nitrogen oxides, carbon oxides, and particulate matter, of which sulfur oxides and nitrogen oxides are the most harmful to the atmosphere and human beings [[2](#_ENREF_2)]. As few tail gas filters are installed on ships, the tail gas pollutants drift to coastal and inland port cities with the wind, aggravating urban environmental pollution. Sulfide and nitride produced by heavy oil consumption will seriously impact the natural environment and public health. The problem of ship exhaust emissions is a global environmental protection problem. The tail gas generated by heavy oil burning of various ships contains sulfide, nitrogen oxides, and other toxic and harmful substances, which has caused long-term harm to the port city and coastal residents and further caused global environmental protection problems. Given the unique position of shipping in the world trade, reducing sulfur emissions from ships is of great significance for improving the air quality of the port area and port city, protecting the environment of the coastal regions and the ecology of the whole planet. To reduce the emission of atmospheric pollutants from ships, the government and organizations have established the Emission Control Area (ECA) to control the use of heavy oil by ships [[3](#_ENREF_3)]. For this reason, relevant international organizations and national governments have set up emission control zones with strict requirements on the sulfur content of fuel used for ships. However, light oil is more expensive than oil. The ship owner may use heavy oil, violating these regulations to save costs.

Because of the problem that ship emissions pollute the atmosphere of port cities, the most common means is establishing a ship emission control zone around the port. In this area, ships are required to use high-quality fuel to reduce relevant pollutant emissions. Although the laws and regulations related to the exhaust emission control area have been issued because high-quality fuel will increase the navigation cost of ships, ship violations are common. For the supervision of ship exhaust emissions, the current practice requires many supervisors to screen or conduct surprise inspections on incoming and outgoing ships, which is insufficient in monitoring strength and coverage and wastes many workforces and material resources [[4](#_ENREF_4)]. Drone sniffing technology is used for periodic monitoring of the ECA area, which has the advantages of fast, high efficiency, no regional impact, high inspection quality, and high security [[5](#_ENREF_5)]. Applying this monitoring method and optimizing and improving the patrol inspection path through scientific methods will significantly increase the monitoring intensity and coverage of sulfur emissions in emission control areas, thoroughly crack down on illegal emissions, effectively curb illegal emissions, and effectively promote the implementation of many environmental regulations, including ECA and the sulfur limitation order, which is of great significance for the governance of ship exhaust emissions and the improvement of the global environment. The maritime drones have the following significant advantages: fast response speed, comprehensive coverage, low operating cost, and low safety risk by carrying such mission loads as optoelectronic equipment, airborne AIS (Automatic Identification System), airborne VHF, hyperspectral imaging equipment, sea search radar, oil pollution sampling equipment, etc. to achieve the main functions of cruise law enforcement, administrative inspection, search and rescue emergency, oil (chemical) pollution emergency, communication relay, maritime security, and navigation mapping. At the same time, due to the wide range of patrol sea areas and the uncertainty of climate conditions, the use of drones will also incur related costs. Therefore, the patrol path should be optimized to reduce the operations cost of drones.

This study examines the drone scheduling problem considering multiple drone base stations. In an ECA, multiple drone base stations cooperate to manage the emission detection tasks by scheduling drones. Typically, a drone base station will determine when and dispatch which drone to visit the ships’ exhaust gas. At a station, AIS receivers will detect the offshore ships and verify whether they are crossing the ECA borders or floating in the ECA. Then, the station will dispatch drones to handle the ships based on the ships’ present positions, velocities, and moving directions. The AIS receivers can get these data or estimate them based on the received data. However, the ships may travel for a long range in the ECA, especially of a long belt. So, it is necessary to coordinate the drone base stations to handle the ships because it is enough to detect a ship’s emission once in the ECA if the ship does not leave and ECA, and we can presume that it will not change the fuel. In other words, the drone base stations should cooperatively determine detection frequency to reduce the operations costs while ensuring the administrative effects.

This study contributes to the studies on ECA administration and drone scheduling problems. In the studies on ECA, the policies and operations methods are examined. Some research and practices on ship emission detection activate this study to investigate the possibility and operations models using drones as a new and emerging technology in ECA studies. Indeed, using drones in ship emission detection has been tested and examined in practice. However, it incurs two distinct features. First, the ships are moving when the drones are scheduled and flying to the ships. So, the drone and the ship to be detected should be coordinated. Second, the drone base stations should decide which takes the detection task and schedule a drone. In this study, we formulate models considering these features.

The rest sections are organized as follows. Section 2 reviews the related studies on ECA and drone scheduling problems. Then, we investigate the modes of scheduling drones for immobile ships, a meeting model for a drone and a ship, and the model for scheduling drones for mobile ships in Sections 3, 4, and 5. We conducted a series of numerical experiments to examine the proposed models and algorithms in Section 6. Finally, we conclude the study in Section 7.

# 2. Related studies

## 2.1. Emission Control Area (ECA)

The pollution of shipping exhaust has become the third largest source of air pollution after vehicle exhaust and industrial enterprises. Most ports are concentrated in densely populated areas along the coast and rivers, and carcinogenic waste gases envelop the port cities, causing great harm to residents. It is urgent to strengthen the control of shipping pollution. SOx, NOx, and PM2.5 emitted by ships are one of the "main culprits" of air pollution in port cities, which seriously endanger human health [[6](#_ENREF_6)].

An ECA is established to control the emission of atmospheric pollutants from ships. It reduces the emission of sulfide and nitride by limiting the use of heavy oil. When ships are near the sea, they often travel along the coastline, and the ECA is ribbon-shaped. When a ship sails in the inland sea, its navigation area often presents the outline of the inland sea. In both cases, the moving space of the ship is continuous. The current control area is usually established in the sea area close to land to reduce the impact of atmospheric emissions from ships on the natural environment and human health.

Therefore, it is necessary to take adequate measures to monitor the discharge of ships in the emission control area, which can be used as an auxiliary basis to judge whether ships use heavy oil.

Table 1 summarizes studies on ECA in three aspects: the problem features, methods, and corresponding regions or ports. The ECA is a general emission control solution, so most governments and ports have developed policy tools. The investigated studies on various problem features, including ECA shaping, impacts assessment, ECA-based scheduling optimization, and stakeholders’ behaviors. The studies use four methods: data-driven or principal analytical methods, optimization, behavior, and assessment. In summary, the ECA studies range widely and correlate with many aspects and levels.

Table 1. Pioneering studies on emission control areas

|  |  |  |  |
| --- | --- | --- | --- |
| Study | Research problem | Method | Region/Port |
| [[7](#_ENREF_7)] | An ECA location problem minimizes the impact of Sulphur emissions on human health. | MILP | China+Africa |
| [[8](#_ENREF_8)] | Impacts of ECA regulations on ports efficiency. | DEA | EU+North America |
| [[9](#_ENREF_9)] | Reducing fuel costs by rescheduling voyage plans, speeds, and sailing patterns. | MILP+Tabu |  |
| [[10](#_ENREF_10)] | The impacts of ECAs on global shipping; route-choosing behavior of liner shipping through ECA. | A | Mediterranean Sea |
| [[11](#_ENREF_11)] | Impacts of Panama Canal Authority pollution tax on emissions from ships transiting the Panama Canal. | A | Panama Canal |
| [[12](#_ENREF_12)] | Reschedule ports-of-call sequences, ship route, and speed to minimize total sailing costs. | NLP+GA | North America |
| [[13](#_ENREF_13)] | Coordinate ECA programs to align conflict interests between governments and shipping companies | EGT | China |
| [[14](#_ENREF_14)] | The trade-off between cost and emissions (CO2 and SOx) reduction considering ECAs. | MILP+GA | - |
| [[15](#_ENREF_15)] | Green vessel schedule recovery strategies, including vessel sailing speed adjustment and port skipping. | NLP | - |
| [[16](#_ENREF_16)] | Assess the effect of China's ECA policy and determine the optimal ECA width. | BLP | China |
| [[17](#_ENREF_17)] | Examine dual environmental effects of ECAs in liner-service markets. | A | Shanghai+  Persian Gulf |
| [[18](#_ENREF_18)] | Route and speed optimization to simultaneously reduce sailing cost and time, considering ECA regulations and weather conditions. | MOP+ TOPSIS | US Coast |
| [[19](#_ENREF_19)] | ECA boundary design and emission reduction assessment. | NLP | North America |
| [[20](#_ENREF_20)] | Optimize vessel speeds, and ship fleet sizes considering ECAs. | NLP |  |
| [[21](#_ENREF_21)] | Investigate potentially different effectiveness of ECA policies in port cities located in a specific region | A | China |
| [[22](#_ENREF_22)] | a total emission control method was proposed with an emphasis on water environmentally sensitive areas. | A | Yangtze Delta |
| [[23](#_ENREF_23)] | Impacts of emission tax on vessels and port operations for emission control in port areas. | GT | - |
| [[24](#_ENREF_24)] | Impacts of ECA on reduction of SO2 concentrations | A | China |

Note: A=Analytical data-driven or principal models; BLP=Bi-level program; DEA=Data Envelopment Analysis; EGT=An evolutionary game model; EU= European Union; GA=Genetic algorithm; GT=Game theory; MILP=Mixed-integer linear program; MOP=Multi-objective optimization; NLP=Non-linear program; Tabu=Tabu search. Research problem Method Region/Port.

## 2.2. Drone scheduling problem

Among the existing ship emission monitoring methods, the use of drones is a good choice because the operating mode of drones has the advantages of automation, unmanned, accurate collection of information, the timely transmission of information, and can overcome geographical obstacles [[5](#_ENREF_5)]. However, the fixed cost of purchasing drones and the variable cost of using drones are still high. Optimizing the flight path of drones can save the cost of using drones. At present, many countries have begun to use the monitoring method of fixed-wing aircraft and gas sensors in the aspect of emission control area supervision, that is, through the fixed-wing aircraft carrying a variety of high-precision gas detection sensors or gas collection devices, to monitor the ship exhaust in the emission control area [[25](#_ENREF_25)]. Compared with the previous cumbersome processes, such as law enforcement personnel boarding, document inspection, fuel sampling, and detection, drone-based monitoring has dramatically improved the efficiency of supervision and can achieve non-contact supervision.

The ship emission monitoring system comprises an exhaust gas sensing module, power supply system, pod shell, exhaust gas data control, processing, and transmission system, GPS (Global Positioning System) module, drone control-end software system, and server-end software system. Users can attach the ship emission monitoring system to the drone rack and control part of the working state of the monitoring pod system through GSM (Global System for Mobile Communications) mode at the remote-control end of the drones during the actual operation of the system. At the same time, the ship emission monitoring system transmits the monitored exhaust monitoring data and GPS data to the data server through GPRS (General Packet Radio Services).

The drone flight platform is classified into multi-rotor, fixed-wing, unmanned helicopters, and composite-wing drones in terms of morphology. Considering that the drones need to achieve accurate hovering and synchronous movement at the exhaust emission position of the ship when monitoring the pollution gas from the ship, the drone needs to have strong maneuverability, excellent portability, extensive expansion, and other characteristics. A multi-rotor drone is suggested as a flight platform for patrolling, law enforcement, and evidence collection.

In Table 2, we summarize some pioneering studies in three aspects. The drone scheduling problem occurs in various scenarios, mainly delivery, surveillance, and communication relay systems. Related to this study, the applications on delivery (mainly including emergency delivery and city logistics) can inspire the model and algorithm developments. We can observe three distinct features of the drone scheduling problems, including the coordination between drones and other devices (e.g., trucks), the battery and its endurance problem, and the dynamics of the drone flying and services. In the context of ship emission detection, the drone scheduling problem also reflects these features to some extent.

Table 2. Pioneering studies on drone scheduling problems

|  |  |  |  |
| --- | --- | --- | --- |
| Study | Research problem | Methods | Scenario |
| [[26](#_ENREF_26)] | The flying speed of the drone is optimized while ensuring that it completes the route within a specific time and without depleting its battery. | NLP+DP | Surveillance |
| [[27](#_ENREF_27)] | Energy trading between the drones and charging station. | GT | Delivery |
| [[28](#_ENREF_28)] | A parcel delivery system using drones | MILP+H | Delivery |
| [[29](#_ENREF_29)] | Parallel drone scheduling traveling salesman problem; a set of customers requiring a delivery is split between a truck and a fleet of drones. | MILP+H | Delivery |
| [[30](#_ENREF_30)] | Drone mobility in the lateral or vertical path leads to the time-selective and frequency-selective wireless channel for a low-altitude drone. | A | Communication |
| [[31](#_ENREF_31)] | A drone-based delivery scheduling method considering drone failures to minimize the expected loss of demand. | SA | Delivery |
| [[32](#_ENREF_32)] | Drone flight scheduling under uncertainty on battery duration and air temperature | ML | - |
| [[33](#_ENREF_33)] | A hybrid battery charging approach with dynamic wireless charging systems | NLP | - |
| [[34](#_ENREF_34)] | A drone-based diagnostic testing kit delivery scheduling problem with one truck and multiple drones. | H | Emergency delivery |
| [[35](#_ENREF_35)] | Authenticating drones and verifying their charging transactions with charging stations | PSO+GT | - |
| [[36](#_ENREF_36)] | Delivering perishable items to remote demands accessible only by helicopters or drones. | A | Emergency delivery |
| [[37](#_ENREF_37)] | A drone scheduling problem for delivering small parcels to remote islands considering wind direction and speed | RO | Island delivery |
| [[38](#_ENREF_38)] | Coordinating a truck and multiple heterogeneous drones for last-mile package deliveries. | SA+VNS  VNS | Delivery |
| [[39](#_ENREF_39)] | 5G-powered drone video transmission | ML | Video streaming |
| [[40](#_ENREF_40)] | On-time delivery of packages. | MILP  GA+PSO | Warehouse |
| [[41](#_ENREF_41)] | Deriving actions at a battery swap station when explicitly considering the uncertain arrival of swap demand, battery degradation, and replacement. | DP | Delivery |

Note: DP = dynamic programming; H = Heuristics; MILP = mixed-integer linear program; ML = machine learning; NLP = non-linear program; PSO = particle swarm optimization; RO = robust optimization; SA = Simulated Annealing; VNS = variable neighborhood search.

# 3. Scheduling drones for immobile ships

In the following, we investigate the drone scheduling problem in three steps. First, we consider that the ships wait at the positions, and the drones fly to check the ships’ emissions. Indeed, as the premise, the drone flying speed should be far greater than the ships.

## 3.1. Problem statement

As depicted in Figure 1, two drone base stations dispatch drones for ship emission detection tasks. A drone flies from its hosted station to the ship, whose position can be determined by the AIS receiver at the drone base station or other facilities connected with the station. However, the presumption that the ship waits for emission detection does not always meet. When the drone flies to the pre-determined position, the ship moves forward in its direction.

|  |
| --- |
|  |
| Figure 1. A conceptual diagram of drone routing for emission detection |

## 3.2. Formulation

The drone scheduling problem described above concerns two sets, the set of ships, , indexed by ; and the set of drone base stations, , indexed by . denotes the time that a drone flies from the station to the ship ; and denotes the number of available drones at station . The binary decision variable is 1 if the drone base station dispatches a drone to visit the ship ; 0, otherwise. Using these data and variables, the drone scheduling model [M1] determines the assignment of ships to drone base stations.

|  |  |
| --- | --- |
|  |  |
| Subject to |  |
|  | (1) |
|  | (2) |
|  | (3) |

The objective of [M1] is to minimize drone fly times. It also equals the time waited by the ships. In Constraint (1), every ship is visited by a drone base station. In (2), a drone base station can send drones of a limited number to the ships. In the model, it is presumed that there are enough drones for the ships. Namely, . In (3), the scheduling relation is formatted by binary variables.

When the drones reach the pre-determined positions, the ships move far from these positions. The total distance can be calculated by (4). If a drone tries to chase the ship , the time can be determined by (5). It is presumed that the drones always fly fast the ships’ movement speeds, namely . Besides, we can compute the time and distance of chasing the ship by the drone from the base station , denoted by and in (5)-(8).

|  |  |
| --- | --- |
|  | (4) |
|  | (5) |
|  | (6) |
|  | (7) |
|  | (8) |

We can denote the solving of [M1] and the results of it by,

# 4. A meeting model for a drone and directional mobile ship

## 4.1. Formulation

As studied above, when the drone flies to the pre-determined position of the ship, the ship will move to its destination position. So, it is beneficial to coordinate the drone and ship’s movements. We compute the meeting position considering their movements and then dispatch the drone to the estimated position.

A ship , located at , targets in the direction , with a moving speed, . A drone base station , locates at . If the station dispatches a drone with speed to visit the ship , the drone should fly for the time to meet the ship while the ship is moving in the target direction.

The position at which the drone meets the ship is shown in Figure 2. The ship travels from point to point . We can draw two circles, one for the drone with the center and radius , another for the ship with the center and the radius . The intersection of two circles on line is the meeting point. We can compute the intersection by solving the model (9), where are given in (10) and (11).

|  |  |
| --- | --- |
|  | (9) |
|  | (10) |
|  | (11) |

|  |
| --- |
|  |
| Figure 2. A meeting model for a drone and directional mobile ship |

## 4.2. Solution algorithm

To solve (8), we devised a binary search algorithm. First, select the midpoint of segment , and compare the time () when the ship and the drone arrive at this point . If , then select the midpoint between and ; If , then select the midpoint between and . The specific algorithm is shown in Algorithm 1. The sequential insertion algorithm is shown in Algorithm 2.

|  |  |
| --- | --- |
| Algorithm 1 | Dichotomy algorithm (DA) |
| Input | the ship ’s position; |
|  | the ship ’s target position;  the drone base position;  : the ship ’s speed;  : The speed of the drone. |
| Output | : the position and time. |
| Variable | : the lower and upper bounds of the intersection position of the drone and ship; |
|  | : the time when the ship travels to the intersection point;  : tolerance. |
| Steps |  |
| Step 1 | Initialize and . |
|  | ;  ;  . |
| Step 2 | Compute |
|  | . |
| Step 3 | While : |
| Step 3.1 | If : |
|  |  |
| Step 3.2 | Else: |
|  |  |
|  | End if |
| Step 3.3 | Update . |
|  | . |
| Step 3.4 | Update |
|  | . |
| Step 4 | Return |

We can get the meeting position and flying time for a drone at the base station and a ship by the above model [M2], denoted by,

The above model and algorithm are denoted by a function as follows,

# 5. Scheduling drones for mobile ships

## 5.1. Problem statement

Figure 3 depicts a conceptual diagram of the drone routing problem based on the ships’ present positions and moving directions. The drones from the left base station fly to ships 1, 2, and 3, while those from the right base station fly to ships 4, 5, and 6. Taking Ship 4’s emission detection as an example in the figure, the ship moves from the present position to the target. The drone from the right base station flies directly to the meeting position.

As studied above, the meeting position can be pre-calculated by .

|  |
| --- |
|  |
| Figure 3. A conceptual diagram of drone routing for emission detection |

As studied above, we denote the -th drone base position by , the ship set , the ship ’s position , the target position , and the speed . The speed of the drone is . To formulate the drone routing problem, we introduce a tri-tuple variable , representing the position and time where the detection action occurs. Thus, we can order the tuples by and to obtain the sequence of visits to the ships, denoted by . And denotes the arc lists starting from the drone base and ending at the base station.

## 5.2. Formulation

Using the above notations, we formulate the drone routing problem in [M1].

|  |  |
| --- | --- |
|  |  |
| subject to |  |
| Constraints . |  |
|  | (12) |

Formally, [M3] does not change the form of [M1] but changes the parameter () generation scheme. [M1] and [M3] are both typical set-covering problems, integer linear programs solvable by on-the-shelf solvers, e.g., Cplex and Gurobi.

Similarly, we can denote the objective of solving [M3] by , and compute by Eq. (4). Because [M3] uses the meeting model [M2], .

We can denote the solving of [M3] by,

# 6. Numerical experiments

## 6.1. Parameter estimation

As studied in Section 4, there are two key parameters: the drone's and ships' velocities. In the experiments, we set meters/second. The ships travel in the ECA with the velocities, knots/hour, namely, meters/second approximately. We consider the ECA at the Yangtze River estuary in a range of . To avoid references to real-world facilities, we use such a virtual area to represent the ECA with generality in methodology. The endurance mileage of the drone depends on battery technology, and thus different types differ. In this study, we assume that the endurance is adequate, which may affect the ships and the virtual area settings.

## 6.2. Dataset generation

We generate the datasets using the following criteria. First, the virtual ECA is separated into two parts - the data area and the idle area (Figure 4). The ships’ present and target positions are located in the data area. When generating two positions, the far one represents the present position, while the close one is the target.

|  |
| --- |
|  |
| Figure 4. A background diagram for dataset generation |

We generate the ships’ present and target positions in the range (). A pair of present and target positions determines the moving direction of the ship. The drone’s initial position is . The dataset name is formatted as “KkNnVvXxYY”. K represents the number of drone base stations; N represents the number of ships generated; V represents the flying speed of the drone; X represents the horizontal range; Y represents the vertical range. For example, “K2N5V25X20Y10” indicates that the drones from two base stations are at the ECA of the range , five ships’ emissions need to be detected by the drones with a speed of .

## 6.3. Experimental results

We conducted three groups of experiments to study the devised models [M1], [M2], and [M3].

### 6.3.1. Demonstration of [M1] and [M3]

We use the dataset “K2N20V25X20Y10” as presented in Table 3 to demonstrate [M1] and [M3]. Figure 5(a) depicts the solution of [M1], where we presume that the ships wait for the drones for emission detection. In the figure, two groups of drones fly from the two base stations and visit ships one by one. The grey line arrows represent the flight of the drones, and the black ones represent the moving directions of ships. Figure 5(b) depicts a much more complicated diagram of the drone’s flying tracks, the ships’ moving tracks, and their moving directions. The line with two arrows presents two segments of a ship’s movement. Namely, the first segment is ship movement from the origin position () to the position meeting the detection drone. The second segment represents the moving direction.

Table 3. A dataset K2N20V25X20Y10 used in the demonstration

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |  |  |  |  |
| 1 | 9 | 8 | 7 | 4 | 6 | 11 | 10 | 12 | 7 | 4 | 5 |
| 2 | 4 | 4 | 9 | 5 | 8 | 12 | 8 | 1 | 7 | 4 | 9 |
| 3 | 15 | 14 | 7 | 4 | 6 | 13 | 4 | 4 | 8 | 4 | 7 |
| 4 | 0 | 17 | 8 | 5 | 7 | 14 | 19 | 18 | 7 | 6 | 5 |
| 5 | 17 | 19 | 9 | 6 | 5 | 15 | 16 | 13 | 7 | 6 | 8 |
| 6 | 16 | 13 | 7 | 6 | 6 | 16 | 4 | 11 | 7 | 5 | 8 |
| 7 | 17 | 5 | 8 | 5 | 6 | 17 | 15 | 10 | 9 | 5 | 6 |
| 8 | 8 | 13 | 7 | 6 | 5 | 18 | 11 | 9 | 7 | 4 | 7 |
| 9 | 9 | 19 | 9 | 6 | 7 | 19 | 11 | 15 | 9 | 4 | 6 |
| 10 | 0 | 13 | 7 | 4 | 8 | 20 | 1 | 18 | 9 | 6 | 5 |

|  |  |
| --- | --- |
|  |  |
| (a) [M1] | (b) [M3] |
| Figure 5. Demonstrating the solutions with or without the meeting model [M2] | |

Table 4 presents six criteria for the two solutions, while [M3] only concerns two. As shown in the table, using [M1] incurs 41.112% () more flying time and 189.777% () drones’ distances for chasing the ships.

Table 4. Flying times and distances metrics of solving [M1] and [M3]

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Solving |  |  |  |  |  |  |
| [M1] | 2.524 | 0.856 | 3.381 | 56.886 | 77.069 | 133.955 |
| [M3] | 1.991 | 0 | 1.991 | 46.227 | 0 | 46.227 |

### 6.3.2. Comparing [M1] and [M3]

To compare the solutions of [M1] and [M3], we generate 18 datasets with varying parameters (the drone base stations and the ships, ) and three constant parameters (the drone flying speed, and the two coordinate ranges, ). Thus, the group of datasets can be denoted by “KkNnV25X20Y10”. For each dataset, we employ ten assessment metrics representing the results of [M1] and [M3]: the drones’ flying time , chase time and all time; the drones’ flying distance () and the distances for chasing the ships (), and all the distances; the flying time () and distance () of solving [M3]; finally, we define two metrics for the ratios of flying time () and distance () changed by using the meeting model [M2], as follows,

Table 3 presents the ten metrics of solving [M1] and [M2] for the 18 datasets. We further divide these metrics into three groups and depict them in Figures 6, 7, and 8. In the figures, “” means the datasets have drone base stations. In Figure 6, the values of time-related metrics for the datasets with three drone base stations are lower than those with two. In Figure 7, we can get similar results that more drones will get less flying distances. Figures 8 and also 6, and 7 show that using [M3] will get fewer flying times and distances than [M1]. Figures 6 and 7 show that the datasets with more ships will incur more flying times and distances almost linearly. However, in Figure 8, we can see that from 45 to 50 ships, the ratios optimized by [M3] drop while they are still positive.

Table 5. The comparative results of solving [M1] and [M3]

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| K | N |  |  | Sum |  |  | Sum |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
| 2 | 10 | 1.23 | 0.42 | 1.65 | 27.40 | 37.36 | 64.75 | 6.35 | 41.12 | -7.17 | 36.50 |
| 2 | 15 | 1.95 | 0.71 | 2.66 | 45.69 | 63.79 | 109.48 | 9.35 | 62.93 | 2.45 | 42.52 |
| 2 | 20 | 2.52 | 0.92 | 3.44 | 59.84 | 82.49 | 142.33 | 11.70 | 74.65 | 5.51 | 47.55 |
| 2 | 25 | 3.29 | 1.26 | 4.55 | 80.87 | 113.68 | 194.55 | 15.16 | 102.85 | 7.39 | 47.14 |
| 2 | 30 | 4.08 | 1.55 | 5.63 | 99.41 | 139.11 | 238.52 | 17.77 | 121.58 | 12.31 | 49.03 |
| 2 | 35 | 4.69 | 1.84 | 6.53 | 117.02 | 165.52 | 282.54 | 20.81 | 145.07 | 11.41 | 48.65 |
| 2 | 40 | 5.53 | 2.22 | 7.75 | 140.28 | 199.49 | 339.77 | 23.86 | 165.62 | 14.49 | 51.26 |
| 2 | 45 | 6.36 | 2.52 | 8.88 | 159.38 | 226.60 | 385.97 | 27.10 | 186.57 | 15.22 | 51.66 |
| 2 | 50 | 6.81 | 2.78 | 9.58 | 174.55 | 250.12 | 424.67 | 30.38 | 213.94 | 11.97 | 49.62 |
| 3 | 10 | 1.10 | 0.38 | 1.48 | 25.02 | 34.38 | 59.40 | 5.93 | 38.61 | -11.31 | 35.01 |
| 3 | 15 | 1.79 | 0.64 | 2.43 | 41.41 | 57.54 | 98.94 | 8.92 | 60.09 | -1.93 | 39.27 |
| 3 | 20 | 2.26 | 0.81 | 3.07 | 53.27 | 73.23 | 126.50 | 11.14 | 70.76 | -0.75 | 44.06 |
| 3 | 25 | 2.98 | 1.15 | 4.13 | 73.60 | 103.59 | 177.18 | 14.37 | 97.19 | 3.35 | 45.15 |
| 3 | 30 | 3.78 | 1.42 | 5.20 | 91.52 | 127.81 | 219.34 | 16.96 | 115.73 | 9.40 | 47.23 |
| 3 | 35 | 4.32 | 1.70 | 6.02 | 108.13 | 153.17 | 261.30 | 19.65 | 136.45 | 9.29 | 47.78 |
| 3 | 40 | 5.06 | 2.01 | 7.07 | 127.64 | 181.11 | 308.76 | 22.72 | 157.18 | 10.80 | 49.09 |
| 3 | 45 | 5.90 | 2.33 | 8.23 | 147.50 | 209.50 | 357.01 | 25.83 | 177.60 | 12.78 | 50.25 |
| 3 | 50 | 6.22 | 2.53 | 8.75 | 159.05 | 227.62 | 386.67 | 28.82 | 202.15 | 8.52 | 47.72 |

|  |
| --- |
|  |
| Figure 6. The time-related metrics for the results of solving [M1] and [M3] |

|  |
| --- |
|  |
| Figure 7. Distance-related metrics for the results of solving [M1] and [M3] |

|  |  |
| --- | --- |
|  |  |
| (a) | (a) |
| Figure 8. Reduced ratio of time- and distance-related metrics for solving [M1] and [M3] | |

### 6.3.3. Sensitivity analysis of speeds by solving [M3]

In [M1], [M2], and [M3], the drones’ and ships’ speeds are technology and investment-dependent parameters. Speeding up ships’ speeds and drones will generally incur higher energy costs and more emissions. Moreover, the technologies will constrain the speeds of drones. Speeding up drones may require innovation and additional investments. In the following, we investigate the impacts of varying the drones' and ships’ speeds on the time and distance-related metrics, and .

Table 6 presents the sensitivity of the ships’ speeds () by varying them -5% and 5%. The variances affect the time metrics less than 1%, while affecting the distance matrics more, about 4-5%. In Table 7, we can see similar results. Speeding up the drones will optimize the drones’ flying distances more than time.

Table 6. Sensitivity of the ships’ speeds () of solving [M3]

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |
| K | N | -5% |  | +5% | -5% |  | +5% |
| 2 | 10 | -0.73 | 1.76 | 0.71 | 4.28 | 41.12 | -4.22 |
| 2 | 15 | -0.43 | 2.60 | 0.46 | 4.57 | 62.93 | -4.77 |
| 2 | 20 | -0.63 | 3.25 | 0.61 | 4.37 | 74.65 | -4.32 |
| 2 | 25 | -0.62 | 4.21 | 0.60 | 4.41 | 102.85 | -4.37 |
| 2 | 30 | -0.76 | 4.94 | 0.74 | 4.26 | 121.58 | -4.21 |
| 2 | 35 | -0.60 | 5.78 | 0.58 | 4.41 | 145.07 | -4.37 |
| 2 | 40 | -0.57 | 6.63 | 0.55 | 4.44 | 165.62 | -4.40 |
| 2 | 45 | -0.65 | 7.53 | 0.63 | 4.35 | 186.57 | -4.30 |
| 2 | 50 | -0.71 | 8.44 | 0.69 | 4.30 | 213.94 | -4.25 |
| 3 | 10 | -0.67 | 1.65 | 0.65 | 4.36 | 38.61 | -4.31 |
| 3 | 15 | -0.56 | 2.48 | 0.61 | 4.41 | 60.09 | -4.41 |
| 3 | 20 | -0.68 | 3.09 | 0.69 | 4.43 | 70.76 | -4.22 |
| 3 | 25 | -0.67 | 3.99 | 0.68 | 4.35 | 97.19 | -4.12 |
| 3 | 30 | -0.79 | 4.71 | 0.79 | 4.23 | 115.73 | -4.14 |
| 3 | 35 | -0.67 | 5.46 | 0.68 | 4.24 | 136.45 | -4.26 |
| 3 | 40 | -0.62 | 6.31 | 0.60 | 4.39 | 157.18 | -4.35 |
| 3 | 45 | -0.68 | 7.18 | 0.68 | 4.28 | 177.60 | -4.24 |
| 3 | 50 | -0.74 | 8.01 | 0.72 | 4.28 | 202.15 | -4.17 |

Table 7. The sensitivity of the drones’ speeds () of solving [M3]

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |
| K | N | -5% |  | 5% | -5% |  | 5% |
| 2 | 10 | -0.73 | 1.76 | 0.71 | 4.28 | 41.12 | -4.22 |
| 2 | 15 | -0.43 | 2.60 | 0.46 | 4.57 | 62.93 | -4.77 |
| 2 | 20 | -0.63 | 3.25 | 0.61 | 4.37 | 74.65 | -4.32 |
| 2 | 25 | -0.62 | 4.21 | 0.60 | 4.41 | 102.85 | -4.37 |
| 2 | 30 | -0.76 | 4.94 | 0.74 | 4.26 | 121.58 | -4.21 |
| 2 | 35 | -0.60 | 5.78 | 0.58 | 4.41 | 145.07 | -4.37 |
| 2 | 40 | -0.57 | 6.63 | 0.55 | 4.44 | 165.62 | -4.40 |
| 2 | 45 | -0.65 | 7.53 | 0.63 | 4.35 | 186.57 | -4.30 |
| 2 | 50 | -0.71 | 8.44 | 0.69 | 4.30 | 213.94 | -4.25 |
| 3 | 10 | -0.67 | 1.65 | 0.65 | 4.36 | 38.61 | -4.31 |
| 3 | 15 | -0.56 | 2.48 | 0.61 | 4.41 | 60.09 | -4.41 |
| 3 | 20 | -0.68 | 3.09 | 0.69 | 4.43 | 70.76 | -4.22 |
| 3 | 25 | -0.67 | 3.99 | 0.68 | 4.35 | 97.19 | -4.12 |
| 3 | 30 | -0.79 | 4.71 | 0.79 | 4.23 | 115.73 | -4.14 |
| 3 | 35 | -0.67 | 5.46 | 0.68 | 4.24 | 136.45 | -4.26 |
| 3 | 40 | -0.62 | 6.31 | 0.60 | 4.39 | 157.18 | -4.35 |
| 3 | 45 | -0.68 | 7.18 | 0.68 | 4.28 | 177.60 | -4.24 |
| 3 | 50 | -0.74 | 8.01 | 0.72 | 4.28 | 202.15 | -4.17 |

## 6.4. Discussions and managerial implications

Drones have become an emerging technology in monitoring offshore ship emissions, with lower costs, higher flexibility, and efficiency. Although there are still challenges in drone technologies and operations management capabilities, drones can be essential in undertaking advanced technologies with controlled risks. Due to the pollution burden, port cities and authorities have anticipated developing ECA and propelling the ships to use cleaner fuel in the ECA. To achieve this objective, the maritime departments must monitor the fuel usage of the ships by regulations and accurate monitoring and enforcement. In this study, we formulated the ship emission detection problem as a drone scheduling problem.

We make the following generations as managerial implications based on the experimental results.

1) Drone scheduling problem is dynamic with simultaneous movements of drones and ships. When drones fly far faster than ships’ movements, we can assume that the ships are waiting for the drones’ visits. However, in practice, the drones’ speeds may be about three times that of ships. It is not applicable to neglect the ships’ movement.

2) Multiple drone base stations help decrease the flying costs and increase the coverage of the ECA, while too many stations will incur high fixed charges. Therefore, considering the endurance of the drones, we can optimize the configuration of the drone base stations.

3) In this study, we examine the drone scheduling problem at the operations level, while the coordination mechanisms and information systems will pre-determine the operations performances. First, the drone scheduling system must use the information from the AIS receivers to locate the ships dynamically. Second, the drone base stations must share the schedules and be organized under a top-level scheduling system. So, drones can be scheduled globally. Third, the local ECA authorities should share the ship emission detection schedules and results with each other.

# 7. Conclusion

Ship emissions become an essential source of pollution in port cities, especially in some regions with prosperous ports and shipping industries. Shanghai is such a city facing significant challenges because it is a mega port in the world in the estuary of the Yangtze River. The endless flow of ships makes this city powerful and brings enormous pollution. Thousands of ships may cross the river's estuary and berth at Shanghai Port’s various terminals. Although Shanghai had set up the ECA and conducted strict monitoring programs, it is still beneficial to use advanced technologies to detect ship emissions. Shanghai maritime department created an application for drones to monitor the ships, including emission detection. In such background, we investigate the drone scheduling problem at the operations level, especially considering multiple drone base stations for long ECA ranges.

We conduct the research after examining the relations studies, technologies, and applications. Considering the simultaneous movements of drones and ships, we devised models for immobile and mobile ships. The two models can share the same model while changing the traveling time matrix through a meeting model between a drone and a ship. The models are demonstrated and investigated by experiments. We can extend the present studies in the following aspects. First, we assume that each ship has a fixed moving direction and velocity, while the ships may change their directions slowly in practical situations. We can get the dynamics of the moving directions and speeds through AIS data. Second, the drones are presumed to start from the drone base stations and return after the one-ship task. When endurance permits, a drone can perform several detection tasks. By extending the devised models, we can conduct new studies to make the solutions suitable for more practical situations and support ship emission detection.

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