A Modelling Framework of Drone Deployment for Monitoring Air Pollution from Ships

Jingxu Chen[1,2], Shuaian Wang[1], Xiaobo Qu[3], Wen Yi[4]

[1]Department of Logistics & Maritime Studies, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong
wangshuaian@gmail.com (S Wang) shenqiudeliming@163.com (J Chen)

[2]Jiangsu Key Laboratory of Urban ITS, Jiangsu Province Collaborative Innovation Center of Modern Urban Traffic Technologies, Southeast University, China
zhiyuanl@seu.edu.cn

[3] Department of Architecture and Civil Engineering, Chalmers University of Technology, SE-412 96 Gothenburg, Sweden
xiaobo@chalmers.se

[4] School of Engineering and Advanced Technology, College of Sciences, Massey University, Auckland, New Zealand
yiwen96@163.com

Abstract

Sulphur oxide (SOx) emissions impose a serious health threat to the residents and a substantial cost to the local environment. In many countries and regions, ocean-going vessels are mandated to use low-sulphur fuel when docking at emission control areas. Recently, drones have been identified as an efficient way to detect non-compliance of ships, as they offer the advantage of covering a wide range of surveillance areas. To date, the managerial perspective of the deployment of a fleet of drones to inspect air pollution from ships has not been addressed yet. In this paper, we propose a modelling framework of drone deployment. It contains three components: drone scheduling at the operational level, drone assignment at the tactical level and drone base station location at the strategic level.

1. Introduction

International shipping usually uses heavy fuel oil (HFO), whose sulphur content can be up to 3.5%, 3,500 times higher than levels of Euro V fuel used in automobiles. When ocean-going vessels approach container terminals, they emit a substantial amount of SOx. For example, in Hong Kong, about 3.8 million people live in close proximity to the Kwai Tsing container terminals and risk direct exposure to ship related SOx emissions, which account for 44% of the total SOx emissions in Hong Kong. In practice, sulphur oxide (SOx) emissions impose a serious health threat to the residents and a substantial cost to the local environment. To formulate environmentally conscious and sustainable policies, many countries and regions advocate fuel switch at berth. Ocean-going vessels are mandated to use low-sulphur fuel with maximum sulphur content (e.g. 0.5%) when docking at emission control areas (ECA).

Currently, there are three frequently used methods to verify whether ships have switched to low sulphur fuel in ECA. (i) The first one is fuel sampling. Fuel sampling for sulphur testing at laboratories is the most reliable way to verify the sulphur content of the fuel being used on board. However, fuel sample is costly and time consuming, and therefore is only carried out when there are clear signs of non-compliance (Fung, 2016). (ii) The second one is on-board inspections of fuel-related documents, such as bunker delivery notes and log books. A major deficiency of this method is that these materials may not be sufficient for proving that compliant fuel has actually been used on board. (iii) The third one is fixed-point remote measurement, often using the sniffing method which can identify gross emitting ships from afar. Because of the higher uncertainty of remote measurement results, remote sensing results are used as a cost effective means of screening ships suspected of using non-compliant fuel. Suspected ships will have their fuel sampled at the next port of call for lab test. The fixed-point sniffing method can only inspect ships in small territorial water areas as the exhaust gases of ships must be close to the measurement equipment. Moreover, once ship operators learn the locations of the measurement equipment, they can adapt to it by switching to low sulphur fuel only when the ship is close to the measurement equipment (Fung, 2016).

In recent years, airborne surveillance methods, typically drones equipped with sniffers, have been identified as an efficient way to pre-screen ships that are more likely to be non-compliant. Drones offer the advantage of covering a much wider range of surveillance areas (Ning, 2016). This enables regulators to be able to effectively target suspected emitting ships for follow-up on-board inspections. Moreover, a drone could follow a ship, and transact multiple times across the plume in order to obtain a more reliable estimate. Another advantage of using drone technology is that it is much cheaper to deploy than traditional on-board inspection methods.

The usage of drones has been steadily gained attention from local government, industrial community and research community due to its high efficiency and convenience. In several countries, the local authorities have started piloting the use of drones to support regular ship inspection programs. For instance, Denmark announced it will spend about a million Euro to employ aerial sniffer drones to inspect the sulphur content of engine exhaust of ships (Collum, 2015). Turkey announced it will use drones to complement existing enforcement mechanisms to monitor marine pollution, improve surveillance and enforce penalties (Roberts, 2016). In industrial community, the Trident Alliance, which includes Maersk Line and 37 other companies, has given its endorsement to the idea of using drones for effective enforcement of ECA rules (Marine Electronics and Communication, 2015).

Furthermore, some studies focus on the technological aspects by developing sonar and optical flow sensors suitable for application to ship emission inspections. These studies have provided beneficial technical support of using drones to monitor ship emissions from the technological perspective. As the continuous increase of drone uses, efficient management of the drones will be vital to the enforcement of ECA rules. However, the managerial perspective of the deployment of a fleet of drones to inspect air pollution from ships has not been addressed particularly. From the perspective of academic research, although vehicle scheduling (Kuang et al., 2015; Qu et al., 2015, 2017; Liu et al., 2016, 2017a, b; Huang et al., 2016) and vessel scheduling (Zhen et al., 2017a, b, 2018) have been extensively studied, drone scheduling related research is scarce.

The optimal deployment of drones is a practical research topic which provides significant value in addressing climate change and environmental sustainability by reducing SOx emissions from shipping. To this end, this study aims to build a modelling framework of drone deployment (DP) for monitoring air pollution from ships. The DP modelling framework subsumes three main components, namely drone scheduling, drone assignment and drone base station location, which is elaborated in the next section.

2. Modelling Framework

In this section, we present the modelling framework for the deployment of drones. It can be decomposed into three components that span operational, tactical and strategic decisions: (1) Design the optimal schedule on a real-time basis for each drone, including which ships to be inspected by the drone and when to inspect each ship, at the operational level, (2) Identify the optimal assignment of drones to base stations on a daily basis at the tactical level, and (3) Evaluate the optimal locations of base stations for drones at the strategic level. The overall DP modelling framework is shown in Figure 1.

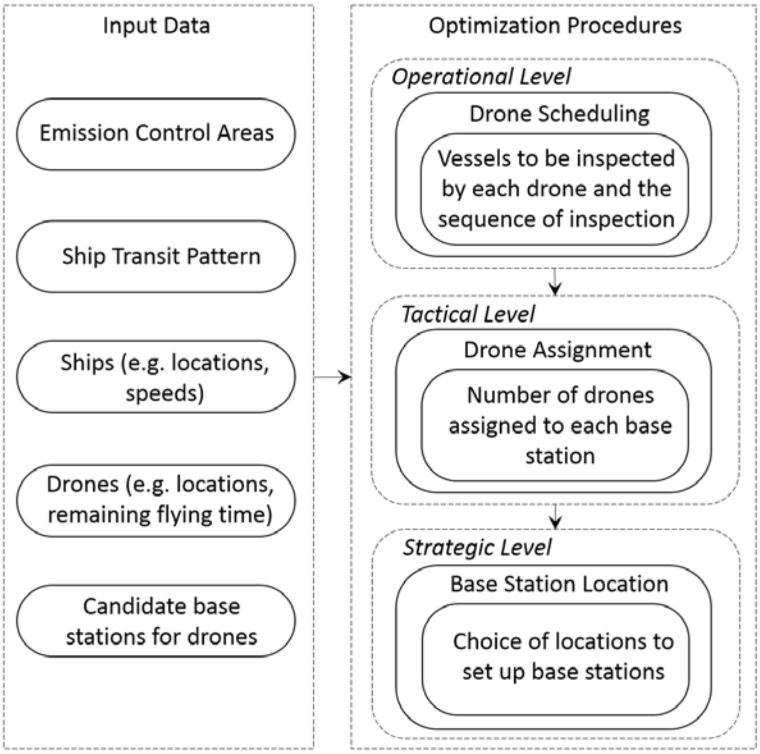

Figure 1: Overall DP modelling framework

When drones leave a base station, they begin to follow ships in emission control areas, and transact multiple times across the plume in order to monitor ship emissions. Nevertheless, drones have flying time limitation. They can generally fly for up to two hours and associated flying distance is less than 100 km. After that, they have to return to a base station to replace depleted batteries with fully charged ones.

Meantime, to avoid ship collision, all ships are equipped with an automatic identification system (AIS). Information provided by the tracking system AIS also includes the identification of the ship, its position, sailing direction, and speed. According to AIS data (Marine Traffic, 2017), we can obtain the real-time locations and speeds of all of the ships in the world.

2.1. Drone Scheduling

At the operational level, the optimal schedule needs to be determined for each drone at each station, including which ships to inspect by each drone and when to inspect each ship (or equivalently, the sequence of inspecting the ships). In addition, the schedule for a drone also includes information on when the drone should return to its base station for battery change.

In practice, there are a larger number of ships transiting the ECA and it may not be possible to inspect all of them. The purpose of drone scheduling is to maximize the total "weighted" number of ships that are inspected. The "weight" of a ship is the ship's chance of noncompliance. For example, ships with noncompliance history and ships whose operators have no prior experience of fuel switching should have a higher "weight", and ships that have already been inspected in other zones should have a lower "weight". Drones can be rescheduled every e.g. 10 min, by updating the AIS data of the ships, the inspection history of the ships (some ships have been inspected at dockside or in other zones), and the drone information (current location and remaining travelling distances before its battery is depleted).

The drone scheduling problem is related to the Vehicle Routing Problem with Time Windows (VRPTW) (Cordeau et al., 2000): a base station is a depot, a drone is a vehicle, a ship is a customer, and each ship has time window during which the ship should be inspected (otherwise the ship will sail out of ECA). The VRPTW has been proved to be strongly NP-hard, meaning that there is no polynomial-time or even pseudo-polynomial-time algorithm for it unless P=NP. A number of algorithms, such as column generation, branch and cut, branch and price, and meta-heuristics, have been proposed to identify optimal solutions for small-scale instances or good solutions for large-scale instances (Desrochers et al., 1992; Ho and Haugland, 2004; Bräysy and Gendreau, 2005; Kallehauge, 2008).

However, the drone scheduling problem is much more difficult than the VRPTW because ships are sailing rather than stationary in the emission control area. In other words, the scheduling of drones should be carried out in a dynamic manner. Assuming the drone speed is fixed, the time required by a drone to fly from ship u to ship v, denoted by $d_{uv}(t)$, is dependent on the start flying time t from ship u. By contrast, in the VRPTW, $d_{uv}(t)$ is equal to a constant d_{uv} for all t. In this sense, droning scheduling is a three-dimensional VRPTW.

We can formulate a mathematical optimization model for the drone scheduling problem. The decision variables are as follows:

$z_v \in \{0,1\}$: equal to 1 if ship v is inspected, and 0 otherwise;

$x_{uvk} \in \{0,1\}$: equal to 1 if drone k inspects ship v immediately after inspecting ship u, and 0 otherwise;

$t_{vk} \geq 0$: start inspection time of ship v when inspected by drone k.

The inputs to the model mainly include the following:

w_v: the "weight" of ship v, i.e., the importance of inspecting ship v;

$[a_v, b_v]$: time window of ship v during which it should be inspected;
$d_{uv}(t)$: time required by a drone to fly from ship u time t to ship v;
Δ: Time required by a drone to inspect a ship;
Θ: Maximum flying duration of a drone without changing batteries.

Suppose that base station s has n_s drones. A basic version of the scheduling model for all of the n_s drones is as:

$$R_s(n_s) = \max \sum_v w_v z_v \tag{1}$$

subject to:

$$x_{uvk}(t_{uk} + \Delta + d_{uv}(t_{uk} + \Delta) - t_{vk}) \le 0 \tag{2}$$

$$a_v \le t_{vk} \le b_v \tag{3}$$

$$\text{Total flying time of drone } k \text{ between two returns to base station} \le \Theta \quad , k = 1, 2, ..., n_s \tag{4}$$

and other constraints. The objective function (1) maximizes the total "weighted" number of ships that are inspected, denoted by $R_s(n_s)$. Constraint (2) ensures that there is sufficient time interval for drones to fly from one ship to the next. Constraint (3) guarantees that a ship must be inspected during its time window. Constraint (4) enforces the maximum flying duration of drones.

In Constraint (2), $d_{uv}(t)$ is generally a non-convex, non-differentiable function of t; moreover, $d_{uv}(t)$ may not even have an analytical expression. To overcome this difficulty, we plan to propose two solutions approaches. (i) For base stations with a small number of drones and ships to inspect, the time t can be discretized into small time intervals. After discretization, $d_{uv}(t)$ will be transformed into linear expressions with extra integer variables. Then, the above model can be transformed into a mixed-integer linear formulation, and we can develop exact algorithms to derive the optimal solution. (ii) If a base station has a large number of ships to inspect, the computational time of exact algorithms will be too long for practical application. We will hence design heuristics or meta-heuristics to obtain near-optimal solutions in reasonable time (Wang et al., 2013a; Liu et al., 2014; Zhen et al., 2016a).

2.2. Drone Assignment

Suppose that there are S base stations. To facilitate drone management, the ECA can be divided into S zones, one for each base station (see Figure 2). Given a fleet of N drones, we need to decide how many drones to assign to each base station. This mainly depends on how many ships will transit each zone. Since the ship transit patterns on different days of a week (as well as on holidays) is different, drones may need to be repositioned every day from one base station to another. The drone assignment problem decides, for each day, based on the ship transit pattern, the number of drones n_s to assign to each base station $s = 1, 2, ..., S$. In section 2.1, Eq. (1) provides the maximum "weighted" number of ships that can be inspected by n_s drones assigned to base station s. The drone assignment model, which maximizes the "weighted" number of ships that can be inspected by all of the N drones, can be formulated as:

$$\max_{n_s \text{ nonnegative integer}} \sum_{s=1,2,...,S} R_s(n_s) \tag{5}$$

subject to:

$$\sum_{s=1,2,...,S} n_s \le N \tag{6}$$

The above drone assignment model is an integer linear program. If $R_s(n_s)$ is concave in n_s, then this problem can be solved in polynomial time using the greedy algorithm proposed in Wang and Wang (2016). If $R_s(n_s)$ is not concave, then we can use dynamic programming to identify the optimal solution (Zhen et al., 2017c). In the dynamic programming procedure, there are S stages, each of which represents a base station; at each stage s, there are at most N states, each of which representing the total number of drones that have already been assigned to stages $1, 2, ..., s-1$. The running time of the dynamic programming solution is $O(SN)$, and hence the optimal solution can be obtained efficiently.

2.3. Base Station Location

In ECA, there can be many possible locations for establishing base stations for drones. A total of S base stations should be chosen from the candidate locations in order to maximize the value in Eq. (5). If there are W candidate locations, then the number of feasible solutions is $O(2^W)$. Moreover, to evaluate the quality of each solution, we need to solve the drone assignment problem, embedded with the drone scheduling problem. As a result, the base station location problem is a three-stage decision process that is extremely computationally intensive (Zhen et al., 2016b).

We can use a multi-start local-search algorithm to identify the locations to establish the base stations. The algorithm will start from many initial solutions. A local search procedure is applied to each initial solution, meaning that the solution will be repeatedly compared with its “neighboring” solutions, and be replaced by the best neighbor, until there is no neighbor that is better than it.

3. Conclusions

Drones have been identified as an efficient approach to monitor ship air pollution. Previous studies mainly focused on technical issues of using drones to monitor ship emissions from the technological perspective. Yet, the managerial perspective of the deployment of a fleet of drones is limited. This study proposed a modelling framework of drone deployment drones to inspect air pollution from ships. The framework contained three components which span operational, tactical and strategic decisions. At the operational level, the optimal schedule was designed on a real-time basis for each drone, including which ships to be inspected by the drone and when to inspect each ship. At the tactical level, the optimal assignment of drones to base stations was conducted on a daily basis. At the strategic level, we evaluated the optimal locations of base stations for drones. The proposed optimization models and algorithms would be conducive to enhancing the efficiency of drone deployment and then reducing SOx emissions from ships.

4. Acknowledgment

This research is sponsored by Environment and Conservation Fund Project 92/2017 and the Youth Program (No. 71501038), General Project (No. 71771050), Key Projects (No. 51638004) of the National Natural Science Foundation of China, and the Natural Science Foundation of Jiangsu Province in China (BK20150603). The views and opinions expressed in this article are those of the authors and do not necessarily reflect the official policy or position of any agency of government.

5. References

[1] Fung, F. Enforcement of Fuel Switching Regulations – Practices adopted in the US, EU and other regions, and lessons learned for China. Accessed April 2017 from http://www.nrdc.cn/information/informationinfo?id=168.

[2] Ning, Z. "Drone" technology update in port and ship emission monitoring and management. Accessed April 2017 from https://www.polyu.edu.hk/cee/MOVE-2016/4b-12-NING.pdf..

[3] Collum, J. Meeting the SECA Challenge. Accessed April 2017 from http://www.maritime-executive.com/magazine/meeting-the-seca-challenge.

[4] Roberts, L. Drone detection of marine fuel sulphur emissions. Accessed April 2017 from http://www.clydeco.com/insight/article/drone-detection-of-marine-fuel-sulphur-emissions.

[5] Marine Electronics and Communication. Drones lead the way in emissions compliance. Accessed April 2017 from http://www.marinemec.com/news.

[6] Kuang, Y., Qu, X., Wang, S. A tree-structured crash surrogate measure for freeways. Accident Analysis & Prevention, 77, 137-148. (2015)

[7] Qu, X., Wang, S., Zhang, J. On the fundamental diagram for freeway traffic: A novel calibration approach for single-regime models. Transportation Research Part B: Methodological, 73, 91-102. (2015)

[8] Qu, X., Zhang, J., Wang, S. On the stochastic fundamental diagram for freeway traffic: Model development, analytical properties, validation, and extensive applications. Transportation Research Part B: Methodological, 104, 256-271. (2017)

[9] Liu, Z., Wang, S., Chen, W. and Zheng, Y. Willingness to Board: A Novel Concept for Modeling Queuing Up Passengers, Transportation Research Part B, 90, 70-82. (2016)

[10] Liu, Z., Yi, W., Wang, S. and Chen, J. On the Uniqueness of User Equilibrium Flow with Speed Limit, Networks and Spatial Economics, DOI:10.1007/s11067-017-9343-4. (2017a)

[11] Liu, Z., Wang, S., Zhou, B., and Cheng, Q. Robust Optimization of Distance-based Tolls in a Network Considering Stochastic Day to Day Dynamics, Transportation Research Part C, 79, 58-72. (2017b)

[12] Huang, D., Liu, Z., Liu, P, Chen, J. Optimal transit fare and service frequency of a nonlinear origin destination based fare structure, Transportation Research Part E, 96, 1-19. (2016)

[13] Zhen, L., Wang, S., Zhuge, D. Analysis of three container routing strategies. International Journal of Production Economics, 193, 259-271. (2017a)

[14] Zhen, L., Liang, Z., Zhuge, D., Lee, L. H., Chew, E. P. Daily berth planning in a tidal port with channel flow control. Transportation Research Part B: Methodological, 106, 193-217. (2017b)

[15] Zhen, L., Wang, K., Wang, S., Qu, X. Tug scheduling for hinterland barge transport: A branch-and-price approach. European Journal of Operational Research, 265(1), 119-132. (2018)

[16] Marine Traffic. Accessed April 2017 from https://www.marinetraffic.com/.

[17]Cordeau, J. F., Desaulniers, G., Desrosiers, J., Solomon, M.M. and Soumis, F. The VRP with Time Windows. Montréal: Groupe d'études et de recherche en analyse des décisions. (2000)

[18]Desrochers, M., Desrosiers, J. and Solomon, M. A new optimization algorithm for the vehicle routing problem with time windows. Operations Research, 40(2), 342-354. (1992)

[19]Ho, S. C. and Haugland, D. A tabu search heuristic for the vehicle routing problem with time windows and split deliveries. Computers & Operations Research, 31(12), 1947-1964. (2004)

[20]Bräysy, O. and Gendreau, M. Vehicle routing problem with time windows, Part I: Route construction and local search algorithms. Transportation Science, 39(1), 104-118. (2005)

[21]Kallehauge, B. Formulations and exact algorithms for the vehicle routing problem with time windows. Computers & Operations Research, 35(7), 2307-2330. (2008)

[22]Wang, S., Liu, Z. and Meng, Q. Systematic network design for liner shipping services. Transportation Research Record: Journal of the Transportation Research Board, 2330, 16-23. (2013a)

[23]Liu, Z., Meng, Q., Wang, S. and Sun, Z. Global intermodal liner shipping network design. Transportation Research Part E: Logistics and Transportation Review, 61, 28-39. (2014)

[24]Zhen, L., Wang, S. and Wang, K. Terminal allocation problem in a transshipment hub considering bunker consumption. Naval Research Logistics, 63(7), 529-548. (2016a)

[25]Wang, S. and Wang, X. A polynomial-time algorithm for sailing speed optimization with containership resource sharing. Transportation Research Part B: Methodological, 93, 394-405. (2016)

[26]Zhen, L., Wang, S. and Zhuge, D. Dynamic programming for optimal ship refueling decision. Transportation Research Part E: Logistics and Transportation Review, 100, 63-74. (2017c)

[27]Zhen, L., Zhuge, D., Zhu, S. L. Production stage allocation problem in large corporations. Omega 73: 60-78. (2016b)