Ship Fouling Cleaning

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Ship fouling has significant adverse effects on vessel performance and environmental sustainability. Therefore, it is imperative to regularly clean ship hulls to reduce the adverse impacts of biofouling. A bi-level programming model to simultaneously optimize cleaning equipment deployment by cleaning service providers in the upper level and cleaning decisions by shipping companies in the lower level is developed to achieve the goal.

Keywords: ship fouling ; fouling cleaning ; cleaning equipment deployment

1. Introduction

Maritime shipping is a crucial component of global logistics, responsible for delivering over 80% of global trade by volume in 2022 according to the United Nations Conference on Trade and Development (UNCTAD). During shipping voyages, various marine organisms, such as algae, plants, and small animals, attach to the surface of a ship's hull, leading to ship fouling. Such ship fouling has significant adverse effects on both vessel performance and environmental sustainability. First, it increases hydrodynamic drag, which in turn increases fuel consumption and greenhouse gas emissions. Utama and Nugroho [1] provide an overview of the relationship between biofouling, ship drag, and fuel consumption. Hakim et al. [2] conclude that fuel consumption increases by about 10% in a year due to marine fouling. Second, ship fouling can facilitate the transport and introduction of non-native species, leading to ecological disturbance and potential damage to marine ecosystems. Fitridge et al. [3] show that a conservative estimate of the direct economic losses caused by biofouling on the aquaculture industry is 5%–10%. Therefore, it is imperative to regularly clean ship hulls to reduce the adverse impacts of biofouling. There are two main approaches to keeping a ship's hull clean: the first approach is to use antifouling coatings [4], and the second is hull cleaning [5][6]. Antifouling coatings, as the name suggests, involve the application of special coatings to the surface of a ship's hull to reduce the attachment of pollutants and marine organisms. These coatings typically contain additives that deter biofouling, making the surface of a ship's hull easier to clean than in the absence of such coatings. Conversely, hull cleaning involves the physical or chemical removal of pollutants and marine organisms that have already attached to the surface of a ship's hull. Methods used include scraping, high-pressure water cleaning, high-frequency ultrasonic cleaning, and chemical cleaning.

The hull cleaning process involves two parties: cleaning service providers and shipping companies. The former provide cleaning equipment and services, aiming to maximize their profits, whereas the latter decide whether and where to use the cleaning service such that their cost is minimized. To formulate the interaction between the two parties, a bi-level non-linear programming model was developed. In the upper level of the model, the service provider makes decisions regarding the deployment of equipment, considering factors such as service revenue and equipment costs. Meanwhile, in the lower level, shipping companies optimize their cleaning decisions by balancing the cost of fouling cleaning, the additional fuel cost caused by fouling, and the availability of cleaning equipment. The problem is challenging from a computational standpoint due to the interaction between the decisions at both levels and the non-linearity of the lower-level problem. To address the complexity of the problem, the bi-level non-linear model is transformed into a single-level linear model using the big-M method, a mathematical technique used in linear programming to handle constraints with binary decision variables. The transformed problem can be easily solved by the off-the-shelf Gurobi solver (version 10.0), a widely-used software package for linear programming (LP), mixed-integer linear programming (MILP), quadratic programming (QP), mixed-integer quadratic programming (MIQP), and other related optimization problems. Numerical experiments are conducted to compare the performance of the proposed solution method with a heuristic algorithm that iteratively solves the upper-level and lower-level problems in sequence until the upper-level solution remains unchanged. The results demonstrate that the proposed method, which transforms the bi-level model into a single-level model, is well suited to the problem as it significantly speeds up computation compared with the heuristic algorithm. Furthermore, the results of the numerical experiments suggest that cleaning service providers engage in partial demand fulfillment to maximize profit. In addition, it is recommended that equipment procurement be prioritized in the first year. Sensitivity analyses are performed to explore the impact of key parameters. The findings reveal that requiring full demand satisfaction results in a USD 27 million loss in profit for the cleaning service providers.

2. Ship Fouling Cleaning

Research on ship fouling has garnered attention for more than 40 years. Evans [7] summarized important findings on the biology of fouling algae, which have proven valuable for the advancement of antifouling technologies. Additionally, Callow [8] provided comprehensive information on various solution methods to combat fouling, encompassing both traditional and modern approaches. These methods include the use of antifouling paints, copper, organo-tin, tributyltin, and fluoropolymers of silicones. Since ship fouling has significant negative impacts on vessel performance and environmental sustainability, there are many studies aimed at quantifying these effects. Townsin [9] elucidated ship speed and power performance penalties caused by slime, shell, and weed separately. Monty et al. [10] assessed the ship drag penalty caused by light calcareous tubeworm fouling. Demirel et al. [11] analyzed the effect of barnacle fouling on ship resistance and powering. Coraddu et al. [12] developed a data-driven digital twin of the ship using information collected from on board sensors to predict the speed losses caused by fouling. Demirel et al. [13] investigated frictional resistance coefficients under a range of representative coating and fouling conditions. Farkas et al. [14] and Song et al. [15] carried out simulations to investigate the impacts of different fouling conditions on different ship types. The results show that the influence can vary significantly amongst different ship types. Farkas, Degiuli, and Martić [16] divided biofouling into soft and hard fouling, where the latter has greater impact. To quantify the influence of hard fouling, they developed a roughness function through simulation to measure the resistance caused by fouling. Erol, Cansoy, and Aybar [17] used data collected from all automation systems instead of noon reports to improve the measurement accuracy of the relationship between fouling and ship performance. In addition to quantifying the impacts, there are also studies investigating the effectiveness of different cleaning methods. Tribou and Swain [18] assessed the effectiveness of grooming with a five-headed rotating brush to clean biofouling. Experiments show that the effectiveness of the tool depends on the fouling condition. Oliveira and Granhag [19] investigated the maximum wall shear stress and jet stagnation pressure that do not cause damage or wear to antifouling coatings. Zhong et al. [20] conducted experiments to verify the feasibility of ultrasonic-enhanced submerged cavitation jets in the cleaning of ship fouling. Given the importance of determining the optimal timing for cleaning methods, several researchers have contributed to this field. Farkas, Degiuli, and Martić [21] address the challenge of rapidly predicting propeller performance with fouled surfaces when making maintenance schedules. Farkas, Degiuli, and Martić [22] also developed a model to rapidly predict the effect of biofouling on a ship's hydrodynamic performance during maintenance schedule optimization. Georgiev and Garbatov [23] performed conceptual multipurpose vessel design and fleet sizing considering hull form, resistance and propulsion, and other dimensions crucial to vessel design. Degiuli et al. [24] optimized the maintenance schedule for containerships considering fouling penalties under real environmental conditions. While the literature has extensively examined the effects of fouling, cleaning methods, and cleaning schedules, there remains a gap in comprehensive research that simultaneously addresses the optimal locations and timing for ship cleaning, as well as the appropriate number of devices to be deployed.

Bi-level optimization involves two levels of optimization interacting with each other (typically involving a leader in the upper level and a follower in the lower level), where the decisions made in the upper level affect the solution of the lower level and the solution of the lower level in turn influences the objective function or constraints of the upper level. Bi-level programming problems arise in many different applications, such as transportation management [25][26], facility location [27][28][29], and logistics optimization [30][31]. In the shipping industry, many problems are also formulated as bi-level models. Qi, Wang, and Psaraftis [32] conducted a comprehensive review of bi-level optimization models for air emission management in the shipping industry. Wang et al. [33] proposed a novel bi-level model aimed at optimizing the energy consumption of a fleet. The upper-level optimization model determined the loading and speed of each ship, taking into account relevant factors such as port information, the navigational environment, time requirements, and ship parameters. The lower-level problem was formulated as a dynamic model, optimizing energy consumption by considering varied environmental factors and port information. Zhu, Shen, and Shi [34] developed a bi-level multi-objective model for the allocation of carbon emission allowances. In this model, the government acted as the leader initiating the allocation process, while shipping companies served as followers and made decisions regarding carbon emissions within their operations. Yang, Pan, and Wang [35] reconstructed liner shipping networks considering the impacts of two new railway systems built under the one belt one road policy. The upper-level liner shipping company decided shipping routes while the lower-level shippers decided delivery amounts along the routes. Zhuge et al. [36] investigated the effects of different policies regarding vessel speed reduction in a port area. Four policies were compared and two bi-level subsidy design models were formulated. Ziar et al. [37] designed an environmentally friendly intermodal transportation network. The government in the upper level decided the location of dry ports, while the freight carriers in the lower level optimized shipping routes. Wang, Wang, and Zhen [38] optimized the subsidy plan for scrubbers and shore power through a bi-level mixed-integer programming model, where the government at the upper level minimized the total subsidy amount while ship operators at the lower level chose the most cost-effective energy supply. Cai et al. [39] used a bi-level mixed-integer programming model to determine the type and amount of search and rescue equipment allocated to activated stations. Although bi-level models have been widely used in maritime operation optimization involving two decision parties, no research has been conducted to explore ship fouling cleaning when cleaning service providers and ships interact with each other.

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