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Heuristics for dynamic and stochastic routing in industrial shipping

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A R T I C L E I N F O

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A B S T R A C T

Maritime transportation plays a central role in international trade, being responsible for the majority of long-distance shipments in terms of volume. One of the key aspects in the planning of maritime transportation systems is the routing of ships. While static and deterministic vehicle routing problems have been extensively studied in the last decades and can now be solved effectively with metaheuristics, many industrial applications are both dynamic and stochastic. In this spirit, this paper addresses a dynamic and stochastic maritime transportation problem arising in industrial shipping. Three heuristics adapted to this problem are considered and their performance in minimizing transportation costs is assessed. Extensive computational experiments show that the use of stochastic information within the proposed solution methods yields average cost savings of 2.5% on a set of realistic test instances.

1. Introduction

Maritime transportation is an important component of international trade, and more than seven billion tons of goods are carried by ship annually [37]. The costs related to ships can be very high, with daily time-charter rates and fuel costs that can amount to tens of thousands of USDs. Proper planning of routes and schedules is crucial for shipping companies to achieve a good fleet utilization and reduce costs. The interest in research on ship routing and scheduling has therefore quickly increased in the last decades as can be seen from the literature reviews by Ronen [30,31] and Christiansen et al. [7,8].

This paper considers industrial shipping, in which the ship operator owns or controls both the cargo to be transported and the ships performing the transportation. The focus of the operator is therefore to minimize the total transportation costs while ensuring that all cargoes are transported. The planning of ship routes and schedules in industrial shipping, as well as in the other transportation modes, is to an increasing degree performed with the assistance of optimization-based decision support systems, as illustrated by Fagerholt [10], Fagerholt and Lindstad [11] and Kang et al. [21]. In practice, this often involves using heuristic solution methods to solve deterministic optimization problems based only on known information. This is done on a continuous basis as new relevant information, such as the occurrence of a new cargo, arrives, or at given time intervals. Most algorithms for ship routing and scheduling thus solve static and deterministic versions of the problem.

In land-based transportation, the previous work on dynamic and stochastic routing has indicated that the inclusion of stochastic information within a dynamic planning process is valuable [2,16,17]. The hypothesis tested in this paper is that the potential savings observed in the previous studies on land-based transportation will carry over to the maritime setting studied here. That is, that the results of Bent and Van Hentenryck [2] and Hvattum et al. [16,17] will be reproduced, despite now considering a different routing problem. The problem studied here differs from those studied previously by having a pick-up-and-delivery structure (as opposed to only picking up and returning to a depot), a heterogenous fleet (as opposed to all vehicles being identical), the option to hire external capacity to deliver some cargoes (as opposed to minimizing the number of cargoes not transported), and using a different topology (traveling on a sphere instead of a plane).

To test this hypothesis, a discrete event simulation is used to reproduce a planning environment in which new cargo requests arrive over time. Whenever a replanning action is scheduled, heuristics are run to produce solutions consistent with currently available information. Three different heuristics are then considered. In the first heuristic, called the myopic dynamic heuristic

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(MDH), a deterministic subproblem is solved using an adaptation of the tabu search presented by Korsvik et al. [22]. This method does not utilize any stochastic information, but corresponds to actual practice for many shipping companies. The second heuristic is based on the multiple scenario approach with consensus (MSAC) of Bent and Van Hentenryck [2] and relies on generating a set of scenarios that consist of the currently known cargoes along with a sampled realization of future cargoes. Each of these scenarios is solved using the tabu search, and one of the solutions produced is selected based on a consensus function: the chosen solution is the one that is the most similar to other solutions. The third heuristic is an adaption of the branch-and-regret heuristic (BRH) of Hvattum et al. [17]. Again, scenarios are generated and solved using tabu search. Rather than selecting one of the resulting solutions, however, an iterative procedure is followed in which parts of the solution are gradually fixed in each of the scenarios until all scenarios have converged to the same solution. We test the three heuristics on a number of realistic, but randomly generated test instances.

The remainder of the paper is organized as follows. A literature review is presented in Section 2. Section 3 gives a description of the industrial ship routing and scheduling problem, including a mathematical formulation of the static and deterministic version of the problem. In Section 4 we present the three heuristics, the simulation procedure, and a tabu search that is used in all three heuristics. A computational study is presented in Section 5, while concluding remarks are given in Section 6.

2. Review of the literature

This section presents an overview of related work which is divided into three parts. We first survey work on dynamic routing problems, with a particular focus on problems that have a pick-up and delivery structure similar to that of the industrial ship routing and scheduling problem. Second, we discuss the previous work on stochastic and dynamic routing problems. Third, we review the literature on maritime routing problems explicitly incorporating stochasticity.

As explained by Psaraftis [29], a problem is dynamic if some of the problem inputs are not known beforehand but are revealed as time goes by. In these conditions, the decision maker must solve the problem in a sequential fashion by gradually adapting the solution to the new information. To this end, two main strategies can be used. One is to solve a new problem from scratch every time new information becomes available. Another one is to solve a deterministic problem with the information known at the beginning of the planning horizon and to repeatedly update this solution as the unknown information is revealed.

Dynamic vehicle routing problems have received significant attention in the literature as witnessed by the surveys of Psaraftis [28,29] and Ghiani et al. [15]. An important variant of dynamic vehicle routing is the *dynamic pickup and delivery problem* (DPDP) which arises, for example, in the management of urban courier services. In the DPDP, items must be transported between specific origins and destinations by multiple capacitated vehicles which must also respect time windows on pickup and delivery times. Some requests for transportation are known at the beginning of the horizon but others arrive dynamically as transportation is being performed. One of the first heuristics for the multi-vehicle DPDP was introduced by Savelsbergh and Sol [32]. The algorithm considers a rolling horizon and decomposes the dynamic problem into a series of static problems which are solved by a branch-and-price based heuristic. More recently, Mitrović-Minić and Laporte [25] have also developed a heuristic based on a rolling horizon framework for the uncapacitated DPDP with time windows. Again, the problem is solved as a series of static problems, and each problem is optimized with tabu search. The approach was then extended by Mitrović-Minić et al. [26] to consider a double horizon that concurrently optimizes a short-term objective of minimizing traveled distance and a long-term objective of maximizing the slack available to introduce new requests. Another heuristic combining tabu search with an adaptive memory was later described by Gendreau et al. [14]. Dynamic pickup and delivery problems have also been extensively studied in the context of passenger transportation where they are commonly referred to as *dial-a-ride problems* (see for example [24]). For a recent survey on dynamic pickup and delivery problems, we refer the reader to Berbeglia et al. [3].

When probabilistic information concerning the unknown problem inputs is available, one faces a stochastic optimization problem. Stochastic routing problems are most often treated as static, rather than dynamic, problems (see the survey of [13]). Nevertheless, the literature on stochastic and dynamic vehicle routing problems is growing quickly. The vehicle routing problem with stochastic demands is often treated as a static problem, but one variant exists where the problem is modeled as a Markov decision process. The most recent contribution is by Secomandi and Margot [34] who presented partial reoptimization heuristics for the case with a single vehicle. Thomas [36] also modeled a dynamic and stochastic routing problem as a Markov decision process, considering a single uncapacitated vehicle. The author analyzed the problem and was able to characterize the optimal policy for the case of a single dynamic customer. Based on this, a heuristic was developed. Swihart and Papastavrou [35] examined a single-vehicle pickup and delivery problem with the goal of minimizing the expected time in the system for the demands, looking at the problem both from a routing and a queueing perspective. Similar analyzes have been discussed by Bertsimas and Simchi-Levi [4] and Bullo et al. [5], showing how certain policies fare based on the asymptotic analysis. Powell [27] formulated a stochastic and dynamic model applied to truckload dispatching, where the important decision is which load to take by each truck at the current moment in time.

Ichoua et al. [19] studied a dynamic and stochastic vehicle routing problem with soft time windows, where the objective function is first to minimize the number of unserved customers and second to minimize the sum of travel time and lateness. They incorporated information from probability distributions by selectively adding dummy customers representing forecast requests to the vehicle routes. Bent and Van Hentenryck [2] considered a dynamic and stochastic vehicle routing problem with hard time windows, where the only goal is to minimize the number of unserved customers. They proposed to generate multiple scenarios, each one containing a different set of forecast requests. Each scenario is solved separately, and one of them is selected on the basis of a consensus function, yielding a distinct routing plan. Later, Van Hentenryck et al. [38] proposed calculating a regret function to determine which customer to visit next, instead of relying on a consensus function to select the solution of a chosen scenario. The idea of representing information about future events using scenarios was also pursued by Hvattum et al. [16,17], who developed two different heuristics. The problem considered was similar to that of Bent and Van Hentenryck [2], but the objective function included the minimization of the number of vehicles used and travel distance. Hvattum et al. [17] extended the problem by allowing the demand to be unknown for customers that had placed an order in advance. Schilde et al. [33] considered variants of the methods of Bent and Van Hentenryck, as well as two variants of variable neighborhood search, for a *dynamic stochastic dial-a-ride problem*. Flatberg et al. [12] considered issues arising when trying to apply heuristics for stochastic and dynamic vehicle routing problems in practice, including how to model probabilities for future events based on historical data.