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Current State and Trends in Tramp Ship Routing and Scheduling

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Current State and Trends in Tramp Ship Routing and Scheduling

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Purpose: This paper discusses the current state of routing and scheduling in tramp shipping, an important planning problem on the operational level in maritime logistics. The purpose is to report and compare the existing methods and to investigate possible future additions and improvements. Furthermore, an outlook on potential applications of machine learning for this optimization problem is given.

Methodology: In this paper an extensive literature review of reports and journal papers on cargo routing in tramp shipping of the last seven years is conducted. The wide range of findings are categorized by the different considered characteristics. The results are analyzed and trends are pointed out.

Findings: Optimization problems in tramp shipping differ in their main properties from liner shipping or classical vehicle routing problems. Thus, different approaches and implementations are required when developing or adapting existing optimization algorithms. The real-world problem is often limited in the optimization, so found solutions are improvements, but cannot fully reflect reality yet.

Originality: This paper provides a comprehensive overview of tramp ship routing and scheduling. Although optimization of routing and scheduling in liner shipping is fairly well researched, the publications on tramp shipping are sparse in comparison. This leaves room for future research, as the findings for liner shipping and vehicle routing are not directly applicable to tramp shipping.

1 Introduction

The global volume transported on sea in 2018 was 10.7 billion tons, 53.5% of which was bulk cargo and 29.4% oil and gas (UNCTAD 2019). As these cargo types are mainly transported in tramp ship mode, the significance of tramp shipping in the world trade becomes apparent. Since the competitive pressure among tramp shipping companies is high, savings through targeted planning of routes and schedules are an enormous competitive advantage. The objective of this paper is to report and compare the existing methods to the tramp ship routing and scheduling problem (TSRSP) and to identify possible future research directions. An additional outlook on potential applications of machine learning for the TSRSP is given.

In general, commercial cargo shipping is differentiated into three basic modes: liner shipping, tramp shipping and industrial shipping. In the liner mode, ships travel according to published time tables and transport cargo on the associated routes, comparable to a bus line. In tramp shipping the vessels follow the available cargoes. Sticking with the analogy, this transport mode can be compared to a taxi service. Operators in liner shipping as well as tramp shipping aim to select a route and schedule for each ship in order to maximize their profit. In industrial shipping, where the operator owns cargoes and ships, the operator tries to minimize their costs (Christiansen et al. 2007). In recent years, a shift from industrial shipping to tramp shipping could be observed (Christiansen, Fagerholt & Ronen 2004; Christiansen et al. 2013). As tramp shipping and industrial shipping both have the optimization problem of cost reduction or profit maximization by transporting spot cargoes additionally to the mandatory cargoes, industrial shipping is treated as a sub-problem of tramp shipping in this paper.

The optimization problem of tramp shipping differs in its main properties from liner shipping or classical vehicle routing problems. One of the main differences of maritime transportation and transportation on land is that ships usually operate 24 hours a day and under all weather conditions which leads to a high planning uncertainty. In addition, the demand tends to be more dynamic compared to the static planning of schedules in liner shipping (Christiansen et al. 2004). Thus, different approaches and implementations are required when developing or adapting existing optimizations. As ships operating in tramp shipping do not necessarily have a home depot, the definition of a planning period is often time and not location-dependent. This leads to cases where a planning period finishes while ships of a tramp fleet are still on voyage. The length of planning horizons varies greatly over the reviewed publications depending on whether a short-sea or a deep-sea problem was investigated. Naturally deep-sea planning problems have longer planning horizons compared to short-sea planning problems, as the travel times are considerably longer. The optimization problem of the TSRSP is often limited, so the found solutions are improvements, but cannot fully reflect reality yet.

Since the research interest in the field of TSRSP is growing steadily, more articles on the TSRSP have been published in the recent years. In the past, several literature reviews on ship routing and scheduling have been published (Ronen 1993; Christiansen et al. 2004; Christiansen et al. 2013). This paper aims at taking a similar perspective on the topic while taking the latest publications into account.

This paper is organized as follows: a problem definition as a general mathematical formulation is given in Section 2. In Section 3, different solutions

and approaches for the TSRSP are categorized and presented. Section 4 provides a brief analysis of the reviewed literature. The last section contains the concluding remarks and points out possible future research directions.

2 Problem Definition

For a better understanding of the complexity of the TSRSP as an optimization problem, a mathematical formulation of the basic TSRSP presented by Christiansen et al. (2013) is repeated here. Optional spot charters of ships are included in order to describe the basic optimization problem on which many publications are based. Although, short-sea shipping and deep-sea shipping have very different topologies and thus different planning horizons, this mathematical approach is valid for both. The set of vessels in a fleet is denoted by V and each ship by the index v. The index n denotes the number of cargoes in the planning horizon. Each cargo or node is indexed with i. The set of pick-up nodes or cargoes is described by $N^p = \{1,2,\dots,n\}$ and the set of delivery nodes by $N^D = \{n+1, n+2, \dots, 2n\}$ correspondingly. The set N^P is divided into a set of contract cargoes N^C and a set of optional spot cargoes N^O. A network is formulated as (N_v, A_v) where N_v is a set of nodes which can be visited by a vessel v, including the artificial origin and destination $o(v)$ and $d(v)$. While the artificial origin can be any point at sea or in a harbor, the destination is defined by the found solution and matches the last delivery harbor of vessel v. The set of feasible arcs for a vessel v is denoted by A_v. Thus, the set of feasible pick-up nodes for a vessel v is $N_v^p = N^p \cap N_v$ and the set of feasible delivery nodes is $N_v^D =$

$N^D \cap N_v$ accordingly. The quantity of cargo i is represented by Q_i and capacity of a vessel v is represented by K_v. The sailing time of vessel v between nodes i and j is indicated by T_{ijv}. The time window at a node i is denoted by $\left[\underline{T_i}, \overline{T_i}\right]$ with the start time $\underline{T_i}$ and the end time $\overline{T_i}$ respectively. Let R_i be the revenue for cargo i and C_{ijv} the transportation costs of vessel v between nodes i and j. Christiansen et al. (2013) define the transportation cost C_{ijv} as sailing costs and port costs at node i, though different models and approaches define the cost differently. The time at which the service on vessel v at node i starts is t_{iv} and l_{iv} denotes the load onboard of ship v after the service at node i has ended. The binary flow variable x_{ijv} indicates whether a vessel v sails from node i to node j ($x_{ijv} = 1$) or not ($x_{ijv} = 0$). This results in the following formulas:

$$\max \sum_{v \in V} \sum_{(i,j) \in A_v} (R_i - C_{ijv}) x_{ijv} \tag{1}$$

s.t.
$$\sum_{v \in V} \sum_{j \in N_v} x_{ijv} = 1, \qquad i \in N^C \tag{2}$$

$$\sum_{v \in V} \sum_{j \in N_v} x_{ijv} \leq 1, \qquad i \in N^O \tag{3}$$

$$\sum_{j \in N_v} x_{o(v)jv} = 1, \qquad v \in V \tag{4}$$

$$\sum_{j \in N_v} x_{ijv} - \sum_{j \in N_v} x_{ijv} = 0, \quad v \in V, i \in N_v \setminus \{o(v), d(v)\} \tag{5}$$

$$\sum_{i \in N_v} x_{id(v)v} = 1, \qquad v \in V \tag{6}$$

$$x_{ijv}(l_{iv} + Q_j - l_{jv}) = 0, \qquad v \in V, j \in N_v^p, (i,j) \in A_v \tag{7}$$

$$x_{i(n+j)v}(l_{iv} - Q_j - l_{(n+j)v}) = 0, \qquad v \in V, j \in N_v^p,$$
$$(i, n+j) \in A_v \tag{8}$$

$$0 \leq l_{iv} \leq K_v, \qquad v \in V, i \in N_v^p \tag{9}$$

$$x_{ijv}\left(t_{iv} + T_{ijv} - t_{jv}\right) \leq 0, \qquad\qquad v \in V, (i,j) \in A_v \qquad (10)$$

$$\sum_{j \in N_v} x_{ijv} - \sum_{j \in N_v} x_{(n+i)jv} = 0, \qquad v \in V, i \in N_v^p \qquad (11)$$

$$t_{iv} + T_{i(n+i)v} - t_{(n+i)v} \leq 0, \qquad\qquad v \in V, i \in N_v^p \qquad (12)$$

$$\underline{T_i} \leq t_{iv} \leq \overline{T_i}, \qquad\qquad\qquad v \in V, i \in N_v \qquad (13)$$

$$x_{ijv} \in \{0,1\} \qquad\qquad\qquad\qquad v \in V, (i,j) \in A_v \qquad (14)$$

The goal is to maximize the revenue in objective function (1) under the constraints (2) – (14). Sometimes, especially in industrial shipping, the objective function is defined to minimize the overall costs (e.g. Hemmati et al. (2014), Christiansen et al. (2007), Gatica & Miranda (2011), Wen et al. (2016)). The transportation requirement for the mandatory contract cargo is given in constraint (2), the requirement for the optional spot cargo is given in constraint (3). The sailing route of a vessel is defined by constraints (4) – (6). In constraint (7) and (8) the shipload onboard a vessel at each pick-up and delivery node is documented. Constraint (9) guarantees the load does not exceed the capacity of a vessel v. Constraint (10) describes the compatibility between schedules and routes for a vessel v. Constraint (11) ensures the vessel which visited the pick-up node also visits the corresponding delivery node, while constraint (12) keeps the visits in the correct order, meaning no delivery node can be visited prior to its corresponding pick-up node. The time window at a node i is defined by constraint (13). As prior mentioned, the binary variable x_{ijv} is listed in constraint (14). The combination of restrictions paired with the amount of ships and cargoes in a TSRSP, makes the routing and scheduling in tramp shipping a complex optimization problem. The TSRSP is a NP-hard problem (see Lin & Liu (2011)) and thus often solved using heuristic approaches.

3   Solutions to the TSRSP

As prior mentioned, the model for TSRSP is not uniformly defined, leading to different approaches and therefore to different solutions. Various treatments of initial ship locations or for shiploads (full-shipload, less-than shipload or mixed shipload) and diverse assumptions for example on costs or cargo constraints, make it difficult to compare approaches and solutions to the TSRSP directly. This section attempts to sort the various solution approaches to the TRSRSP according to their focus area in order to provide a good overview of the current state of research.

Hemmati et al. (2014) present benchmark instances and a benchmark generator for tramp ship routing and scheduling problems with the goal to provide test instances representing realistic planning problems. The benchmark generator is applicable to short-sea and deep-sea voyages, full-shiploads or mixed shiploads. The authors aim to provide a basis for future development of better solution algorithms, thus each presented instance includes the best known solutions for the instance specific TSRSP. Solutions are generated using a commercial mixed-integer programming solver for small-scale instances and a large adaptive neighborhood search (ALNS) heuristic for large-scale instances. The following restriction is applied when calculating the solutions: all ships sail with a fixed speed in a heterogeneous fleet with the options of spot charters.

3.1   TSRSP with Variable Speed

Several approaches in solving the TSRSP include a speed optimization or variable speeds in order to reduce fuel consumption and as a positive side

effect emissions and thus increase the overall profit of a tramp fleet. A simple mathematical model for including speed optimization in the TSRSP is provided by Fagerholt & Ronen (2013), who prove the benefits of speed optimization. Approaches with speed optimization or variable speeds are presented in more detail in this section.

The work of Castillo-Villar *et al.* (2014) is based on the model of Gatica & Miranda (2011), who introduced variable speed to a TSRSP. In the approach of Castillo-Villar *et al.* for a ship routing and scheduling problem with variable speed and discretized time windows it is assumed all cargo is known at the beginning of each planning period, thus there is no distinction between spot and contract cargoes. A heuristic based on a variable neighborhood search algorithm is proposed to solve the test instances. The values for speed and the discrete time windows are fixed in the test instances. As the results are compared to exact solutions generated with the solver CPLEX, only instances where CPLEX was able to find solutions are considered. The optimal gap to the optimal solutions is 6% to 8%. The authors do not compare their found solutions to the ones of Gatica & Miranda, so no statement on possible improvements can be made.

Wen et al. (2016) presented a branch-and-price approach for solving the TSRSP with variable speeds. To reduce the time needed for computational calculations infeasible routes are removed beforehand. A heterogeneous fleet with different speed ranges depending on the individual vessel with the following restrictions is considered: ships can either sail in ballast or in laden and other operating costs than fuel consumption (e.g. crew or maintenance costs) are neglected. The authors vary the fuel price in the calculations, resulting in the finding that the fuel price has significant influence on the calculated speed and amount of transported cargoes. Wen et

al. (2016) show that while the sailing speed is often contractually agreed between ship owner and cargo owner, allowing speed variation could improve the profit and the amount of transported cargoes. Although the approach of Wen et al. (2016) is similar to the one of Gatica & Miranda (2011), one significant difference is the calculation of the fuel consumption. While the latter only considers the sailing speed as a factor for the fuel consumption, Wen et al. (2016) calculate the fuel consumption as a function of ship-load and sailing speed.

To optimize the sailing speed for tramp ships Yu *et al.* (2017a) proposed a fast elitist non-dominated sorting genetic algorithm (NSGAII). The goal is to optimize the sailing speed under two aspects: minimization of the operation costs for the tramp shipping company, the carrier, and maximization of the satisfaction of the cargo owner, the shipper. The shipping costs are assumed to be only speed dependent, reducing the total costs to the cost of the fuel consumption, which can be lowered by reducing the sailing speed. The service satisfaction of the shipper is measured using fuzzy time windows, since it is assumed the satisfactions decreases with deviation from the desired delivery time. As the ship routes and transported cargoes are known beforehand and thus spot and contract cargo are not distinguished, Yu *et al.* do not investigate a typical TSRSP. Nonetheless, the found results are of interest, as they confirm the tradeoff between low shipping costs for the carrier, and on time delivery for the shipper.

3.2   TSRSP under Environmental Aspects

In 2018 the International Maritime Organization (IMO) adopted an initial strategy to reduce the greenhouse gas emissions. The goal is to reduce the total emissions by 50% compared to the reference year 2008 (IMO 2018).

Together with the growing environmental awareness in society, tramp shipping companies are under pressure to adapt to more environmentally friendly transportation.

Wang et al. (2019) investigate the influences of two market-based measures for CO2 reduction on operational decisions in a TSRSP with variable. They used the mathematical model presented in Section 2 extended by constraints for variable speed and charter in-options. The impacts of a bunker levy, similar to a carbon tax on profit, on average travel speed, on the amount of served cargoes as well as on the emissions are evaluated. The fuel consumption rate FC of a vessel is defined as a function of its speed s and its payload p, where A, B and C are ship-specific empirical parameters.

$$FC = (A \cdot s^2 + B \cdot s + C) \cdot (0.8 + 0.2 \cdot p) \tag{15}$$

In the bunker levy scheme, an additional tax is charged on every ton of consumed fuel. The resulting costs are subtracted from the revenue function. Test instances based on the benchmark suite of Hemmati et al. (2014) are used to investigate the bunker levy scenario further. A commercial routing and scheduling software developed by the Norwegian Marine Technology Research Institute is used to solve the instances. The authors conclude that with increasing levies and/or fuel prices, the profit, the average travel speed, the amount of served cargoes and the CO2 emissions decrease. As Wang et al. focus on the operational planning horizon, the influences of market-based measures for CO2 reduction on strategical planning are unknown.

Furthermore, the publication of Wen et al. (2017) on a general ship routing problem with speed optimization for either liner or tramp shipping should be mentioned. They considered fuel consumption as a function of ship payload and include fuel price, freight rate and costs of in-transit cargo in order

to calculate the total transportation cost with the goal to minimize the costs and thus minimize the emissions. Their test instances are solved using a branch-and-price method or a constraint programming model.

3.3   TSRSP with Extended Cargo Constraints

While most approaches to the TSRSP consider basic cargo constraints, such as deadweight restrictions of a ship, other approaches go into more detail and consider several ship restrictions or different approaches such as cargo coupling or split-loads. Considering more details leads to solutions which can reflect reality more closely, as Fagerholt & Ronen (2013) show in their publication on the basis of a TSRSP with split-loads and a TSRSP with flexible load sizes.

Fagerholt et al. (2013) look into the routing and scheduling problem of project shipping. Project shipping is considered a sub segment of tramp shipping, as cargoes tend to be more unique, e.g. parts of machinery or wind turbine blades. These cargoes lead to tougher requirements regarding the stowage onboard and more precise stowage constraints are introduced. Additionally, the authors include cargo coupling constraints. Some cargoes are coupled and can be solely accepted or rejected as a set and thus have to be evaluated as a sfithough the constraints regarding stowage and cargo coupling are fairly detailed, Fagerholt et al. neglect the deadweight restrictions of ships. They solve the TSRSP using a tabu search heuristic, which has been implemented in a tool for shipping companies (see Fagerholt 2004). The results are compared to exact solutions and show a good solution quality.

Stålhane et al. (2014) are the first to introduce Vendor Managed Inventory (VMI) to a TSRSP. According to their research replacing the standard Contract of Affreighment (CoA) with VMI could lead to combined economic benefits for charterers and tramp shipping companies. The transport conditions of most contract cargoes in tramp shipping are defined in a CoA, which defines the amount of cargoes to be transported in a fixed time frame between defined ports. Usually the payment per ton, but not the amount of cargo per ship is agreed upon in a CoA (Stopford 2003). VMI has the opportunity to introduce more flexibility in cargo quantities and delivery times and could improve the whole supply chain. The authors develop a hybrid approach with a priori path generation of all feasible routes and a branch-and-price network which generates the schedules dynamically to solve the basic TSRSP with VMI. The results are compared with exact route generation instead of the proposed heuristic route generation. Stålhane et al. conclude that the VMI could increase the profit for tramp shipping companies significantly, especially if the market is poor and few spot cargoes are available, although the realization of VMI in the tramp market is questionable.

Hemmati et al. (2015) develop a method to solve realistic scaled instances based on the preliminary work of Stålhane et al. (2014). They introduce a two-phase heuristic, which first converts the inventories into cargoes. The routing and scheduling problem is then solved using an ALNS method. In order to reduce the computing time, feasible combinations are clustered by a k-means algorithm and subsequently solved using the ALNS algorithm. In the second phase the solution is analyzed, then the cargoes are updated, and an iteration process is started. Using the described heuristic, Hemmati et al. achieve shorter computational times and show that the benefit of VMI

depends on the fleet composition, the number of spot cargoes available, and the amount of contracts converted to VMI.

Besides Fagerholt et al. (2013), Stålhane, Andersson & Christiansen (2015) also investigate project shipping with cargo coupling and include synchronization constraints in addition. Synchronization constraints define restrictions with regard to delivery times of the first and the last cargo of a set. A branch-and-price method is used to solve the routing and scheduling problem. The results are benchmarked against the ones of Andersson, Duesund & Fagerholt (2011), as the same test instances are used. The authors prove a bench-and-price algorithm reduces the computational time. They conclude that large-scale instances in project shipping are simpler to solve than for example in regular tramp shipping, as the cargo ship capability restrictions are stricter, leaving less feasible cargoes.

3.4   TSRSP with Bunkering Decisions

The tramp ship routing and bunkering problem is a niche problem in the TSRSP, but no less important. The fuel consumption causes the main variable costs of a tramp ship voyage, therefore a bunkering strategy and buying fuel cheaply can lead to a competitive advantage.

Vilhelmsen, Lusby & Larsen (2014) investigated the influence of integrating bunkering decisions in the TSRSP in order to maximize the profit. They consider spot and contract cargo with the following restrictions: ships can sail either in ballast or full shiploads and each ship sails at the most economic, most cost-efficient speed. Thus, ship speed as well as costs are calculated dependent on the shipload. A dynamic column generation is used to solve the TSRSP with bunkering decisions. The developed solution is tested on instances with variable percentage of spot cargo and different bunker

prices. Vilhelmsen et al. (2014) discover that the fluctuations of bunker prices have the most effect on instances with a high percentage of spot cargo, as contract cargo has too many restrictions to choose from different ports to bunker.

Meng, Wang & Lee (2015) examine the TSRSP under the goal to determine the amount fuel to bunker at each port in order to maximize the profit using a branch-and-price method. Although the approach is similar to Vilhelmsen et al. (2014), several differences can be pointed out. Meng et al. assume fixed travel speed and do not allow detours for bunkering. Solely loading and unloading ports can be used for bunkering. The test instance are randomly generated.

Although Besbes & Savin (2009) do not study the classical TSRSP (according to the definition in Section 2), their groundwork for refueling decisions in liner and tramp shipping are worth mentioning here. They included stochastic bunker prices which creates further complexity in optimal routing decisions. Therefore, concerning tramp shipping the authors investigate a single ship and not a fleet with deterministic sailing time between ports and consider only spot cargoes.

3.5   TSRSP under Uncertainties

Maritime operations are subjected to different kind of uncertainties, which affect routing and scheduling of ships. Examples for such uncertainties are weather factors, cargo demand, or waiting time for berth at harbors. Some authors include uncertainties in the TSRSP to improve the overall quality of routing and scheduling in tramp shipping.

Guan et al. (2017) take uncertain time windows in the TSRSP into account. They conduct a survey on the waiting time of ship for berth and focused

their study on harbors with a large export volume. Neither the definition for waiting time on berth nor the quantification for large export volume is given which results in a lack of clarity and preciseness. Guan et al. use a column generation algorithm to solve large-scale test instances with a homogeneous fleet and fixed speed. The information generated from the survey combined with the time a ship owner is willing to spend waiting for berth is used to generate and assess random waiting days for each test instance. The aim of this publication is the classification of ships in the fleet into three categories: (1) long time charter, (2) short time charter and (3) no further decision at the current point of time.

Yu et al. (2017b) take two uncertainties into account while solving the TSRSP. First, Seasonal fluctuations of demand are considered in the form of freight rates, which change every three months in the test instances and thus influence the profit of a tramp shipping company. Second, weather conditions are included in form of statistics. Yu et al. permit the possibility of discarding contract cargoes under a penalty factor in order to maximize the profit during a planning period. This is a questionable choice in practice, as a tramp shipping company could damage their reputation beyond the planning horizon by abandoning contract cargoes. A genetic algorithm is applied in order to solve different test instances with static cargo demand and uncertain cargo demand in form of additional available cargoes during the planning horizon. The profit increases with decreasing penalties for discarding contract cargoes and static cargo demand, which is to be expected. Yu et al. do neither compare their results to an exact solution nor to real-life data.

By including a choice inertia of cargo owners, Zhao & Yang (2018) try to eliminate one uncertainty in tramp shipping. The authors assume that the

past decisions of cargo owners remain in their memory and will affect current decisions when choosing a tramp shipping company on the spot market. The market share of a tramp shipping company on a segment between two ports is calculated by a logit model and based on the size of the company and the number of completed voyages on this specific segment. Zhao & Yang include quarterly fluctuations of the freight rate as a function of the sailing distance and a seasonal factor, which was found using data fitting based on the Baltic Dry Index of 2015. To solve the TSRSP, a genetic algorithm is used. The influences of the choice inertia and of the fluctuations in the freight rate are tested in a test case with a homogeneous fleet and fixed sailing speed considering only spot cargoes. The found results include more than 40% ballast voyages for each ship in the planning horizon of one year. The authors conclude from these results that ballast voyages pay off by securing a greater market share on a specific segment between two ports when looking at the whole planning period.

3.6   TSRSP with Miscellaneous Extensions

In this section several approaches on solving the TSRSP, which do not fit in the previous presented categories, are listed.

An uncommon approach to the TSRSP is chosen by Moon, Qiu & Wang (2015) in form of a hub-and-spoke-network for container ships. Usually container ships operate in liner shipping mode, which might not be economically profitable for ultra large container ships (ULCS) with more than 10.000 TEU capacity. In order to fully utilize a ULCS, the authors suggest that feeder container ships travel between spokes and hubs in order to collect cargoes for ULCS, which travel between hubs. To create a network design

as well as solving the TSRSP, a genetic algorithm is used. In each test instance all demands are known beforehand, all cargoes have to be transported and time windows are neglected. The results show a significant reduction of the computing time with equally good results compared to the solver CPLEX.

Armas et al. (2015) adopted the modeling approach of Gatica & Miranda (2011) and also the one of Castillo-Villar et al. (2014) without variable speed. They proposed a hybrid heuristic consisting of a greedy randomized adaptive search procedure to find initial feasible solutions and a variable neighborhood search, which is used to improve the found solutions. Armas et al. (2015) compare their results with the ones of Castillo-Villar et al. (2014), as they neglect the variation of speed in their test instances. Additionally, the found solutions are benchmarked against exact solutions. The solution quality and computing time could be improved significantly, but both depend on the level of discretization of the time windows.

Vilhelmsen, Lusby & Larsen (2017) investigate the TSRSP with voyage separation requirements. These ensure a time-wise evenly-spread of similar voyages, which is a common requirement in CoAs. They presented a mixed-integer programming formulation consisting of a dynamic column generation algorithm and a branch-and-price method. The authors assume fixed speeds for full shipload and ballast cases in all test instances. The results show that including voyage separation requirements has a minimal negative influence on the profit, but can represent reality more closely.
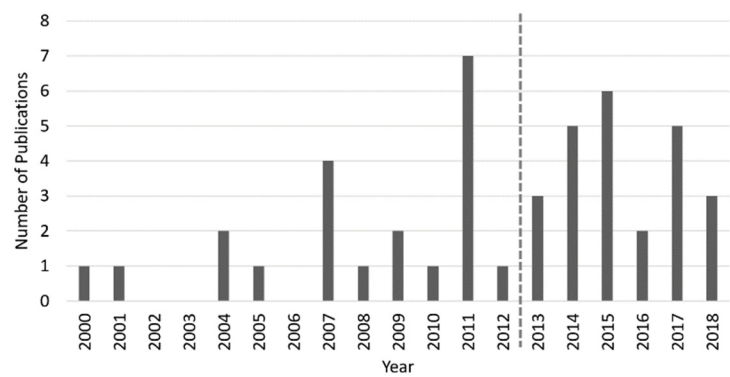
Figure 1: Publications on the TSRSP since 2000, including grey literature

4   Methodology and Analysis of the Literature Review

This section aims to describe the methodical approach of literature search and to analyze the reviewed publications. Similar restrictions as in prior literature reviews (see Section 1) are applied: this review includes literature focusing on cargo routing in tramp shipping published from 2013 until May 2019 in English in refereed journals, books, or conference proceedings. Online search tools (e.g. "Scopus", "Google Scholar") were used to search for the terms "routing", "scheduling", and "tramp shipping" or variations thereof. During the search process the snowballing technique in which new publications are discovered by searching the references of relevant papers was applied (Booth, Sutton & Papaioannou 2016).

Figure 1 illustrates the increase in publications fitting the search criteria since 2000, publications from 2019 are omitted in this Figure, since the year is ongoing. The dashed line marks the lower time limit set in this paper. This

overview includes unreviewed publications. The increase in publications is related to the cost pressure associated with the shipping crisis, as well as rising crude oil prices. Although the search has been carried out thoroughly, it cannot be ruled out that individual publications may have gone unnoticed. Since the literature analysis is limited to a period of less than seven years, long-term trends cannot be detected.

Table 1: Test Instance Parameters by Publication

Publication	Planning Horizon in Days	Number of Ships	Number of Cargoes
Wang et al. (2019)	-	6 to 20	25 to 50
Zhao and Yang (2018)	365	6	-
Guan et al. (2017)	300 to 360	17	94
Vilhelmsen, Lusby and Larsen (2016)	90 to 150	10 to 32	4 to 13
Wen et al. (2017)	-	3	6 to 31
Yu et al. (2017)	-	1	4
Yu, Wang and Wang (2017)	365	5 to 25	500
Wen et al. (2015)	30 to 90	20 or 32	40 to 160
Armas et al. (2015)	-	4 to 7	30 to 50
Hemmati et al. (2015)	-	4 to 8	10 to 30
Meng, Wang and Lee (2015)	-	20 or 40	20 to 60

Publication	Planning Horizon in Days	Number of Ships	Number of Cargoes
Moon, Qui and Wang (2015)	-	-	-
Stålhane, Andersson and Christiansen (2015)	-	3 or 4	10 to 32
Stålhane et al. (2014)	-	4	6 to 15
Christiansen and Fagerholt (2014)	-	-	-
Hemmati et al. (2014)	-	3 to 50	7 to 130
Vilhelmsen, Lusby and Larsen (2014)	30 to 60	7	30 to 60
Castillo-Villar et al. (2014)	-	4 to 7	30 to 50
Fagerholt et al. (2013)	-	2 to 8	6 to 63

For a brief overview on the reviewed literature, the different parameters of test instances by publication are listed in Table 1. If the planning horizon is not fixed, the element in the Table is marked with a dash ("-"). The size of test instances for each proposed solution for the TSRSP varies greatly, depending on problem definition and the used data. This makes a comparison of the solution quality and applied
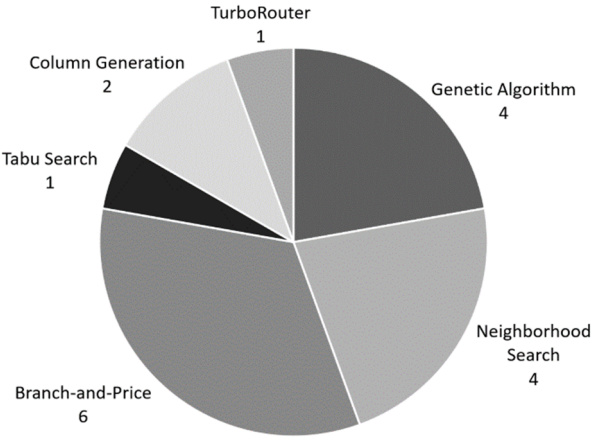
Figure 2: Quantitative comparison of the used methods respective solvers

algorithms impossible, e.g. larger test instances tend to require more computing time and are generally more difficult to solve. An overview of the methods used to solve the TSRSP in the presented publications is shown in Figure 2. This comparison of the ratios of each algorithm type aims to demonstrate the common applied algorithms. The branch-and-price method is used in six of the reviewed publications and the most popular, as its combination of column generation and branch-and-bound algorithm leads to short computing times. A trend wave of using genetic algorithms to solve the TRSRSP is observed, as all reviewed publications using genetic algorithms have been published between 2015 and 2017.

5   Outlook and Concluding Remarks

An extensive literature review of reports and journal papers on tramp ship routing and scheduling of the last seven years is conducted. The wide range of findings is categorized by the different considered problem characteristics and an overview on the current state of research is provided. This section recaps and presents future research directions.

A general trend in publication on the TSRSP is the use of randomly generated data. The use of artificial data can be attributed to the lack of real-life data, but implies the risk of developing impractical solutions for real-world problems. Although instance generators are provided (see Hemmati et al. 2014), without real-life data no statements about actual improvements in the day-to-day planning business can be made. A continuous trend is simplification of mathematical models, which are certainly easier to solve but far from real conditions as Fagerholt & Ronen (2013) state. Psaraftis (2019) sees possible future improvements if the focus is shifted from the development of solution methods to modeling processes of the real-world problem. An increase in applications of machine learning methods as a solver to the TSRSP can be observed, but leaves still room for further research directions.

The stowage onboard is crucial for the ship stability and hence for the safety of crew and environment. The solution with the greatest profit does not necessarily have to meet the legal requirements of ship stability, but this is rarely taken into account. Introducing stability constraints regarding cargo could lead to more realistic solutions of the TSRSP in future research. Another open question is how a cargo priority scheme which goes beyond the classification of spot and contract cargo can be formulated.

A few publications include seasonal fluctuations of demand or patterns in freight rates, although these affect the revenue in tramp shipping business directly. Future studies on not only seasonal, but also geographical fluctuations could improve and raise the operational TSRSP to a tactical level. With better knowledge on seasonal and geographical patterns, tactical ship allocation to regions or decisions on charter contracts can be made more effective. Further research needs to investigate how waiting times for berthing influence the profitability of cargoes. Since available real-life data on TSRSP is limited, a higher data accuracy or a larger amount of data can be achieved through the additional use of data from the Automatic Identification System (AIS). AIS data enables researchers to predict travel times on specific routes, which enables improved speed prediction and thus leads to a better assessment of fuel consumption. This opens up new opportunities for tramp shipping companies, as they are able to select cargoes based on more exact forecast of shipping costs.

In summary, the TSRSP offers many opportunities and possibilities for further research and improvement on a methodical as well as on a practical level.

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